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Data-driven artificial intelligence applications for tyre-road-noise prediction and road condition monitoring: A review and future directions

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ABSTRACT

Noise is an important environmental issue that affects quality of life and health, especially in urban areas. With the widespread adoption of electric vehicles, engine noise inside the car has decreased significantly, making tyre-road noise the main noise source, which also accounts for a large proportion of traffic noise. The powerful tool that is artificial intelligence (AI) has emerged in recent years for noise management and monitoring. AI-based systems can classify noise sources, create noise maps and develop control strategies. As a result, some studies have focused on improving road, vehicle mechanics, and tyre textures and improving the sound quality of tyre-road noise. However, research specifically on tyre-road noise prediction is quite limited. Studies in the literature have generally focused on predicting road damage, surface quality and weather conditions, with less emphasis on tyre-road noise prediction. Many of these studies estimate tyre-road noise by modeling. However, it is not possible for modeling to capture real environment data. Therefore, more data-based studies on tyre-road noise optimization, monitoring and prediction are needed in this area. This paper focuses on data-based studies and is a discussion of techniques such as data acquisition, feature extraction and selection, and artificial intelligence algorithms that have been or could be used in this area. Data-driven artificial intelligence methods, such as deep learning, are highlighted for their significant potential in tyre-road noise monitoring and prediction. As a result, future research is expected to focus more on deep learning applications, opening new perspectives for further development in this field..

1. Introduction

Noise has been widely studied by researchers, companies and municipalities due to its strong impact on health and environmental quality. Studies have examined acoustic comfort in cities [1], classrooms [2], and vehicles [3–5], as well as health impacts such as sleep disturbance and cardiovascular risks [6,7]. Environmental noise has also been investigated in noise mapping, real-time monitoring and AI-based assessment [8–10]. These studies have covered different sources, including railroads, ports and airplanes, and have evaluated mitigation methods such as noise barriers [11–13].

Among transportation-related noise sources, engine and powertrain noise has traditionally been the most significant source, particularly in internal combustion engine vehicles [14]. In recent years, with the widespread use of electric vehicles (EVs), the overall noise profile of vehicles has changed [15]. While EVs reduce engine-related noise at low speeds [16], other sources such as tyre and aerodynamic noise, become more prominent as vehicle speed increases.

Abbreviations: **OBSI**, On-Board Sound Intensity; **CPX**, Close Proximity Method; **GMM**, Gaussian Mixture Model; **RF**, Random Forest; **GBM**, Gradient Boosting Machines; **PSD**, Power Spectral Density; **RFE**, Recursive Feature Elimination; **L0**, Zero-Norm Minimization; **RVM**, Relevance Vector Machine; **PSC**, Power Spectrum Coefficients; **MFCC**, Mel-Frequency Cepstrum Coefficients; **LPC**, Linear Predictive Coefficients; **PCA**, Principal Component Analysis; **WT**, Wavelet Transform; **OCT**, Octave Frequency Spectrum; **SVM**, Support Vector Machine; **LDA**, Linear Discriminant Analysis; **CNN**, Convolutional Neural Networks; **ANN**, Artificial Neural Networks; **DAE**, Denoising Autoencoder; **RNN**, Recurrent Neural Networks; **LSTM**, Long-Short Term Memory; **RFC**, Random Forest Classifier; **HC**, Hierarchical Clustering; **LR**, Logistic Regression; **KNN**, K Nearest Neighbors; **LBP**, Local Binary Pattern; **FFT**, Fast Fourier Transform; **STFT**, Short-Time Fourier Transform; **SVR**, Support Vector Regression; **PDF**, Weibull Probability Density Function; **DWT**, Discrete Wavelet Transform; **BPF**, Band Pass Filter; **HW**, Hamming Window; **CA**, Cepstrum Analysis; **PLP**, Portable Laser Profiler; **PL**, Profiling Laser; **OS**, Optical Sensor; **LS**, Laser Scanning; **PCR**, Principal Component Regression; **OLS**, Ordinary Least-Squares Regression; **FGM**, Fourier Correction Grey Model; **TPIN**, Tyre–Pavement Interaction Noise; **GRU**, Gated Recurrent Unit; **IRI**, International Roughness Index; **MFCC**, Mel-Frequency Cepstral Coefficients.

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When combined, these noises from vehicles present a significant environmental noise problem in large cities. Road traffic noise is one of the main causes of environmental noise in urban areas and is a major issue affecting the quality of life for residents [17]. Among the various sources of transportation noise, tyre-road interaction is considered one of the most important causes. Research on this noise is a broad and multidisciplinary field, and tyre-road noise and its underlying mechanisms, their optimization, prediction, and reduction are being investigated.

Since the mid-1970 s, the focus of modern research has been on tyre-road interaction noise for the reduction of engine noise and the improvement of car aerodynamics [18]. The goal is to understand the effects of various parameters on noise levels, which could impact noise management and urban planning [19]. Recent modeling studies have investigated texture-based prediction of tyre–road noise [20]. However, although many modeling studies have been carried out on tyre–road noise [21,22]They are not discussed in detail here, as the present study follows a data-driven approach. Conventional measurement techniques are frequently laborious and time-consuming, thus necessitating the development of more efficient methodologies [23]. To address this, some systems provide an efficient, non-intrusive solution for monitoring road conditions, which is crucial for vehicle safety and maintenance planning [24].

Several factors influence tyre-road noise, including road surface texture [25], tyre tread patterns, vehicle speed, and environmental conditions [26]. Recent research has also examined new contexts. For instance, Huang et al. (2023) looked at how to predict and improve the noise made by electric cars (EVs) when they are on the road. They used a mix of knowledge and data to deal with the noise problems [27]. The acoustic performance of asphalt concrete in urban roads was studied by Paje et all (2008). Researchers aim to evaluate sound absorption and noise reduction in urban areas with significant traffic noise problems [28]. Li et al. (2024) improved the accuracy of the structural health monitoring system by including tyre-road noise interaction in the acoustic emission monitoring of bridges [29].

Among various factors affecting tyre-road noise, temperature has been particularly highlighted in recent studies. Bueno and colleagues (2011) investigated the effect of pavement temperature on tyre-road noise and emphasized the importance of this factor in road design and noise management [30]. The relationship between temperature and road traffic noise was investigated by Sánchez-Fernández et al. (2021) under steady traffic flow conditions. It has been shown by the study that the propagation of road traffic noise is significantly affected by changes in ambient temperature [19]. That's exactly why a lot of studies use temperature as the input parameter.

When reviewing the literature, it is evident that tyre-road noise data have been increasingly used to predict road conditions, detect surface problems, and estimate weather-related parameters. With the increasing availability of big data and high-volume sensor information, it is now possible to significantly enhance algorithm performance and accuracy. At this point, deep learning algorithms offer greater potential. When the studies in this field are examined, a small number of deep learning algorithms have been implemented in tyre-road noise. This observation highlights a clear research gap and the need for further investigation.

This study therefore presents a comprehensive evaluation of existing research, focusing on the monitoring part of it and discussing the application of new deep learning, performance increase, feature extraction and selection, and signal processing techniques. Specifically, the primary objective of this analysis was to provide researchers with information that would help them identify the artificial intelligence techniques that deserve the most attention in future research on tyre-road noise prediction and condition monitoring. These studies demonstrate that tyre-road noise is a complex issue influenced by numerous factors, such as environmental conditions, road structure, and vehicle-related parameters. Despite this diversity, most studies still rely on traditional measurement and modeling methods rather than data-driven approaches.

This study analyzed research based on tyre-road noise and the use of artificial intelligence (AI) for its prediction and classification. Studies not directly related to tyre-road noise were excluded to avoid including irrelevant topics. The search covered the title, abstract, and keyword fields, and data were collected from the Web of Science, Google Scholar, and Scopus databases. To ensure data quality, duplicate and irrelevant document types, such as short notes, some conferences, low-quality journal publications, and editorials, were removed.

The keyword analysis was carried out using VOSviewer, based on the following Scopus query:

TITLE-ABS-KEY("tyre-road noise" OR "tyre pavement noise" OR "road surface classification" OR "road condition monitoring" OR "road texture prediction" OR "road roughness prediction" OR "road sound absorption coefficient estimation" OR "road friction estimation") AND ("machine learning" OR "deep learning" OR "artificial intelligence"). Topics such as traffic noise, urban noise, noise pollution, and the effects of noise on health and other areas are not the main focus of this study. Because there are many studies on these subjects, a filtering process was applied. This work mainly concentrates on data-driven, on-board tyre–road noise approaches. As indicated by the selected keywords, the reviewed studies specifically focus on artificial intelligence applications and tyre–road noise monitoring.

The results (Fig. 1a) showed three main research directions: (i) noise measurement and acoustic analysis, (ii) AI-based prediction and surface classification, and (iii) intelligent transportation and road monitoring. While key terms such as machine learning, deep learning, and convolutional neural networks are seen as having central importance, tyre-road noise, asphalt, and acoustic noise have emerged as specific application areas. This indicates that AI techniques are becoming more common in noise and surface analysis studies. In addition, a trend analysis of publications between 2015 and 2025 was performed (Fig. 1b). The number of studies increased significantly after 2020, showing the growing interest in using AI for tyre-road noise prediction and road condition analysis.

2. General evaluation of literature studies

Before exploring AI-based methods, it is essential to understand the fundamental research that has been conducted on tyre-road noise and its influencing parameters. Previous studies have investigated the tyre–road interaction from various perspectives, focusing on tyre–road noise, in-vehicle noise, road texture and surface quality, macrotexture characteristics, pavement materials, road anomalies, road surface classification, tyre tread patterns, as well as signal processing and machine learning algorithms.

Tyre-road noise is a significant concern for both companies and researchers. Which is why numerous studies have been conducted on this topic. Many review articles have been written to summarize and evaluate these studies. We will examine some review articles that are directly related to this topic. Li (2018) reviewed various techniques for measuring tyre-road interaction noise (TPIN), classifying them based on test environments: roadside, on-board, and laboratory [18]. Li (2018) confirmed that tyre and pavement characteristics affect tyre-road noise. Recommendations include smoother pavements, optimized tread patterns, and consideration of environmental conditions [31]. Several studies have examined the use of AI techniques for predicting, classifying, and diagnosing tyre-road noise. For example, Jia et al. (2023) demonstrated the effectiveness of combining convolutional neural networks (CNNs) and support vector regression (SVR). They used this combination for noise prediction and reduction in electric vehicles. CNNs were used for feature extraction. SVR was used for accurate noise level prediction [32]. The objective of the study by Hong et al. (2018) was to predict tyre-road noise. To accomplish this, they examined the texture characteristics of asphalt surfaces. They analyzed the relationship between texture characteristics and noise levels to develop a

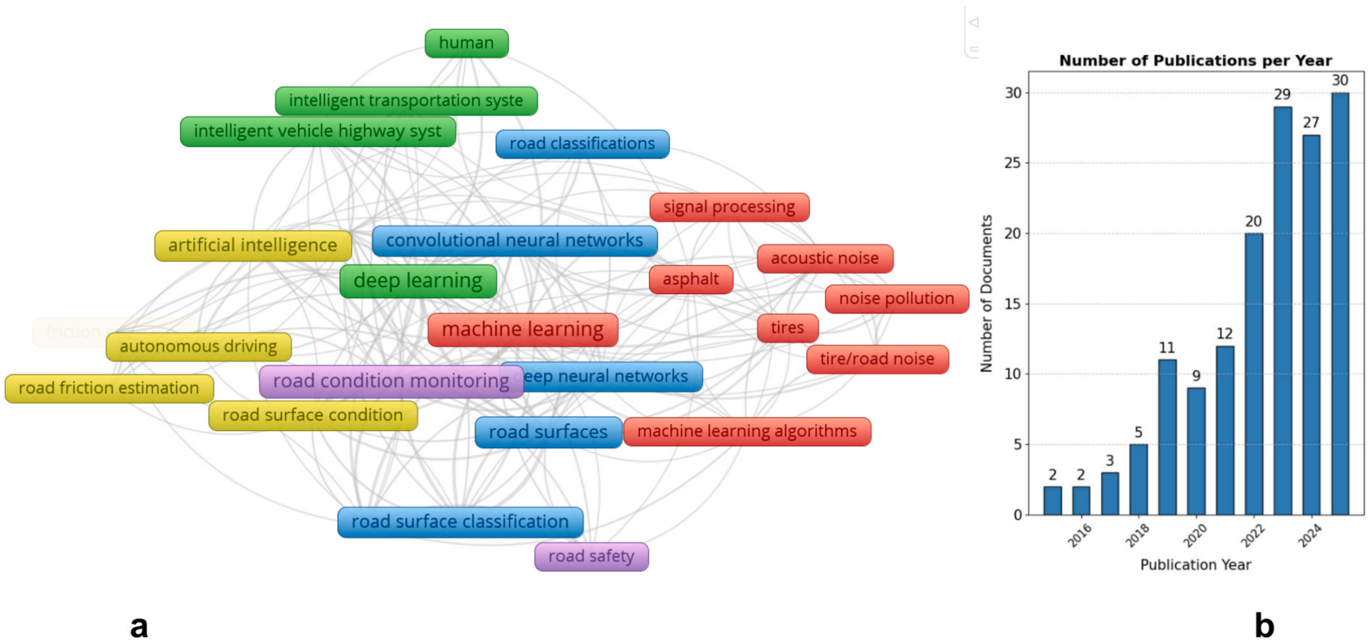

Fig. 1. Publication trend and connection of AI-based studies related to tyre–road monitoring between 2015 and 2025.

predictive model [33].

In addition to research on tyre-road noise, noise inside the vehicle cabin has also been the subject of numerous studies. In-vehicle road noise is an important factor affecting driving comfort. In 2020, Kamineni and Chowdary's research focused on developing methods to reduce in-vehicle noise, particularly noise caused by the interaction between tyres and the road surface. They noted in their study that factors such as tyre design, road surface characteristics, and vehicle speed affect vehicle interior noise, which in turn affects passenger comfort [34]. Pang et al. (2024) proposed a new method for predicting and analyzing vehicle interior road noise. They combined mechanical modeling and time series data analysis [35].

Additionally, studies have been conducted on texture and surface quality. Vázquez et al. (2020) analyzed tyre-road noise, texture, and vertical acceleration to evaluate urban road surfaces. Understanding these relationships can help design better suspension systems for passenger comfort and develop noise reduction strategies [36]. Yintao et al. (2016) examined the sources and characteristics of driving noise generated by heavy truck tyres.). The study analyzed the effect of tyre tread designs, road surfaces, and additional elements to provide guidance for minimizing noise emissions [37]. Li (2020) discussed separating tyre-road noise into tyre tread noise, which is effected by tyre design, and road texture noise, which is affected by surface irregularities [38]. De León et al. (2020) experimentally investigated the interaction between pavement texture and tyre–road noise using CPX and profiling measurements, confirming that surface characteristics strongly affect spectral noise behaviour [39]. Further research by Praticò (2014) demonstrated the strong relationship between pavement texture, porosity, and overall acoustic performance, emphasizing their role in noise emission reduction [40]. Holzmann et al. (2006) proposed a method for predicting the tyre-road friction coefficient using noise data [41]. Ganji et al. (2021) compared noise processing methods to assess their effectiveness in evaluating pavement macrotexture [42]. Researchers evaluated road quality, road material, and weather conditions as input parameters and examined their effects on noise. However, most research in this field has been conducted without the use of AI.

Macrotexture is an additional variable that affects tyre-road noise. It is very important in terms of road safety, fuel efficiency, and noise pollution. Since traditional measurement methods are labor-intensive and costly, researchers have investigated acoustics-based approaches [43]. Over time, factors such as traffic load, weather conditions, and material wear degrade the noise reduction capability of road surfaces [44]. Ohiduzzaman et al. (2017) investigated how the texture, material, and condition of the road surface affect tyre-road noise. They found that open-graded asphalt reduces noise most effectively, while dense-graded asphalt and concrete produce significantly higher noise levels [45]. Wang et al. (2022) presented a method using 3D imaging technology to predict tyre-road noise. This method effectively captures the details of the road surface and helps design quieter road surfaces [46]. De León et al. (2022) presented a CNN-based approach to reconstruct road surface elevation maps from optical images and provided an innovative AI-based framework to evaluate pavement texture and its acoustic effects [47] However, this method requires specialized equipment and precise calibration to ensure accurate measurements. Additionally, external factors such as wind and temperature can also affect the results. These factors highlight the importance of maintaining controlled test conditions [48].

Researchers have sought to identify the best design and materials to minimize noise. Initially, significant noise reduction was achieved with crumb rubber surfacing compared to traditional asphalt surfaces. The acoustic durability of a modified coating surface with crumb rubber to reduce environmental noise was evaluated by Vázquez et al. (2016). The focus was on how well the coating surface maintained its noise reduction properties over time [49]. In a study by Merska et al. (2016) investigatedlow-noise thin road surface coatings and reported noise reductions of several decibels compared to conventional surfaces,and it was found that road traffic noise could be significantly reduced with optimized coating designs [17]. The effect of recycled crumb rubber on reducing coating noise was investigated by Paje et al. (2013). According to tests, crumb rubber pavements significantly reduce road traffic noise compared to traditional materials [50]. In their 2019 study, Ganji et al. investigated the potential of road noise to evaluate the macrotexture of dense-graded asphalt pavements in their study. They used statistical and machine learning methods to investigate the correlation between noise characteristics and macrotexture [23]. The noise-reducing properties of bituminous slurry containing dry-processed crumb rubber were investigated by Bueno et al. (2014). The slurry has shown potential in noise reduction due to its ability to effectively minimize road traffic noise [51].

The studies have made it possible to predict not only tyre-road noise but also road anomalies. Masino et al. (2017) classified road surfaces and evaluated tyre wear using acoustic measurements of tyre void and artificial neural networks (ANN) [52]. Li et al. (2024) investigated the potential of using tyre-road noise to predict crack damage in asphalt pavements. They evaluated the effectiveness of various machine learning algorithms for this task [53]. Identifying wet road surfaces is crucial for improving vehicle safety and preventing accidents. However, studies typically aim to determine road conditions using noise data. An on-board system for identifying wet road surfaces was investigated by Alonso et al. (2014) through the analysis of the noise generated by the interaction between tyres and the road [54]. Kalliris et al. (2019) studied how machine learning algorithms can be used to identify wet road surfaces using acoustic measurements [55].

Many studies have been conducted based on image or sensor data for road surface classification. However, it is not possible to review all of them here. Therefore, only studies closely related to tyre–road noise have been examined. Masino et al. (2017) applied support vector machines. They also used tyre cavity acoustic measurements. They used these to classify road surfaces. They based this classification on acoustic signals [56,57]. The classification of urban road surfaces was explored by Ramos-Romero et al. (2022) through the analysis of tyre-road noise. Various surfaces were sampled, including asphalt, concrete, and cobblestone [58]. In 2023, Lee et al. presented an artificial intelligence (AI) model that can identify 13 different types of roads in real time. This model uses a feature called tyre-road interaction noise to understand how tyres and roads interact, which is particularly useful for autonomous vehicles. The model integrates continuous wavelet transform and convolutional neural network (CNN) technologies [59]. In recent years, tyre–road noise and road image together have also been used for road surface classification. Lee et al. (2024) adopted this approach by developing an artificial neural network model that combines tyre–road noise with road surface images. Since the noise signal directly reflects the roughness and material characteristics of the pavement, the study achieved high classification accuracy (96.84 %) using MFCC-based acoustic features [60].

Researchers have also studied how tyre patterns make noise when the tyres are on the road. Researchers aim to provide insights into how to design quieter tyres and reduce noise pollution by analysing the acoustic characteristics and their relationship to human perception. By incorporating noise prediction early in the design process, manufacturers can develop quieter tyres and contribute to overall noise reduction. Lee et al. (2021) presented a method. It uses convolutional neural networks (CNNs). The method predicts tyre pattern noise. It predicts noise during early design stages. The aim of the study is to have tyre pattern noise be estimated based on tread patterns so that designs for noise reduction can be optimized before physical prototypes are created [61]. The external noise of truck tyres was the focus of an investigation by Marin-Cudraz et al. (2024). The study examined timbre parameters and the factors that contribute to noise unpleasantness. Their study examines how characteristics such as pitch, roughness, and tonal content affect the perceived annoyance of tyre noise(external) [62].

Various sensors produce complex signals that require processing before analysis. These sensors include accelerometers and microphones. These signals are often difficult to interpret. These signals must be made more understandable. Additionally, they must be prepared for analysis. Signal processing algorithms are essential for this because they allow us to transform signals in a way that allows us to detect and analyze specific patterns. There are several ways to accomplish this. Examples include time–frequency analysis, the fast Fourier transform (FFT) [63], and analysing frequency components, amplitude, and power spectral density [56], as well as short time fourier transform(STFT) and wavelet transform [29]. Since using raw signals or data from all sensors directly is not always feasible, feature extraction algorithms are crucial. Examples of feature extraction techniques include time-domain features such as peak amplitude, RMS value, energy, and statistical models [27]. Other techniques include time-domain analysis [54] and signal duration analysis [53].

There are a lot of machine learning algorithms that are used in this field for prediction, classification, and detection tasks. The following are some of the commonly used methods: support vector machines (SVM) [56], K-means, density-based spatial clustering of applications with noise (DBSCAN) [58], decision trees [26], random forests [53], neural networks [53], regression [23], convolutional neural networks (CNNs) [24], K-nearest neighbors (k-NN) (Freitas et al., 2015), support vector regression (SVR) [32], hierarchical clustering [58], and gradient boosting machines (GBM) [53]. In recent years, the increase in available data has led to a growing use of deep learning algorithms in vehicle noise prediction studies. Most of these works aim to reduce interior noise levels and improve acoustic comfort. Recent data-driven studies have explored various deep learning architectures for tyre–road noise and interaction prediction. Yang et al. (2025) developed a transformer-based model for predicting and optimizing electric vehicle road noise [20], while Yu et al. (2025) proposed an improved LSTM approach for vehicle structural noise prediction [64]. Similarly, Ma et al. (2025) introduced an AFW-LSTM model integrating adaptive feature weighting [65], Yoon et al. (2025) applied a CNN-based framework for tyre–road friction estimation [66], and Ma et al. (2025) proposed a physics-informed GRU model combining transfer path analysis with hybrid data [67]. Other recent approaches include an empirical-informed neural network for tyre noise prediction (Dai et al., 2025) [68] and a ResNet-based model for wind noise analysis (Ma et al., 2025) [69].However, many deep learning algorithms have not yet been used in this field.

There is numerous review articles published related to tyre-road noise. However, there is currently no comprehensive review article on the prediction of tyre-road noise using AI. The most significant of these is the review article examining the parameters affecting tyre-road noise. The article is divided into sections such as driver-related, tyre-related, tread pattern, pavement-related, and environmental parameters. Here, it is stated that speed, tyre feature, temperature, road condition and pavement feature are the most important parameters affecting tyre-road noise [31]. Some articles have examined studies on modeling approaches [70]. In this study, monitoring and prediction articles based on sensor data and tyre-road noise data were examined. There are also some review articles examining the measurement techniques for tyre-road noise. The test environment of the measurement techniques are classified as roadside, on-board, and laboratory settings [18]. Another important issue in tyre-road noise is the noise generation mechanism and corresponding reduction techniques. There are some reviews in the literature about these aspects [71]. Pavement macrotexture data is one of the important parameters affecting tyre-road noise. Studies in the literature have summarized findings on this topic [42]. Apart from these, studies on tyre-road friction [72], road mixture composition [73], and road condition monitoring methods [74] were evaluated. Shang et al. (2024) reviewed various AI-based only pavement detection and image processing techniques. Kang et al. (2025) conducted a systematic and quantitative review, analyzing many studies (158 papers) covering various AI techniques, pavement types, performance indicators (like IRI), and data sources [75]. The studies covered a wide range of methods, while our part of the work focused specifically on pavement classification related to tyre–road noise [76]. Based on this body of literature, this study aims to fill the gap by focusing specifically on the sensor-based AI prediction of tyre-road noise.

2.1. Literature review and evaluation of the tyre-road monitoring

Literature on tyre-road monitoring is categorized into four tables based on data collection techniques: Close Proximity Method (CPX), On-Board Sound Intensity (OBSI), microphones directed at the wheel (MDW) or placed between the car fender and body (MPBCF), interior microphones, and their combinations. These categories are presented in Tables 1-4. Among these methods, OBSI and CPX are the most extensively studied and are the most frequently applied techniques in existing

Table 1
Summary of studies using OBSI and CPX methods for tyre–road noise data collection.

	Sensors/Data	Signal Processing	Feature Extraction, Selection	AI Algorithm	Estimated/Predict/ Classification
[28],	OBSI, sound absorption	FFT	——————	——————	3 different road surface classifications
[36]	IAcceleration,CPX,, Semi Anechoic Chamber	FFT	——————	——————	Road/noise, texture, Surface assessment relation prediction
[49]	OBSI Dynamic stiffness, Sound absorption, Odometer	FFT	—————————	—————————	Predict sound absorption
[23]	OBSI	BPF PSD, HW, FFT	PCA, CA	——————	4 different Macro structure prediction
[23]	OBSI	MFCC,. CA	——————————	SVM	Road surface prediction
[136]	GPS, Speed, Accelerometer, Weather info, Tyre Pressure, CPX, OBSI	—————————————	Statistic models	DAE	Road surface classification
[86,85]	OBSI, CTWIST laser scanning, optical sensor	FFT, Power Spectrum	Gaussian curve fitting	NN	Predict Tread Pattern-Related Tyre-Road Noise
[44]	CPX	1/3 OCT,	Global Sensitivity Analysis (GSA)	SVM, ANN,	Modelling of the pavement acoustic longevity
[217]	OBSI	CPX Index	——————————	Regression	Macrotexture classification

Table 2
Studies employing microphone directed at the wheel (MDW) or placed between the car fender(MPBCF) for external tyre–road noise measurement.

Reference	Sensors/Data	Signal Processing	Feature Extraction, Selection	AI Algorithm	Estimated/Predict/Classification
[128]	MPBCF	MFCC, STFT	——————	SVM, RNN-LSTM, NN	2 Class Road condition(dry, wet) classification
[134]	MDW	1/3 OCT—speed	——————	K-Means, HC, SVR, GAM	Road surface classification
[218]	Tyre Cavity Microphone	1/3 OCT	Statistic model	——————	Road surface classification
[55]	MPBCF	Infinite Impulse Response (IIR) bandpass Butterworth filter, FFT	Statistic model	LD, LR, SVM, KNN,	Road condition(dry, wet) classification
[54]	MPBCF	1/3 OCT	RFE, L0	SVM	2 Classes Road surface condition prediction using Tyre-Road noise (dry, wet)
[58,124,219]	MPBCF, smartphone GPS	High-pass Filter, FFT, 1/3 OCT	t-SNE	KNN, Hierarchical clustering	Road surface classification
	speed, acceleration, geo reference	MFCC	———————	SVM, KNN	Road problems detection
[59,88]	PBCF	CWT ––	————————Gaussian curve fitting	CNN	———————————13 different road types classification
[220]	Camera, GPS, MDW, tyre pressure, accelerometer, lazer height sensor	FFT	PCA	Statistic models	Macrotexture Estimation
[43]	MDW	Signal Energy Correlation	————————	Linear Regression	Pavement Macrotexture Monitoring
[221]	MDW	PDF	Pavement condition index (PCI)	—————————————	Road surface condition monitoring
[129]	MDW	DWT	Thresholding	—————————————	Road surface classification
[222]	MDW	PSC, MFCC,	LPC	ANN	Road type classification

Table 3
Studies using in-vehicle microphones for interior tyre–road noise analysis and feature extraction.

Reference	Sensors/Data	Signal Processing	Feature Extraction, Selection	AI Algorithm	Estimated/Predict/ Classification
[27,98]	Interior microphone	FFT	—————————	CNN (Resnet), Genetic Algorithm, Multi-Objective Optimization	Tyre-road airborne noise quality prediction, predict vehicle interior sound
[35]	Interior microphone, outside accelerometer	FFT	—————————	CNN, LSTM, AE-LSTM	Prediction interior noise

research. Studies employing these techniques are discussed in detail in Table 1. In this paper, studies that did not utilize artificial intelligence or signal processing were excluded from evaluation.

In addition, other sensors such as Acceleration, Sound Absorption, Odometer, GPS, Speed, Laser Scanning, Optical Sensor, Smartphone Sensors, Georeferenced Data, Tyre Pressure, Camera, and Laser Height Sensor have been used to detect or predict tyre-road noise and identify road problems. Many long technical abbreviations are employed, and descriptions for these abbreviations can be found below the table. In these studies, the most commonly used signal processing techniques include FFT, MFCC, and 1/3-octave (OCT) analysis, which were applied to process the raw tyre–road noise signals. The Feature Extraction and Selection column shows the methods used to identify and select the most relevant features, including PCA, statistical models, and Gaussian curve

Table 4
Studies integrating multiple sensing techniques for tyre–road noise estimation and road condition analysis.

Reference	Sensors/Data	Signal Processing	Feature Extraction, Selection	AI Algorithm	Estimated/Predict/ Classification
[223]	Microphones installed inside and outside the car	MFCC	————————	CNN	2-classes road roughness
[224,225,225–227]	Interior noise, interior vibration, lab mic different pos.	CWT	———————	——————	Predicting interior noise
[135]	No information	MFCC	Statistic models, LBP, PCA	CNN	Road surface classification
[127]	Internal micro and PBCF	STFT, Mel Frequency	———————	Siamese CNN	Road surface classification by tyre-road noise
[53]	Outside-microphones	Frequency Bands	—————————	Stacking, R F, NN and GBM, AdaBoost, SVC	Crack damage detection using tyre-road noise
[228]	Internal micro and PBCF	LP, MFCC, PSC	LPC	ANN, SVM	4 classes Road surface classification by tyre-road noise
[132]	Internal micro and PBCF	STFT, 1/3 OCT, Overall sound level Sound energy based feature	——————	Bayesian	8 classes Asphalt type prediction

fitting. The AI Algorithm column presents the artificial intelligence and machine learning techniques applied, such as SVM, ANN, NN, and regression models. The Estimated/Predict/Classification column summarizes the main objectives of the studies, such as tyre–road noise estimation, road surface prediction, or macrotexture classification.

Table 2 presents studies that evaluated a microphone directed at the wheel (MDW) or placed between the car fender(MPBCF). Thedefinations of theabbreviations are provided before the introduction. Upon reviewing the literature studies, various signal processing algorithms were applied, including FFT, FIR, Bandpass Filter, Hamming Window, MFCC, Cepstral Signal Processing, STFT, Narrowband Analysis, Power Spectrum, Mel Frequency Scale, Bandpass, Butterworth Filter, High Pass Filter, IIR, CWT, Signal Energy Correlation, PDF, and DWT. Among all the methods reviewed across four tables, FFT was used most frequently. When considering filter techniques, approximately one-third of the studies employed OCT. Unfortunately, many studies have not used or mentioned feature extraction and selection algorithms. The Sensors/ Data column includes additional sensors such as cameras, GPS, tyre pressure, and accelerometers. The Feature Extraction and Selection column presents techniques such as PCA, t-SNE, RFE, and Gaussian curve fitting.. The AI Algorithm column lists models such as SVM, KNN, CNN, and ANN, while the Estimated/Predict/Classification column summarizes the study objectives, mainly focused on road condition and surface classification.

Table 3 includes studies that used interior microphones to measure tyre–road noise and vehicle cabin sound. The most commonly used signal processing technique was FFT, applied to analyse interior noise characteristics. The main objectives focused on predicting tyre–road airborne noise quality and estimating interior sound levels. Feature extraction or selection methods were rarely mentioned in these works. Based on the available information, the most commonly used methods for feature extraction and selection are PCA and various statistical methods. Specifically, PCA, LPC, t-SNE, Statistical Models, RFE, L0, GSA, and Gaussian Curve Fitting were applied. When analyzing machine learning and artificial intelligence algorithms, the following were commonly used: CNN, Linear Regression (LR), ANN, Genetic Algorithm, Multi-Objective Optimization, LSTM, AE-LSTM, SVM, KNN, Hierarchical Clustering, GAM, SVR, K-Means, RNN, Decision Trees (DT), Random Forest (RF), AdaBoost, Correlation Analysis, and RVM. Among these, the most frequently used algorithms are SVM, NN, and CNN.

In Table 4, Studies integrating multiple sensing techniques for tyre–road noise estimation and road condition analysis are examined. There are relatively few studies in the literature focused on estimating tyre-road noise. As a result, all studies that involve this noise were included in this review. These studies estimated various factors such as tyre-road noise quality, vehicle interior noise, road roughness, road surface, crack damage, road type, macrostructure, and road weather conditions. Among these, road surface prediction has been the most extensively studied. In terms of the Sensor/Data used, most studies rely on microphones positioned either inside the tyre cavity or outside the vehicle to capture tyre–road or interior noise. Some studies combine acoustic data with vibration or acceleration signals to represent road roughness and structural response more accurately. The sensor position and type directly influence the noise characteristics and play an essential role in the accuracy of prediction and classification models.

Tables 1-4 provides a comprehensive overview of studies on tyre-road monitoring, categorizing them based on tyre-road noise measurement techniques. These studies cover a range of topics, including road roughness, road surface, crack damage, road type, road macrotexture, road condition, and sound absorption estimation/classification. Additionally, some studies classify different road types using 3D texture images in combination with tyre-road noise data [20]. Another notable study focuses on performing road terrain recognition through tyre-road noise analysis [77].

2.2. Evaluation of the tyre-road noise prediction

Tyre-road noise-based estimation has been the focus of various studies, many of which have utilized data obtained by modeling [26,78,79]. However, this review study specifically examines research that relies on sensor-based data. For example, Ongel et al. (2008) collected data from 72 field pavement sections of different ages of asphalt types using the OBSI technique and used principal components regression for tyre-road noise estimation. They investigated the effect of pavement parameters on noise level [80]. In a different approach, tyre-road noise measurement is done with an internal microphone that measures the noise inside the tyre cavity instead of external microphones. Researchers such as Pinay et al. (2018) investigated the influence of driving speed, tyre load, inflation pressure, and air temperature on tyrecavity noise [81]. The study found an estimated correlation of 1.4 dB(A) between tyre cavity noise and outer tyre-road noise [81].

Many studies use tyre characteristics, tyre-road contact information, and tyre texture as input parameters for noise prediction. The effect of tyre-road contact on noise was investigated by Cesbron et al. (2009), who estimated 1/3 octave band noise. They conducted their study on six different road surfaces and at speeds ranging from 30 to 50 km/h [82]. Using a unique approach, Rapino et al. (2023) collected noise data in a semi-anechoic chamber and trained a neural network with 3D tread patterns and footprint data. They obtained an RMSE of 2.3 dB(A) for 1/3 octave noise estimates [83]. Some researchers integrate additional parameters such as tyre size, rubber hardness, vehicle speed and pavement profiles to predict 1/3 octave or narrowband noise levels. For example, Spies et al. (2023) focused on separating and analysing tyre-road noise, while integrating additional parameters such as tyre size, rubber hardness, vehicle speed, and pavement profiles to predict 1/3 octave or narrowband noise levels. For example, Spies et al. (2023) focused on separating and analysing tyre-road noise [84], while T. Li et al. (2016, 2017) used power spectra from different tread profiles to estimate noise [85,86]. In this field, noise prediction using neural networks (NN) based on tyre parameters only has also been performed [87]. Design-oriented studies have also emerged, such as a study by Lee et al. (2021) in which Gaussian Curve Fitting was used to extract the tread profile pattern feature. Images of 28 different tyres were scanned using a semi-anechoic chamber and CNN structures were used for prediction [88].

Tyre-road noise has also been used to optimize tyre conditions. One study by Chiu & Tu (2015) utilized particle swarm optimization (PSO) to optimize tyre conditions. In this study, parameters such as tyre weight, tread pattern, tyre pressure and the resulting 1/3 octave noise pressure were examined [89]. In another significant work by Mohammadi et al. (2022), tyre-road noise estimation was used in tyre design. The tyre tread pattern and properties are used as input parameters and the tyre-road noise is estimated accordingly and the tyre tread groove depth, angle, and number of transverse were optimized. Approximately 3 dB reduction in noise is observed [90]. Furthermore, research by Dubois et al. (2013) focused on estimating low frequency tyre-road noise from numerical contact forces. For this, road 3d images, tyre-road noise, speed, footprint of tyre information was used [91]. Recent advancements have extended noise analysis into the vehicle interior. Studies by H. Huang et al. (2024) and H. B. Huang et al. (2023) employed cutting-edge methods, including knowledge graph, multitask Resnet estimate and optimize noise levels in various parts of the car and optimization and data collection has been done in the sound absorption chamber and in the real car. Also, different characteristics of the sound have been estimated [27,92]. An overview of these studies, including the types of sensors, signal processing techniques, feature extraction methods, and algorithms employed, is summarized in Table 5. Most studies used OBSI or CPX systems for field measurements, while laboratory microphones and footprint setups were used for controlled tests. Common processing methods such as FFT and 1/3 octave analysis were applied to extract frequency-domain information. Machine learning techniques including SVM, RVM, NN, and CNN were then used to predict tyre–road noise or classify road conditions. In general, the table highlights how combining acoustic data with artificial intelligence techniques improves the understanding and prediction of tyre-road noise.

In summary, these studies underscore the importance of optimizing tyre-road noise through both tyre design and the integration of advanced machine learning techniques, ultimately leading to reduced noise pollution and improved vehicle interior comfort.

3. Study methodology

3.1. Sources and distribution of Vehicle-Borne noise

In addition to tyre-road noise, in-car noise optimization represents a critical concern in in the automotive industry and needs to be optimized. Interior noise is considered a key indicator of vehicle quality, as vehicles are indispensable modes of transport in which people spend a substantial amount of time [93]. The primary sources of interior noise include motor noise [94], gearbox noise, induction and exhaust noise, road noise, and airflow noise (see Fig. 2). The figure illustrates the sources and distribution of sounds. Shown in red are airborne noises (tyre, engine, exhaust) are marked in red, aerodynamics noises in blue, and structure borne noises in yellow. Excessive interior noise can adversely affect ride comfort [95].

Noise propagation in the passenger compartment of a car occurs through two dominant mechanisms: structure-borne and airborne. The vibration of tyres and chassis is the cause of structure-borne noise [96], while sound waves travelling through the air are the cause of airborne noise. Structure-borne noise decreases, and airborne noise increases as vehicle speed increases. Significant progress has been made in the automotive industry through research into reducing interior noise, which has effectively reduced noise levels in the passenger compartment [27,97–100].

3.2. Comparative analysis of vehicle noise sources

Some studies have been carried out on noise sources and their audibility in cars. Balcombe and Crowther (1993) in their experiment on a sports car to find the noise source of the car's noise [101] found that the exhaust system was the dominant noise source among the source of noise. They found engine and transmission noise to be of minor importance. Experiments by Gade et al (1996) with a sound-insulated sports saloon showed that the relative level of each noise source depends on the position of the vehicle on the test track. They found that

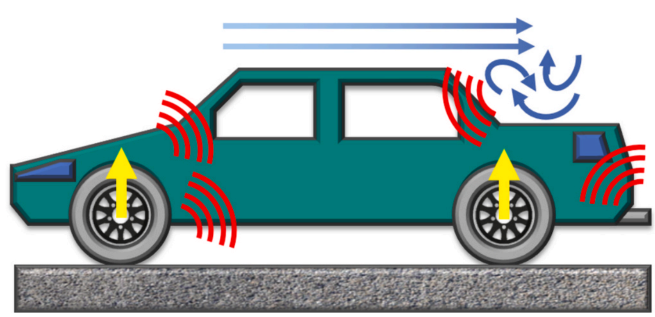

Fig. 2. Sources of sound in the car [95].

Table 5
Studies focusing on tyre–road noise prediction using sensor data, signal processing, and AI techniques.

	Sensors/Data	Signal Processing	Feature Extraction, Selection	AI Algorithm
[80]	OBSI	FFT	Statistical techniques	PCR, OLS
[133]	Lab micro. different pos.	FIR, FFT	—	SVM, RVM
[26]	OBSI, Speed	1/3 OCT	—	SVM, NN
[33]	OBSI, PLP	—	Statistic model	Correlation Analysis
[84]	OBSI, PL, OS	FFT, STFT, velocity spectrum, Narrowband, 1/3 Octave Band	—	NN
[82]	CPX	1/3 Octave Band	Statistical Correlations	—
[83]	Lab micro. different pos., Footprint, 3d Thread Pattern	1/3 Octave Band	—	NN
[90]	Thread Pattern, Tyre Features	1/3 Octave Band	Pixel-based method	SVM, RVM, NN, CNN
[91]	CPX, 3d Road Surface	1/3 Octave Band	—	Linear Regression
[229]	OBSI	FGM	—	Regression Analysis
[85,86]	OBSI, CTWIST laser scanning, optical sensor	FFT, Power Spectrum	Gaussian curve fitting	NN

powertrain noise was highest in the right microphone and exhaust noise dominated the left microphone [102]. Other references report a different sequence of noise sources for pass-through noise tests [103]. This is shown as the highest noise source is tyre-road noise. This was therefore the focus of this study. It was observed that the lowest noise source is surface radiation, load influence and powertrain. Intake system noise, rolling noise and exhaust system noise are in the second and third place. It can be assumed that different vehicle types with certain design configurations lead to different rankings [104].

3.3. Analysis of tyre and road Contributions to Tyre–Road noise

The overall noise level (in dB) depends on both tyre tread and pavement texture. Tread pattern noise is more noticeable at lower frequencies, while pavement texture mainly affects higher frequencies. In real driving conditions, both effects combine and increase the overall sound pressure level. Periodic noise comes from the repeated contact of tread blocks with the surface, while random noise is caused by the irregularities of the road. As shown in Fig. 3, the tread pattern contributes to tyre-road interaction noise through the interaction between the tread blocks and the pavement texture, and through air pumping by compressing and expanding the air in the tread grooves [105–107]. Another factor is pavement texture. Noise varies depending on the condition of the road. In tyre-road noise estimation, tyre-related factors that influence vibration behavior and sound generation include tread structure [89,90], three-dimensional tread profile [108], internal pressure, temperature [82], wear condition, material hardness, and structural layer properties [84]. By directly influencing the frequency, intensity and propagation of the road noise, these features play a critical role in the estimation accuracy of the model. Various sensors are used to collect this data. These include 3D scanners, thermal cameras, TPMS sensors, durometers and state-of-the-art techniques such as ultrasound or X-ray analysis [83].

The features of the road that have an impact on this are the roughness of the road, the thickness of the pavement surface [109], the hardness of the road surface [110], and the sound absorption of the road [111], road texture 3D image [20], coating [112,113], surface type [114], aggregate type [115], surface texture [116], and acoustic and thermal properties. Sensors such as laser profilers, 3D scanners, thermal and RGB cameras, microphone arrays, acoustic tubes and friction testing equipment can be used to measure these. To demonstrate the relationship, tyre-road footprint techniques use ink-based visualisation, dimming, thermal and image processing methods to determine tyre-road interaction [117]. These methods provide detailed information about road surface type, tyre pattern and interaction by analysing the unique characteristics of tyre tracks and the road surface.

3.4. Analysis of factors influencing Tyre–Road noise

Tyre–road noise is one of the main contributors to overall traffic noise, especially at moderate to high speeds, where engine noise becomes less dominant. Tyre-road noise is influenced by a variety of factors resulting from both the vehicle and road characteristics. Key parameters identified in the literature include Vehicle type, Vehicle speed, Temperature, road properties. Among these, the condition of the road surface plays a particularly critical role. Fig. 4 shows different road qualities. In section (a), lower binder levels create a rougher texture, increasing vibration and air pumping effects, which in turn leads to increased tyre-road noise. In section (b), larger aggregates cause stronger impacts and higher noise levels, while smaller aggregates provide softer contact with the tyre, helping to reduce noise. Rough roads with cracks, potholes, and uneven surfaces effect the smooth rolling behavior of tyres. Another important factor is the tyre tread. The sound changes accordingly. Aggressive, large tread blocks on tyres increase air compression and release, generating more noise, while smaller, tightly spaced tread blocks tend to be quieter. Additionally, softer tyre compounds typically produce less noise compared to harder ones. These variations influence the overall sound pressure level and frequency content of tyre–road noise.

4. Developing equipment and data collection

4.1. Sensors used for data collection and their Specifications

One of the main approaches to estimating tyre-road noise is an audio-based method that uses microphones to collect data. With this, pavement properties such as evaluation of pavement texture, condition of the road surface, road surface properties and depth properties can be estimated. In addition, on the contrary, tyre-road noise can be estimated by using these and tyre, road and other temperatures, speed, tyre pressure and tyre vibration data. For this, many signal processing, data feature extraction and selection, and AI algorithms have been used to achieve this. A brief summary of these is given in the tables 1–5. Different data acquisition systems have been developed to evaluate these various features, and a summary of these is presented here. These are CPX, near-the-wheel microphone, in-car microphone, OBSI, GPS information, vehicle data (CAN)(Fig. 5).

4.2. Roadside noise measurement procedure and experimental Setup

There are several well-established methods for roadside noise measurement including Statistical Pass-By, Controlled Pass-By, Coast-By, Statistical Pass-By (SPB) [18], as defined in ISO 11819–1 (1997), is a method used to measure the average traffic noise for a specific road section. A method based on sensor feature extraction with live event detection; noise and speed measurements are performed at the roadside in real case scenarios [118]. The Controlled Pass-By (CPB) method is used to measure the noise generated by passing vehicles [119]. These techniques measure the far-field noise of a moving vehicle. Despite its popularity, the applicability of CPB in urban contexts is compromised because it depends on the conditions of the test site [58]. Some studies in literature are conducted. However, this method is suitable for situations where traffic flow is low, and the microphone collecting the signal is fixed at the roadside, which is easily affected by external noise [71]. However, it should be noted that the effect of ambient noise on the test results cannot be completely eliminated by either the traditional

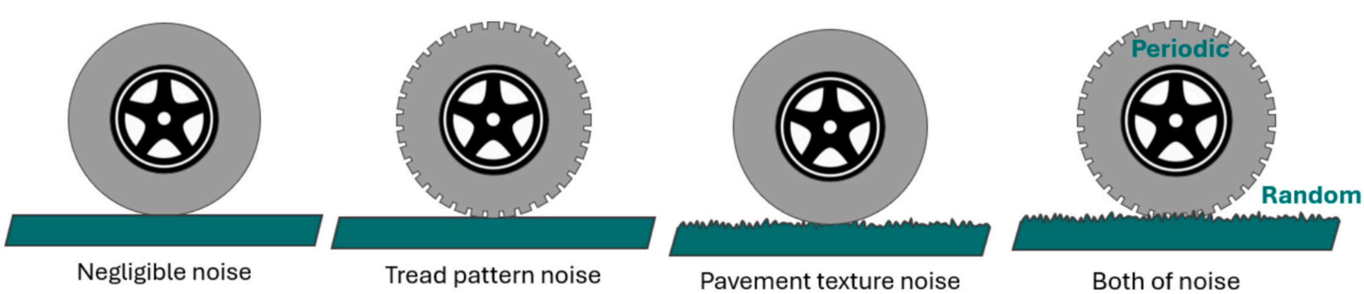

Fig. 3. Tyre-Road Noise Generation [38].

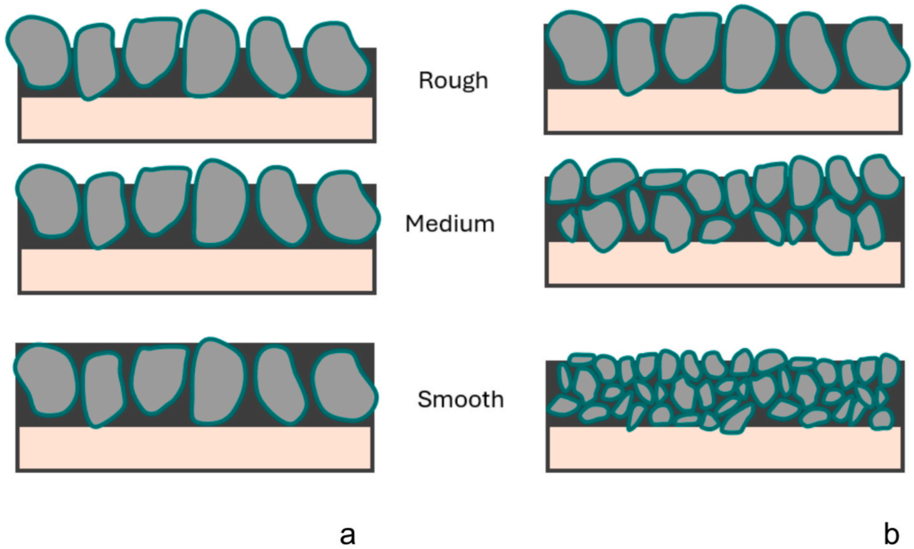

Fig. 4. Different road surface qualities: a) Different binder levels, b) Different rock size.

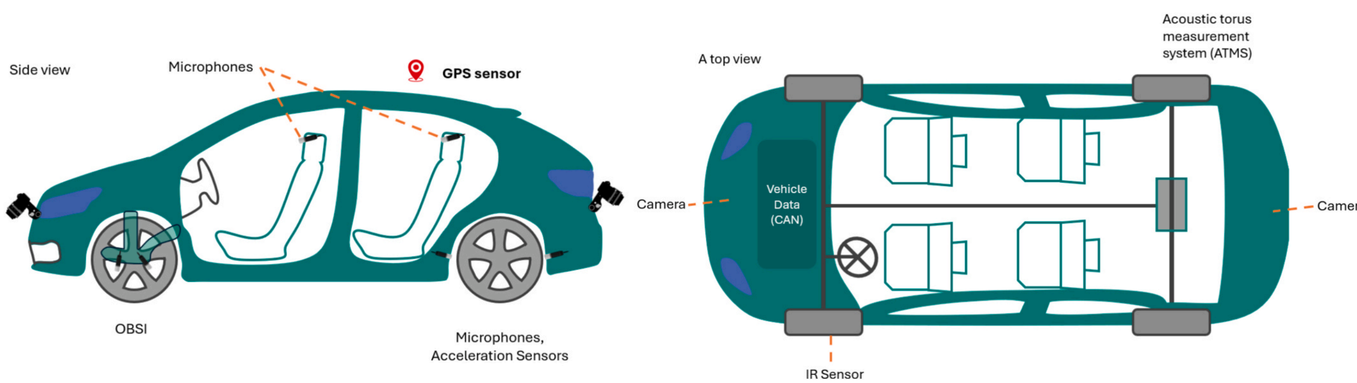

Fig. 5. Use of different sensors for tyre-road noise experiments (Huang et al., 2023).

roadside method or the modified roadside method [71]. Therefore, we did not use this method in the literature review in Table 1-5. Dallasta et al. (2026) proposed an alternative approach for predicting coast-by tyre-road noise using equivalent monopoles derived from indoor tests, offering a practical substitute for costly and time-consuming on-road measurements[120]. Gardziejczyk et al. (2025) evaluated the noise levels of different road surfaces in Poland using the Statistical Pass-By (SPB) method. The study mentions that SPB results were compared with other methods and that both SPB and OBSI measurements can provide complementary insights into tyre–road noise behavior[121]. The growing number of electric vehicles (EVs) is changing traffic noise levels. Licitra et al. (2023) updated the CNOSSOS-EU model by adding new coefficients for EV noise emission based on real measurements [122]. These updates help improve noise prediction for modern traffic conditions. Recent studies show that this technique has the potential to become more widely adopted over time.

4.3. On-board noise measurement Setup and Procedure

Techniques such as Behind the Tyre, Trailer Side by Side, In-Vehicle Sound Pressure, Sound Intensity Area, Tyre Cavity Microphone, Close Proximity Method (CPX) Trailer, On-Vehicle Sound Intensity (OBSI) [18], In-Vehicle, In-Vehicle Sound Intensity are used in studies of tyre-road noise. The techniques used by studies on tyre-road noise in the literature are shown in Fig. 6. CPX and On-Board Sound Intensity (OBSI) [123] are the commonly used techniques. However, these methods are far from being practical and real-life applications. The microphone approach placed inside the car seems better, but it seems to be affected by the noise inside the car and it is difficult to predict the noise outside. A promising approach seems to be the microphone placed between the car body and the fender.

5. Data processing and feature Extraction

Filtering techniques are used to filter the raw signals while preserving the relationship between the sensor signals and the process variables [126]. The noise signals can be filtered using high pass, low pass or a band pass [81] to remove the noise or unwanted signal frequency components. Time domain features such as average, root mean square (RMS), and peak amplitude are easy to analyse. Frequency domain features capture important components such as peak frequency and amplitude and are extracted using transformations such as FFT, DFT and their variations [92]. Time-frequency analysis techniques, including continuous and discrete wavelets, Mel Power Spectrogram [127], MFCC [128], STFTs [84], DWT [129], and empirical modes, provide features that can be extracted [126]. The time domain feature displays different signals instantly and processes them quickly, but it is too noisy. The frequency domain feature specifies the frequencies of interest (e.g. resonance cut-off frequencies). This technique is suitable for stationary systems. However, it is not easy to define the relevant frequency band. The time–frequency domain feature is suitable for unstable systems [126]. However, there is no standard procedure for selecting important

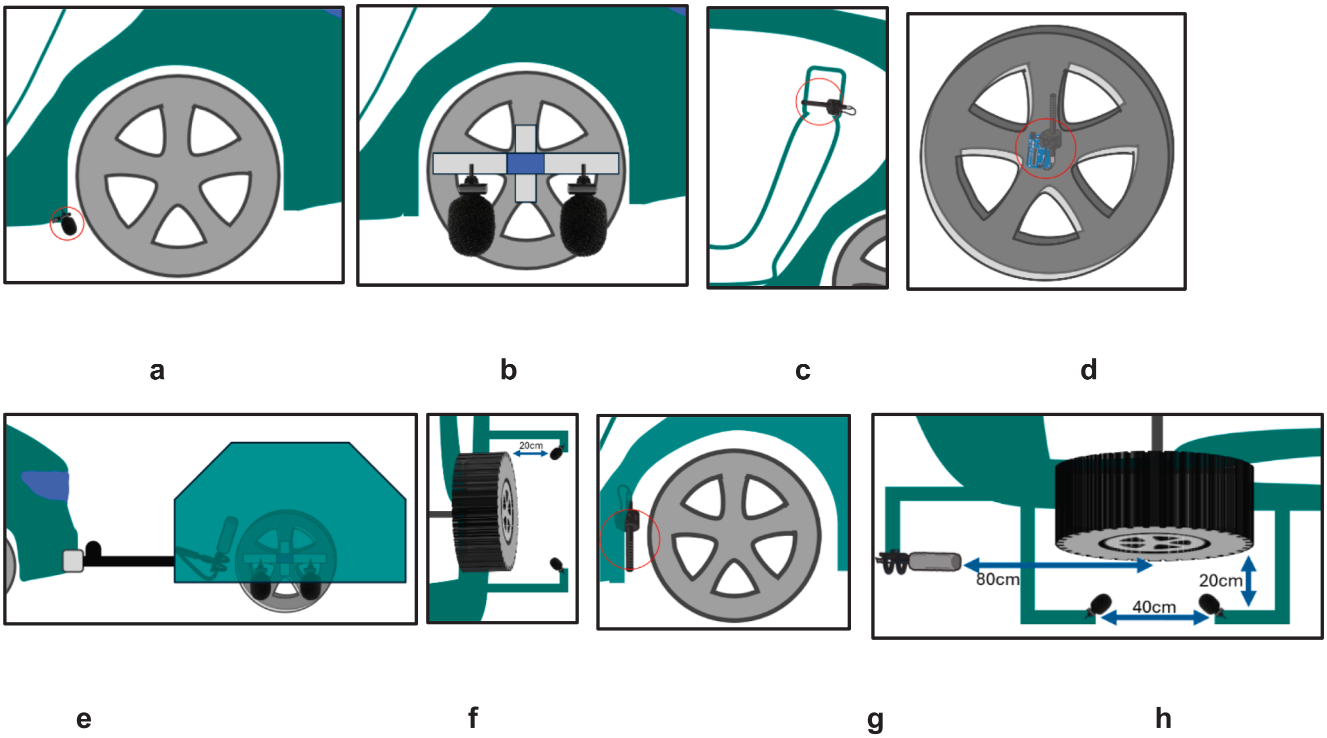

Fig. 6. On-board noise measurement: a)Behind Tyre microphone (Alonso et al., 2014), b)OBSI [48], c)In Vehicle Microphone [35], d)On-Board Sound Intensity [24], e [51], f [124], g [125].

features [126]. In recent years, graph signal processing has been used in many studies. In addition, to estimate tyre-road noise data as sound pressure, the data is transformed with narrow band and 1/3 octave analysis[91].

Apart from signal processing techniques, data selection, reduction of size, and features of image and time series data are extracted. Also, determining the importance of the data is important to determine how much each input variable affects the prediction. The most commonly used techniques for image feature extraction, especially for feature extraction from images, include CNN [83], power spectra [83], profile spectrum [86], edge detection (Canny, Sobel), Gabor, texture analysis (LBP, GLCM), Height Map, DWT, HOG, Gaussian curve fitting [108], Fourier transform and morphological operations. These methods are widely used to analyze tyre patterns, wear levels and road-surface interaction. Classical statistical methods are used for feature extraction from time series noise data. However, new trend algorithms such as TSFresh, Catch22, Deep Feature Synthesis, TsFel have become popular. Instead of classical algorithms such as PCA [42], LDA and t.SNE for reducing data size, techniques such as Autoencoder, UMAP, VAE have been frequently used in different fields in recent years. In determining important input variables, SHAP, attention mechanism, integrated gradient are used in many areas instead of decision tree, lasso, ramdom forest. When working with big data, these algorithms can be used in noise estimation.

In tyre–road noise studies, filtering methods are used to clean raw signals while keeping the relationship between the tyre, road, and sound data. High-pass, low-pass, or band-pass filters help remove unwanted frequencies, and time-domain features such as RMS or peak values describe the general sound level. Frequency-domain methods like FFT show main frequency ranges linked to tyre vibration and road roughness, while time–frequency techniques such as STFT, DWT, or MFCC are useful for signals that change over time. Standard analyses such as 1/3 octave and narrowband are used to calculate sound pressure levels. Image-based methods (e.g., Gabor, HOG, LBP, CNN) can be combined with noise features to examine the relationship between road texture, tyre pattern, and noise. New approaches such as TSFresh, Autoencoder, SHAP, and attention mechanisms help identify the factors that most influence tyre-road noise. These combined methods support a better understanding of how tyres, roads, and environmental conditions affect overall noise behavior.

In recent years, explainable artificial intelligence (XAI) has become more prevalent and is now being applied in this field as well. Gupta et al. (2024) presented an XGBoost–SHAP framework for asphalt pavement condition assessment that combines machine learning and explainable artificial intelligence to increase accuracy and interpretability [130].

6. Artificial intelligence and Machine learning techniques for Tyre–Road noise analysis

6.1. Machine learning (ML)

Tyre-road noise estimation has traditionally been based on classical statistical methods. In recent years, however, ML methods have gained considerable popularity as a complementary approach. Compared to classical methods, ML models are better at capturing more information and providing more robust generalisation capabilities. There are three main steps in traditional ML-based methods for predicting tyre-road noise: feature extraction, feature reduction and feature classification. Each step in this process requires careful design by experienced researchers. This is because each step depends on the previous one. However, the wide applicability of these methods is limited by the fact that they are often task-specific. A promising direction of research to simplify the process and improve performance across different tasks is the development of automatic methods that simultaneously handle feature extraction and classification, which can improve error recognition accuracy [131]. This is where deep learning comes into play. In the literature, almost all known machine learning algorithms, such as ANN [84], Linear Regration [55], Gradient Boosting Machines [53], Bayesian [132], SVM [133], SVC [53], SVR [134], Relevance Vector Machine (RVM) [133], KNN[58], K-Means [134], Decision Trees [62], Linear

Discriminant (LD) [55], Logistic Regression [55], Hierarchical Clustering[134], Linear Regression [134], Random Forest(RF) [53], Adabost is used. It has been used in studies related to the classification of road conditions, road surfaces, and quality. A small number of studies have been carried out on the estimation of tyre-road noise. In recent years, deep learning-based CNN [135], LSTM [35], Autoencoder [136], CNN Resnet [98], Siamese CNN [127], and hybrid AE-LSTM [35] structures have been used. As can be seen from the literature, there are few studies on deep learning. There is a lack of research in this area. Furthermore, due to big data and the success of these algorithms, there is a significant increase in the number of studies in the area of prediction. For this reason, the study concentrated more on deep learning algorithms.

In the field of machine learning, ensemble learning, a methodology that integrates multiple machine learning algorithms, has received considerable attention. Many machine learning algorithms are also available, and it is sometimes very difficult to find the most appropriate one. AutoML has been used in recent years to determine the most appropriate machine learning algorithm [137]. AutoML is also used to improve the performance of algorithms by finding the most suitable algorithm for the data. AutoKeras library is also available. Using this library, the artificial neural network algorithm suitable for the data can be automatically selected.

6.1.1. AutoML

The increasing amount of data has made time series analysis more important. Linear models are simple but can be less accurate. Deep learning (DL) provides better predictions but requires expertise in designing the model and tuning of the hyperparameters. This is indeed an expensive and lengthy process. To overcome these problems, AutoML methods are used [138]. AutoML is capable of automating model selection and optimization, but its application to time series data is under development and requires further investigation. AutoML aims to enable non-experts to use machine learning without prior technical knowledge by automating machine learning tasks with minimal manual effort [139]. The goal is to automate model selection, hyperparameter optimization, and feature selection [140,141]. In this technique, more than 20 machine learning algorithms are trained with the given data, and the best-performing algorithms are recommended to the user. In this way, machine learning algorithms are identified that need to be focused on according to the data. The disadvantages are the need for a GPU and the cost of the computer. In addition, this technique cannot yet be applied to deep learning right now because the process takes a very long time. The general working principle of AutoML is shown in Fig. 7.

6.2. Deep learning

Traditional techniques for time series forecasting are limited in their ability to handle high-dimensional, large-scale data [143]. In addition, developing an effective machine learning system requires data processing or the use of statistical methods. Considerable data expertise is required. More recently, deep learning has emerged. Deep learning identifies models using multiple layers that It represent latent features at a higher and more abstract level. The representations are learned from the data [144]. Although mostly image-based, in recent years deep learning has been successfully applied to the estimation, classification, and prediction of time series data [144]. Deep learning-based prediction methods automate feature extraction and classification from time series data but require time-consuming design and hyperparameters. They also lack interpretability and require large data sets, which is a challenge in real-world applications where data samples are limited [131]. In this study, deep learning algorithms used for new trend prediction are selected and information about them is provided.

6.2.1. Long Short-Term memory (LSTM) and bidirectional LSTM (Bi-LSTM)

Artificial neural networks (ANNs) are machine learning models designed to overcome the limitations of traditional rule-based algorithms [145]. They include Feedforward Neural Networks (FFNN), in which neurons are not connected to each other within the layer, and information flows unidirectionally [146]. Recurrent Neural Networks (RNNs) are neural network in which neurons are connected within the same layer to take into account historical input data. The most important type of algorithm in prediction is the RNNs. Many algorithms are based on RNNs. But Hochreiter and Schmidhuber (1997), to solve the gradient vanishing and explosion problem of RNN, proposed Long Short-Term Memory (LSTM) [147]. In LSTM networks, memory cells are introduced that can hold information over long sequences. Each memory cell has three main components: an input gate, a forgetting gate and an output gate [148]. These gates help to regulate the flow of information into the memory cell and the flow out of the memory cell [148]. Fig. 8 shows the RNN structure in a, the LSTM structure in b, and the comparison of LSTM and Bi-LSTM in c. LSTM has obvious advantages in predicting time series because it can store both long- and short-term dependencies [149]. Bi-directional RNNs (BRNNs), in which two independent networks process input data in opposite order, were introduced by Schuster and Paliwal (1997) [150]. In tyre–road noise prediction, LSTM-based models can capture how vibration, speed, and temperature signals evolve over time and how these variations influence the generated noise level. By learning temporal dependencies between consecutive measurements, LSTMs provide more stable and accurate noise estimation compared to traditional regression-based methods. Bidirectional LSTM (Bi-LSTM) networks further improve performance by processing data in both forward and backward directions, capturing complete temporal patterns in tyre–road interaction. [151,152].

6.2.2. Gate Recurrent Unit (GRU) and Bi-GRU

Gated Recurrent Unit (GRU) is a type of recurrent neural network that is similar to the long short-term memory (LSTM) network, but has a simpler structure [154]. It has been successfully used to build production forecasting models [155–157]. GRU has only two gates. GRU combines the entry gate and the forget gate in LSTM into a single gate called the update gate [158]. Unlike LSTM, GRU does not have an exit

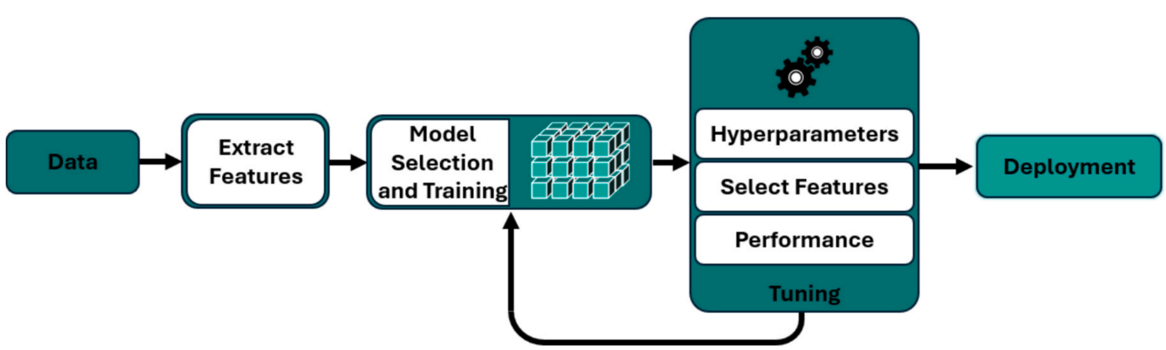

Fig. 7. AutoML Structure [142].

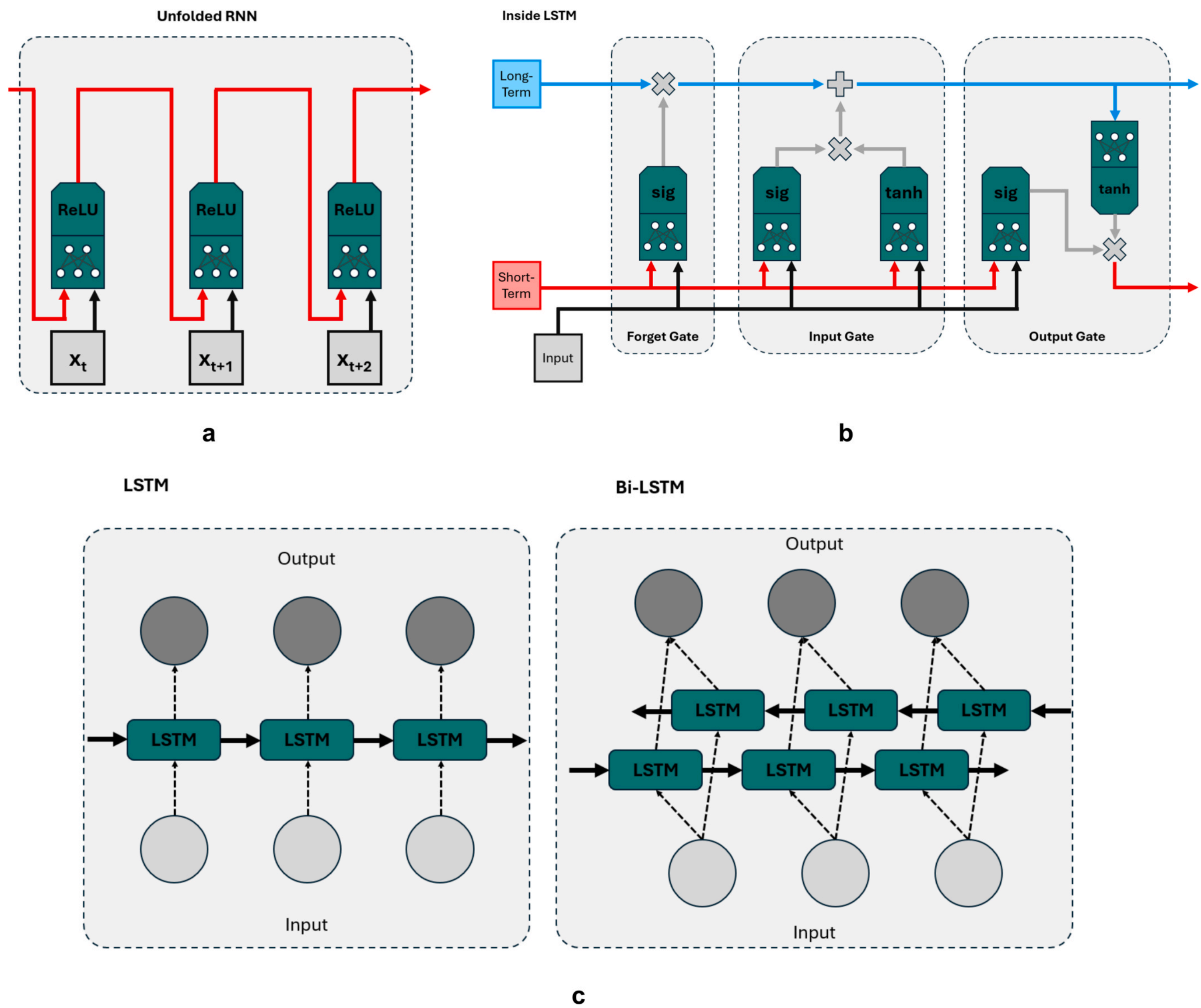

Fig. 8. RNN based Deep Learning a)RNN, b)LSTM, c)LSTM and Bi-LSTM comparison [153].

gate, but instead uses two gates: the update gate (z) and the reset gate (r). These gates are vectors that control what information is sent to the output [159]. The combination of new input with previous memory is determined by the reset gate, while the retention of past memory is controlled by the update gate [158].

These structures are multifaceted and also have many other features. The Bi-GRU model is used to analyse stimulus performance from production data, capturing bidirectional relationships between inputs and

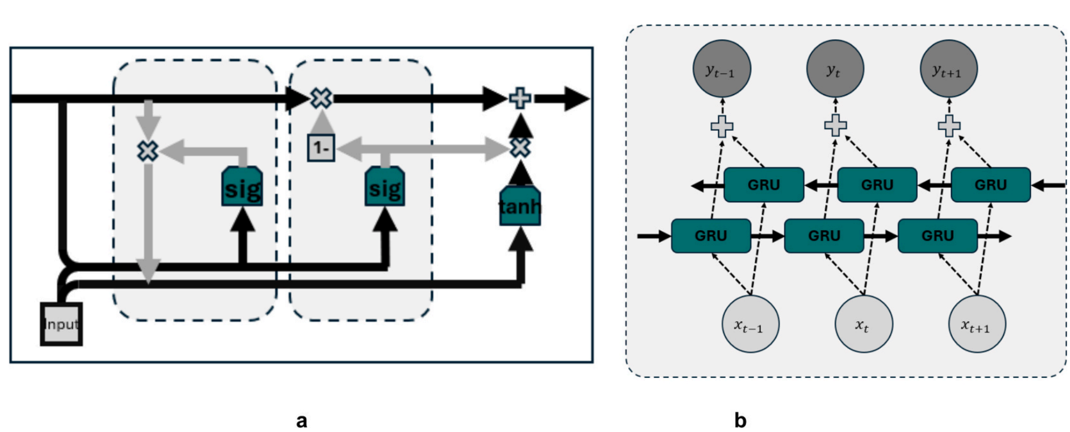

Fig. 9. GRU and Bi-GRU structures[163].

outputs [160]. Important information is extracted from the data using a three-dimensional tensor as input. This is done by a Bi-GRU layer representing samples, history, window size and relevant features [161,162]. The working structure of GRU and Bi-GRU is shown in Fig. 9. Fig. 9a shows the general structure of GRU, and Fig. 9b shows Bi-GRU.

6.2.3. CNN and 1dCNN

Recent research has investigated the use of non-traditional deep learning algorithms for vibration, temperature or noise estimation by eliminating the need for manual feature extraction. Studies show that both 1D and 2D CNNs are highly effective in detecting and localising damage directly from raw acceleration time histories without the need for data pre-processing or manual feature extraction [164]. The methodology resulted in a satisfactory prediction performance for tyre road noise. This was achieved using only raw vibration data. CNNs, which by their nature are well-suited to 2D data such as images or video frames [164]. Time series data can be converted to 2D image size, and 2D CNNs can be used. Otherwise, direct time series data can be estimated using 1D CNN.

In 1D CNN, both the kernel and the exploration target are typically vectors. During the convolution process, a kernel element replaces the source data with a weighted sum of itself and the neighboring data, thereby extracting local features. These features form a set of feature maps, which are reduced by down-sampling techniques such as Max, Mean, or Probabilistic Pooling. For the fully connected layer, the pooled maps are then transformed into a 1D vector. A comparison of different types of CNN-based models shows that 1D CNN has the lowest complexity, but is able to extract to extract spatio-temporal features [165]. Fig. 10 shows 1D and 2D CNN structures. While one works with time series 1D time series data, the other works with 2D image data.

In tyre–road monitoring, CNN-based models are useful for analyzing different types of data such as noise, vibration, and temperature signals. 1D CNNs are suitable for time-series analysis, while 2D CNNs perform better with spectrogram or image-based inputs. These models can automatically capture complex patterns related to tyre–road interaction, surface texture, and operating conditions without manual feature extraction.In addition, CNN architectures are widely used for classifying road surfaces and detecting pavement damage from camera or acoustic data, supporting the development of intelligent tyre–road monitoring systems.

6.2.4. Transformers

Given the great success of Transformer in in natural language processing [167], and computer vision [168], time series analysis has also benefited from powerful new tools based on Transformer architectures [169]. Transformer-based architectures have advanced sequence modelling, with Li et al. (2019) introducing convolutional layers and sparse attention for expanded prediction fields [170]. Iterative methods, which assume known variables except the target, struggle with dynamic inputs that evolve over time [171]. Transformers, which is built on the pure attention mechanism module, is a new network model in deep learning. It can capture the global spatial properties of the input data while overcoming the shortcoming that LSTM neural networks cannot be computed in parallel [172]. An improved version of transformers is temporal fusion transformers (TFT). TFTs are advanced time series forecasting models that combine encoder-decoder architecture with attention mechanisms to focus on relevant historical data (Fig. 11). In tyre–road monitoring, these models can integrate multiple sensor inputs such as noise, vibration, temperature, and speed to highlight important features and their relationships over time. Temporal Fusion Transformers (TFT) further enhance this by combining encoder–decoder structures with attention mechanisms, offering higher accuracy and interpretability compared to traditional models such as LSTM and 1D CNN [173]. Yan et al. (2025) proposed a framework that integrates a diffusion model and a Transformer-in-Transformer (TNT) architecture to detect road surface friction coefficient (RSFC) from video-based road

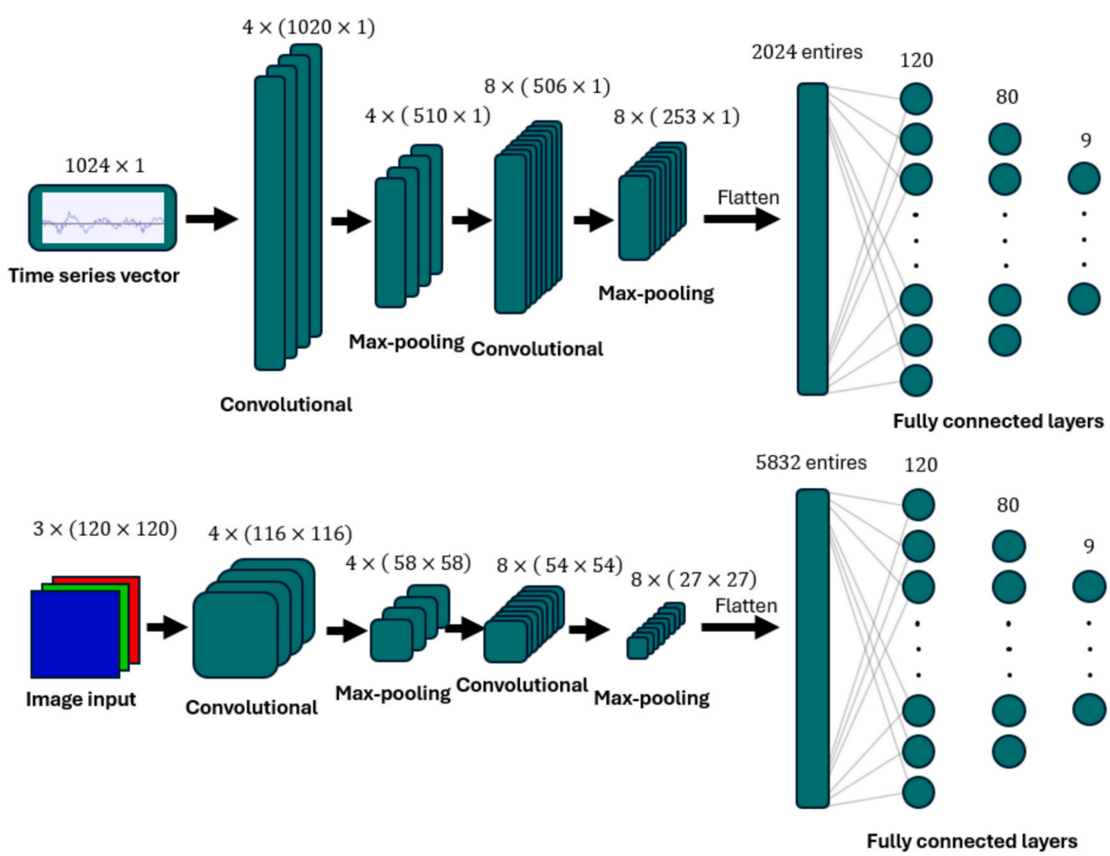

Fig. 10. 1d and 2d CNN Structures [166].

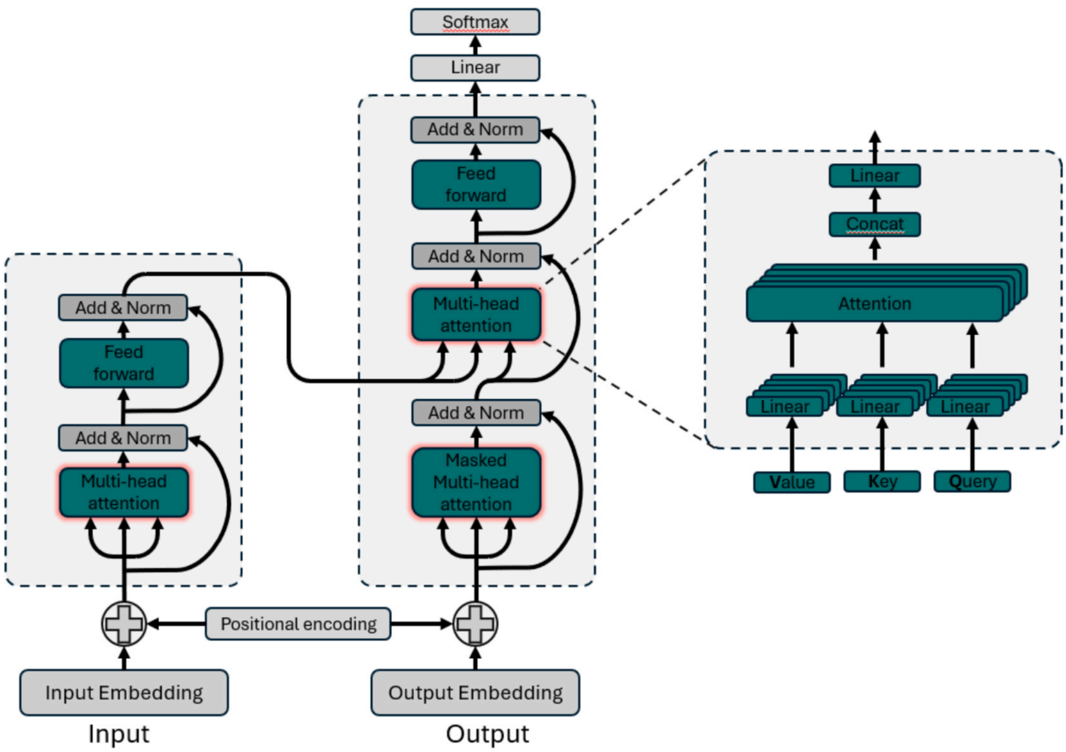

Fig. 11. Transformer Structure [175].

surface images under varying conditions [174].

6.2.5. End-to-End Tyre-Road monitoring process

Fig. 12 illustrates an end-to-end multimodal artificial intelligence framework for tyre–road monitoring. This figure summarizes the general structure of studies conducted in this field. The process begins with multiple input parameters, including weather data, acoustic torus data, sound intensity, acceleration, temperature, tyre–road characteristics, and CAN signals. The data then undergoes cleaning, dimensionality reduction, feature extraction, and signal processing to prepare it for analysis. The processed data are analyzed in different domains: statistical (ARIMA, AR), frequency (FFT), time–frequency (Wavelet Transform, STFT), and image-based representations. Extracted features are then used in various learning models—machine learning methods (SVM, XGBoost, Random Forest, etc.), time-series deep learning models (LSTM, RNN, 1D CNN, etc.), and image-based deep learning architectures (ResNet, VGG, AutoEncoder, GANs, etc.). In the final stage, the framework performs multiple prediction tasks, including tyre–road noise, road surface roughness, road type and anomalies, road weather conditions, and road surface mixture estimation.

6.2.6. Approaches to increase performance

6.2.6.1. Hyperparameter tuning and cross validation. The performance of machine and deep learning models is highly depends on selecting approproatehyperparameter configuration, which often requires expertise and substantial manual effort [176]. However, researchers have developed automated methods to make this easier for non-experts in supervised machine learning. Model-free algorithms (grid search, random search, gradient-based optimization), Bayesian optimization,

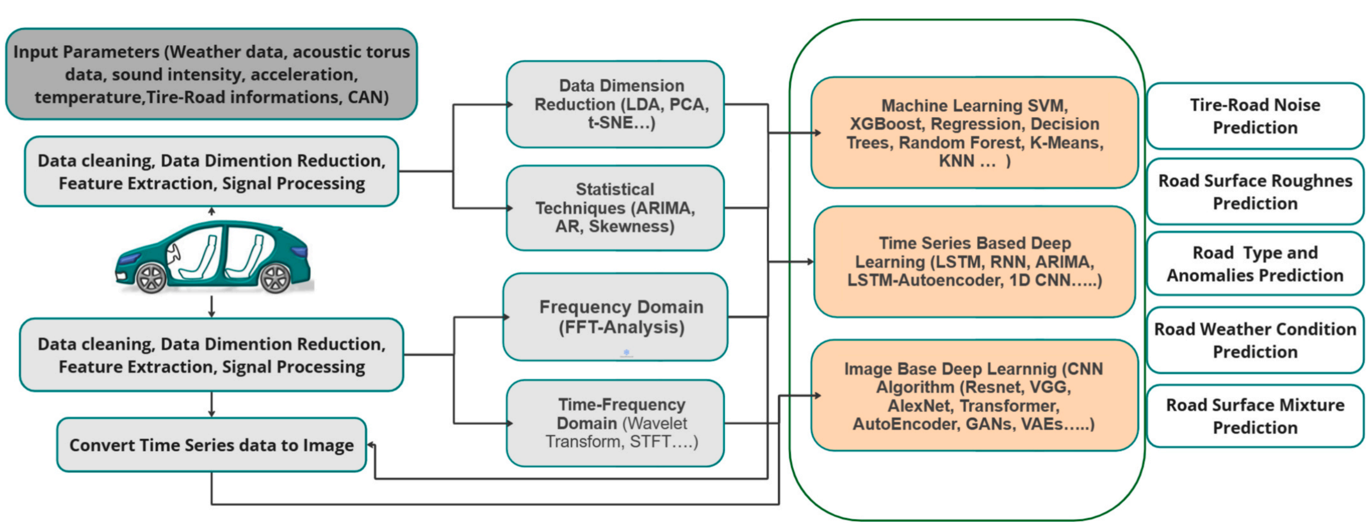

Fig. 12. End-to-End Tyre-Road Noise Monitoring Process.

multi-fidelity optimization algorithms, metaheuristic algorithms (genetic algorithm, particle swarm optimization) are used for hyper-parameter tuning (Fig. 13). Model-free algorithms are widely used. Automatic hyper-parameter optimization methods can replace the time-consuming and inconsistent trial-and-error approach by using techniques such as resampling error estimation to achieve better results [177]. Cross-validation is one of the most important tools used to evaluate forecasting, prediction, classification, and regression methods [178]. Concerns about the use of future data, serial correlation, and non-stationarity make the evaluation of time-series models challenging. Researchers often prefer out-of-sample testing with cross-validation. This is because it provides multiple evaluations [179]. The aim here is to look at the performance by automatically spliding the data from different locations for training, testing, and validation. The principle of operation is shown in Fig. 14. In recent years, transfer learning, hyper-parameter tuning, cross validation have started to be used in this field. Elshaboury et al. (2024) developed a model to predict local road pavement conditions using ensemble machine learning, where the hyper-parameters were optimized through Bayesian optimization, and cross-validation was applied to ensure reliable model performance [180]. Liang et al. (2025) used acoustic data such as sound pressure levels and frequency features together with tyre and road surface parameters as input for tyre noise prediction. The model applied transfer learning to use knowledge from other datasets and improve performance with limited data [181].

6.2.6.2. Performance improvement with changes made to CNN structure. To improve the performance of deep learning algorithms and achieve better results, some changes are made to their structure[183]. Multi-scale CNN is used to simultaneously learn small details and large structures in the data. It extracts more comprehensive and accurate features by working with different filter sizes[184]. This is particularly necessary for complex data that contains information from multiple scales (e.g., road surface, thermal image, noise). Multi-head CNN simultaneously analyses tyre-road noise data from different perspectives (e.g. speed, temperature, surface type). Each head learns different features. The result is a better model of the causes of tyre-road noise and a more accurate estimate of noise levels. Fig. 15 shows the shape of the multi-head structure. Multi-Modal CNN separately processes and combines different types of data, such as thermal images, CAN bus data, and road temperature, to estimate tyre-road noise[185]. Multi-head CNN learns with different filters on the same data, such as temperature and velocity[186,187]. If there is more than one output or prediction, multi-task learning is used. In this field, multi-head approaches have also started to increase in recent years. Liang et al. (2025) used multi-head fusion, the study achieved higher accuracy in predicting tyre–road noise [181].

Apart from the changes made in the CNN structure, there are also techniques for connecting data. The most important of these are the fusion and attention mechanisms. The fusion mechanism combines features extracted from different types of data – such as images, temp, velocity – into a common image. The attention mechanism guides the model by focusing on the most important features among the features that have been combined. For tyre-road noise estimation, fusion brings all the data together, while attention gives more weight to this information, especially in cases where speed and road temperature are more influential. The model makes use of all the data while prioritising the most critical issues. There is an early and a late structure in the Fusion mechanism. In Fig. 16, there is an early structure on the left and a late structure on the right. In addition, the attention mechanism is shown in Fig. 17. With the attention mechanism, weights are assigned to input variables or values with different properties. In Yang et al. (2024), the attention mechanism was used to help the model focus on the most important parts of the tyre noise signal in the time–frequency domain. This made the model more accurate by highlighting key features related to road texture and reducing the effect of irrelevant noise [77].

The new trend is the use of convolution in addition to these structural changes. Enhanced CNN makes noise estimation more general by increasing learning capacity with deeper networks and advanced layers. Deformable CNN uses flexible filters to capture specific patterns, such as road surface distortions or irregularities, for more accurate analysis [191]. Dynamic CNN adjusts the network structure or weight dynamically based on the data to adapt to changing conditions [192]. For the estimation of tyre-road noise, the Enhanced CNN learns general noise patterns, while the Deformable CNN is better at analysing noise changes caused by rough road surfaces [193]. By adapting to environmental factors such as speed and temperature, the Dynamic CNN accurately estimates noise. Combined, these three structures accurately model both general and special situations and provide highly accurate estimates of tyre-road noise. In Fig. 18, the deformable convolution structure is compared with the standard structure.

6.2.6.3. Generative learning. The biggest problem with deep learning algorithms is that they require large amounts of data. However, in many studies, it is difficult to obtain data. At this point, many data augmentation techniques are used. However, more powerful than these, the artificial intelligence-based GANs algorithm has been used recently. At this point, the amount of data can be increased with GANs to improve

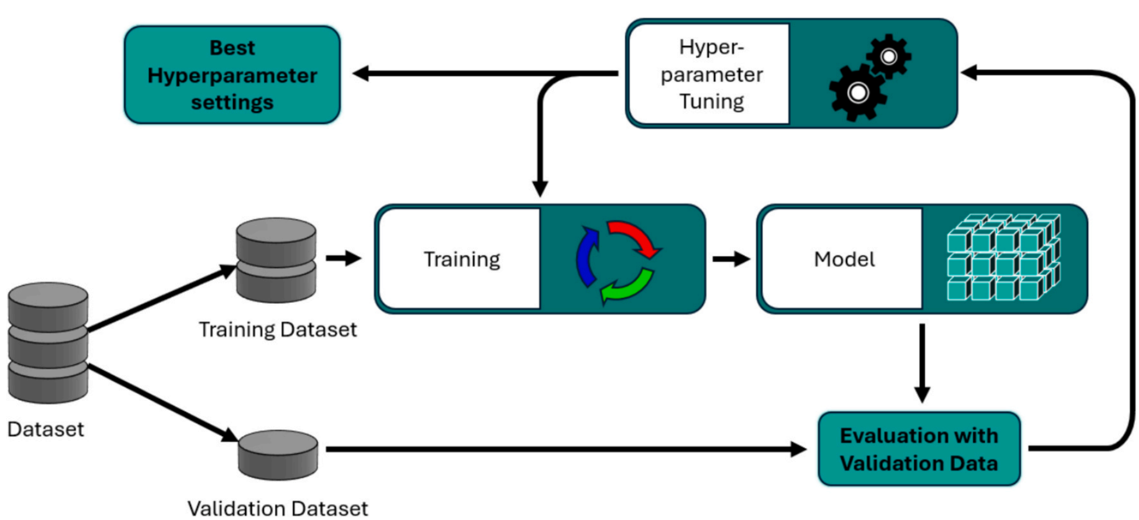

Fig. 13. Hyperparameters tuning [182].

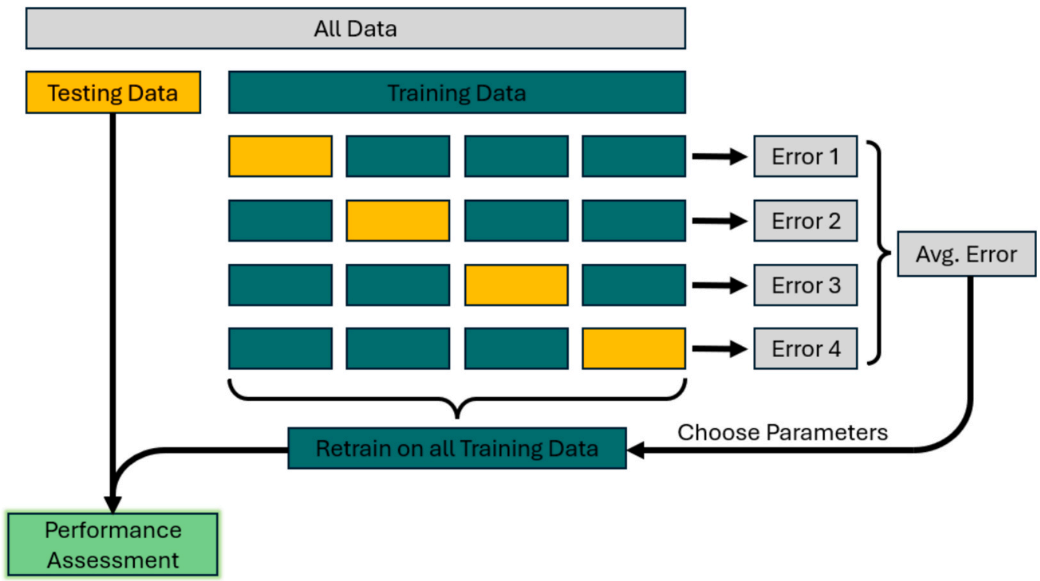

Fig. 14. Cross Validation [182].

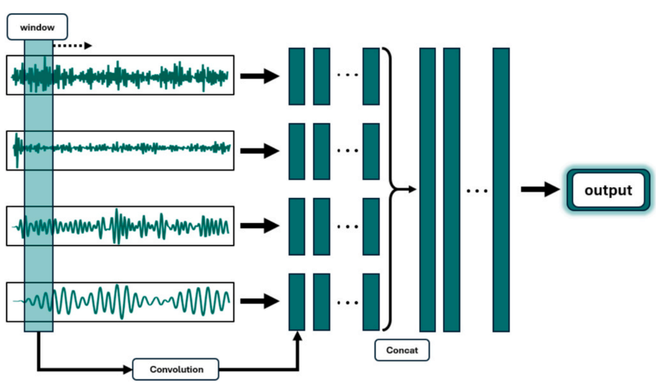

Fig. 15. Multi-Head CNN Structure[188].

the performance of tyre-road noise estimation or time series-based noise estimation. Generative learning, exemplified by Generative Adversarial Networks (GANs), was first proposed in [195,196], addresses data shortages. GANs consist of two networks: a generator and a discriminator [197]. The generator creates synthetic data, while the discriminator determines whether the data is real or fake [198]. These two neural networks are trained iteratively, with the generator helping to generate the realistic fake samples until they are indistinguishable from real data samples [199]. The working principle of GANs is shown in Fig. 19. GANs learn the data distribution and produce realistic synthetic data. Generative Adversarial Networks (GANs) have seen rapid growth, particularly in computer vision, where they've helped create realistic images and videos. Beyond computer vision, the applications of GANs have expanded into a variety of fields, including the generation of time series and sequences. Some GAN structures used in the multiplication time series data are as follows: SynSigGAN, DAT-CGAN, SigCWGAN, Time GAN, NR-GAN, SC-GAN, RCGAN, C-RNN-GAN, Quant GAN, Sequence GAN (SeqGAN)[200].In this field, there are only a few studies that have applied Generative Adversarial Networks (GANs). For example, Que et al. (2023) used GANs for data augmentation in pavement crack classification, improving the performance of an enhanced VGG model by generating realistic crack images for training [201].

6.2.6.4. Hybrid Structures, algorithms. Accuracy is critical when choosing a predictive model. The performance of each algorithm depends on the data, and each algorithm is better at different things. This is because in time series forecasting, linear models capture some data while nonlinear models are needed to more accurately represent other data [203]. To achieve more accurate results in time series modelling and forecasting, hybrid approaches are important and promising. Therefore, the use of hybrid structures in time series prediction is developing rapidly. Hybrid models have been the subject of many studies, and there has been evidence that hybrid models can be

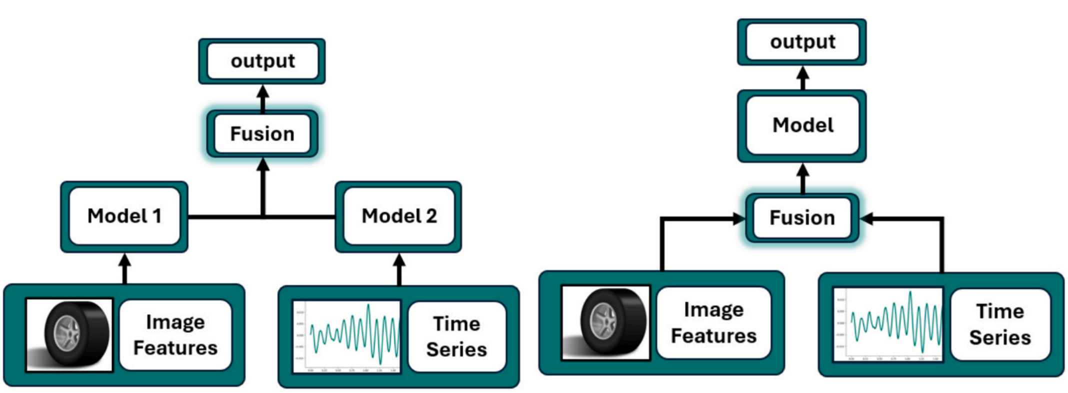

Fig. 16. Fusion Structure[189].

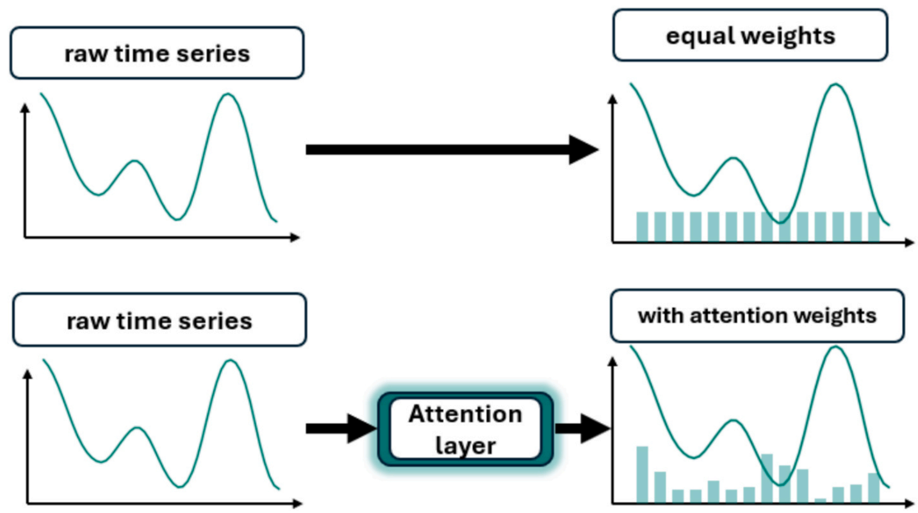

Fig. 17. Attention Mechanism[190].

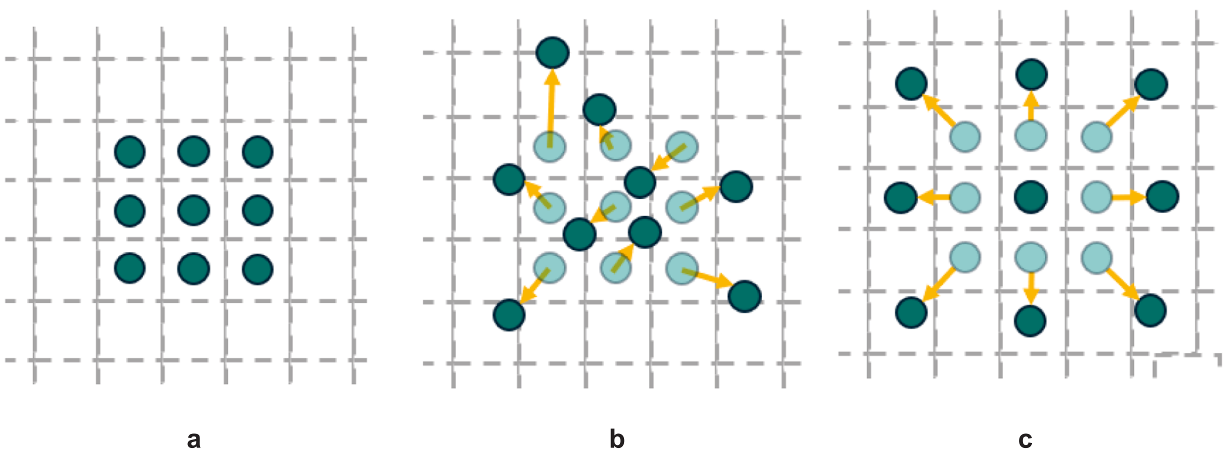

Fig. 18. Deformable convolution structure a) standard convolution b) deformable convolution with offset c) deformable convolution with variant[194].

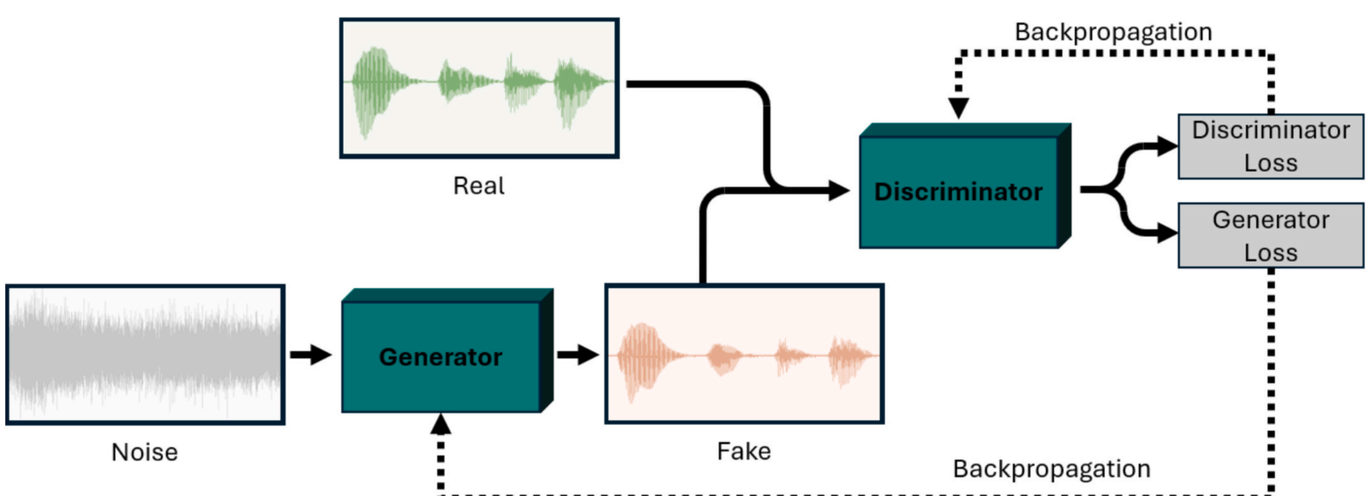

Fig. 19. Generative Learning [202].

successful in improving forecast accuracy [204]. Many studies have been conducted on this topic in recent years. Listing the benefits mentioned in the studies, the following can be noted: improving forecast accuracy, reducing the risk of using inappropriate models, and simplifying the model selection process. An example of a 1D CNN-LSTM hybrid structure is shown in Fig. 20. Using deep learning in feature extraction, using machine learning algorithms in classification and prediction. Or using more than one deep learning algorithm. Some of

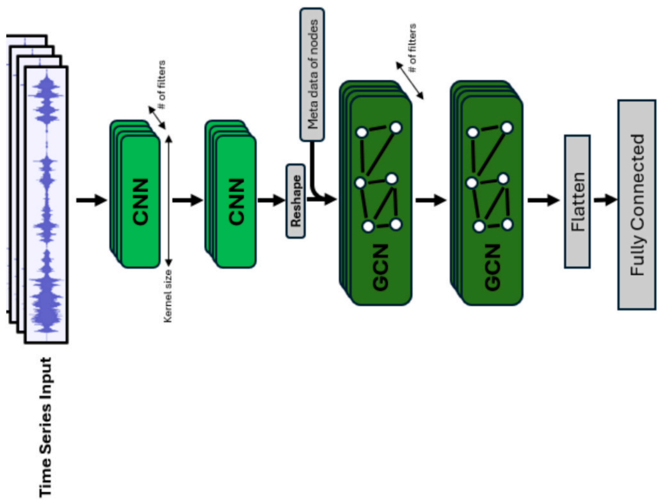

Fig. 20. CNN-GCN Structured Learning [207].

them are Bi-LSTM-Autoencoder, LSTM-1DCNN, Bi-GRU-Autoencoder, GCN-Bi-LSTM etc. The purpose of these structures is to increase the performance of the algorithm. They have achieved this in many studies. In recent years, some studies have also been carried out in this field. Wu (2024) used a deep ensemble learning approach for predicting pavement performance indicators. This method combines different models in a hybrid structure and improves prediction accuracy and stability [205]. Wu et al. (2025) used a hybrid CNN–GRU model to predict pavement roughness (IRI). This deep learning model combines different features and gives better accuracy than traditional methods [206].

7. Conclusion, identified research Gaps, and future works

Deep learning-based models show better accuracy when exploring complex and large data sets. This superiority in feature learning has let to some successful outcomes in many studies. For example, in the time series prediction, obtaining an interpretable result is important for measuring reliability and recent studies have increasingly focused on this aspect. In addition, explainable machine learning has become more widespread to make model decisions transparent and understandable. This growing trend also provides an opportunity for traditional machine learning models to compete with deep learning in terms of interpretability and reliability.

The results of this study aim to identify the most commonly used input parameters and measurement methods in AI-based tyre-road studies, which are critical for accurate noise prediction and monitoring. Finally, by analysing and comparing the studied AI and signal processing-based techniques, the study advances the research field by determining the best-performing AI-based technique for tyre-road noise prediction. In addition, it proposes several future research directions that can guide further studies in this area.

1. Methodological directions:

- One of the biggest problems in AI is speeding up of the learning process. Working with large volumes of data leads to increased computational costs and processing overhead.. There are studies on computational efficiency [208–211]. The progress of deep learning in the coming years depends partly on the developments in GPU technologies [212]. In addition, since it is not fully known what kind of processes are behind deep learning algorithms, this causes them not to be preferred by researchers. For this reason, these techniques are referred as black boxes. To overcome this problem, deep learning algorithms can be used in the feature extraction part, and machine learning algorithms can be used for prediction and classification, combining accuracy with interpretability.
- Apart from extracting features from classical time series data, new trend algorithms such as TSFresh, Catch22, Deep Feature Synthesis and TsFel are becoming widespread. Similarly, Autoencoder, UMAP and VAE have frequently been used for data size reduction in different fields in recent years. When it comes to determining important input variables, SHAP, the attention mechanism and the integrated gradient have become essential tools.
- When the literature is examined, many promising deep learning algorithms have not yet been utilized in this field. For example, Transformers, Graph Neural Networks (GNNs), Bio-LSTM, Bio-GRU, 1d CNN, Transfer Learning, LSTM-AutoEncoder. etc. have not been used. In addition, Genetic Algorithms, Swarm Optimization, Ant Colony, and also Fuzzy Logic could help identify optimal tyre–road conditions. Feature extraction algorithms such as the Deep Autoencoding Gaussian Mixture Model (DAGMM) [213], which have been successfully used in noise and anomaly detection, also show great potential for tyre–road noise research.
- There are several machine learning and tyre-road noise prediction algorithms. At this point, AutoML promises hope for the future of machine learning by finding the most appropriate algorithm. Additionally, if the success of ensemble learning in big data increases, it will be able to compete with deep learning algorithms. Explainable machine learning (XAI) has also become increasingly popular in recent years to make model decisions more transparent and understandable. This growing trend also creates a new opportunity for traditional ML algorithms to compete with deep learning models in terms of interpretability and reliability.

2. Data-related directions

- The use of attention and fusion mechanisms to make better use of different data in training, enhanced deformable and dynamic convolutions to modify the convolutional structure, and multimodal, multitask, multiscale, and multithead structures instead of classical CNN structures has increased in recent years.
- Using tyre-road noise data, road surface, sound absorption, tread pattern, macrotexture, road condition, and road surface condition and anomalies can be estimated or classified. In addition to this, studies on the estimation/classification of surface roughness, sound absorption coefficient and road friction coefficient have become more common.
- Most studies have generally been carried out in dry and perfect environments. The sound changes in icy and wet environments. In addition, the number of cars in the area, and the quality of the road and road damage all affect the sound. Therefore, future research should include more diverse and realistic environmental conditions.
- Many measurements are taken to provide road information as input data for tyre-road noise prediction. These measurements are time-consuming and are difficult to interpret. As an alternative, real-time computer vision methods for road classification and weather detection can simplify and accelerate data acquisition.
- The current designs for tyre-road noise data collection are difficult to use real time monitoring as a product. This is because the current designs that can work together with large wheel and rim systems that can be affected by environmental conditions. Future designs should focus on lightweight, adaptable, and durable structures.
- The biggest problem in this area is the lack of open-source data source regarding tyre-road noise. The TyRoN Tyre Road Noise project, in which we are involved, and which has more than ten partners, aims to fill this gap. It is expected to be a pioneering study in this field.

3. Application-oriented directions

- The study by [60] shows that noise-based road classification gives better results. In this study, they compared image and sound-based systems. This indicates that future studies will likely move toward multi-modal and sensor fusion approaches for more reliable results.
- Moreover, unfortunately, there are few studies on its conversion into products due to these problems. Therefore, efforts should be directed

toward embedded card systems for real-time data collection and evaluation.

- In this area, audio, video, vibration, gyro, etc. can be recorded via mobile phones. Many studies have been carried out to collect data and predict road problems and conditions. However, this cannot be applied to tyre-road noise. In order to turn this into a product, it is necessary to collect internal voice data simultaneously with the phone along with these mechanisms and determine the relationship between them. Future work should explore combining interior sound data with these signals to estimate external noise levels.
- There have been several studies on detecting road conditions and road problems using sensor data. By using computer vision and semantic segmentation, it is possible to detect these problems and conditions and convert them into numerical data and feed them as input to machine learning algorithms. In this way, the prediction performance of tyre-road noise can be improved.
- Hardware limitations of embedded systems (e.g. mobile, robotics, driverless cars) are still remain a challenge [214–216]. Since embedded cards are cheap and easy to use, they should be used more in this area. With such systems, vehicles could adjust their maneuvers dynamically based on road surface conditions.
- It is expected that developments in AI and its adaptation to tyre-road monitoring will lead to new developments in more environmentally friendly road, tyre and vehicle designs.
- This study contributes to broader fields such as smart cities development, noise reduction, improved tyre and vehicle design, advanced road construction, and control of autonomous vehicles.

Deep learning models can effectively process complex tyre–road noise data, but challenges such as high computational cost and limited interpretability remain. Future research should focus on developing faster, explainable, and more efficient AI models. Explainability tools such as SHAP values, attention mechanisms, and feature importance analysis can reveal the factors that most influence tyre-road noise. Multi-output prediction frameworks can also improve the joint analysis of parameters such as road texture, temperature, and speed.

AI applications can support many areas, from analyzing road texture and tyre behaviour to integrating sound, vibration, and image data for better prediction. These advances will enable the development of quieter tyres, better roads, and more sustainable vehicles, contributing to smart and environmentally friendly transportation systems. Although AI-based methods show strong potential for tyre–road noise analysis, most of these applications are still at the experimental or pilot stage, and their validation and accuracy remain limited. Future work should also consider the increasing share of electric vehicles in road traffic, as their reduced engine noise and altered frequency characteristics will influence both road-surface noise modeling and control strategies.

CRediT authorship contribution statement

Mustafa Demetgul: Writing – original draft. **Sanja Lazarova-Molnar:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

References

[1] W. Yang, J. Kang, Acoustic comfort evaluation in urban open public spaces, Appl. Acoust. 66 (2005) 211–229, https://doi.org/10.1016/j.apacoust.2004.07.011.
[2] P.H.T. Zannin, C.R. Marcon, Objective and subjective evaluation of the acoustic comfort in classrooms, Appl. Ergon. 38 (2007) 675–680, https://doi.org/10.1016/j.apergo.2006.10.001.
[3] M.J.M. Nor, M.H. Fouladi, H. Nahvi, A.K. Ariffin, Index for vehicle acoustical comfort inside a passenger car, Appl. Acoust. 69 (2008) 343–353, https://doi.org/10.1016/j.apacoust.2006.11.001.
[4] S. Kanka, L. Fredianelli, F. Artuso, F. Fidecaro, G. Licitra, Evaluation of Acoustic Comfort and Sound Energy Transmission in a Yacht, Energies 16 (2023) 808, https://doi.org/10.3390/en16020808.
[5] X. Zhang, M. Ba, J. Kang, Q. Meng, Effect of soundscape dimensions on acoustic comfort in urban open public spaces, Appl. Acoust. 133 (2018) 73–81, https://doi.org/10.1016/j.apacoust.2017.11.024.
[6] E. Van Kempen, W. Babisch, The quantitative relationship between road traffic noise and hypertension: a meta-analysis, J. Hypertens. 30 (2012) 1075–1086, https://doi.org/10.1097/HJH.0b013e328352ac54.
[7] A. Muzet, Environmental noise, sleep and health, Sleep Med. Rev. 11 (2007) 135–142, https://doi.org/10.1016/j.smrv.2006.09.001.
[8] J. Renaud, R. Karam, M. Salomon, R. Couturier, Deep learning and gradient boosting for urban environmental noise monitoring in smart cities, Expert Syst. Appl. 218 (2023) 119568, https://doi.org/10.1016/j.eswa.2023.119568.
[9] F. Asdrubali, F. D'Alessandro, Innovative Approaches for Noise Management in Smart Cities: a Review, Curr. Pollut. Rep. 4 (2018) 143–153, https://doi.org/10.1007/s40726-018-0090-z.
[10] Y. Liu, X. Ma, L. Shu, Q. Yang, Y. Zhang, Z. Huo, Z. Zhou, Internet of things for Noise Mapping in Smart Cities: State of the Art and Future Directions, IEEE Netw. 34 (2020) 112–118, https://doi.org/10.1109/MNET.011.1900634.
[11] J.G. Nieves, R. Picó, R. Del Rey, J. Alba, J. Redondo, Assessment of the sound reduction index provided by noise barriers with low sound insulation, Appl. Acoust. 220 (2024) 109967, https://doi.org/10.1016/j.apacoust.2024.109967.
[12] A. Ruiz-Padillo, D.P. Ruiz, A.J. Torija, Á. Ramos-Ridao, Selection of suitable alternatives to reduce the environmental impact of road traffic noise using a fuzzy multi-criteria decision model, Environ. Impact Assess. Rev. 61 (2016) 8–18, https://doi.org/10.1016/j.eiar.2016.06.003.
[13] L. Fredianelli, L. Del Pizzo, G. Licitra, Recent Developments in Sonic Crystals as Barriers for Road Traffic Noise Mitigation, Environments 6 (2019) 14, https://doi.org/10.3390/environments6020014.
[14] Y. Azizi, Generation mechanisms of tire/road noise, in: Automot. Tire Noise Vib., Elsevier, 2020: pp. 91–114. https://doi.org/10.1016/B978-0-12-818409-7.00006-4.
[15] J. Cesbron, S. Bianchetti, M.-A. Pallas, A. Le Bellec, V. Gary, P. Klein, Road surface influence on electric vehicle noise emission at urban speed, Noise Mapp. 8 (2021) 217–227, https://doi.org/10.1515/noise-2021-0017.
[16] J.P. Arenas, On the impact of electric vehicle transition on urban noise pollution, Curr. Opin. Environ. Sci. Health 45 (2025) 100623, https://doi.org/10.1016/j.coesh.2025.100623.
[17] O. Merska, P. Mieczkowski, D. Żymełka, Low-noise thin surface course–evaluation of the effectiveness of noise reduction, Transp. Res. Procedia 14 (2016) 2688–2697.
[18] T. Li, A state-of-the-art review of measurement techniques on tire–pavement interaction noise, Measurement 128 (2018) 325–351, https://doi.org/10.1016/j.measurement.2018.06.056.
[19] M. Sánchez-Fernández, J.M.B. Morillas, D.M. González, G.R. Gozalo, Relationship between temperature and road traffic noise under actual conditions of continuous vehicle flow, Transp. Res. Part -Transp. Environ. 100 (2021). https://doi.org/ARTN 103056 10.1016/j.trd.2021.103056.
[20] S. Yang, Y. Wei, Z. Ye, H. Liu, B. Yang, W. Liu, L. Wang, Characterization and modeling of textured cement concrete pavement surfaces for tire-pavement noise prediction, Appl. Acoust. 227 (2025) 110183, https://doi.org/10.1016/j.apacoust.2024.110183.
[21] C. Bückers, T. Beckenbauer, W. Kropp, Analysis of the acoustic characteristics and optimization potential of road surfaces - one focus within the project "Quiet Road Traffic 3," in: 2012: pp. 5545–5556.
[22] J. Winroth, C. Hoever, T. Beckenbauer, M. Männel, Separating the contributions from air-pumping and tyre vibrations by speed dependency analysis of tyre/road noise, in: 2016: pp. 2471–2481.

[23] M.R. Ganji, A. Golroo, H. Sheikhzadeh, A. Ghelmani, M.A. Bidgoli, Dense-graded asphalt pavement macrotexture measurement using tire/road noise monitoring, Autom. Constr. 106 (2019). https://doi.org/ARTN 102887 10.1016/j.autcon.2019.102887.
[24] A. Gagliardi, V. Staderini, S. Saponara, An embedded System for Acoustic Data Processing and AI-Based Real-Time Classification for Road Surface Analysis, IEEE Access 10 (2022) 63073–63084, https://doi.org/10.1109/Access.2022.3183116.
[25] T. Bennert, D. Hanson, A. Maher, N. Vitillo, Influence of Pavement Surface Type on Tire/Pavement Generated Noise, J. Test. Eval. 33 (2005) 94–100, https://doi.org/10.1520/JTE12641.
[26] E. Freitas, J. Tinoco, F. Soares, J. Costa, P. Cortez, P. Pereira, Modelling Tyre-Road Noise with Data Mining Techniques, Arch. Acoust. 40 (2015) 547–560, https://doi.org/10.1515/aoa-2015-0054.
[27] H.B. Huang, T.C. Lim, J.H. Wu, W.P. Ding, J. Pang, Multitarget prediction and optimization of pure electric vehicle tire/road airborne noise sound quality based on a knowledge- and data-driven method, Mech. Syst. Signal Process. 197 (2023). https://doi.org/ARTN 110361 10.1016/j.ymssp.2023.110361.
[28] S.E. Paje, M. Bueno, F. Terán, U. Viñuela, J. Luong, Assessment of asphalt concrete acoustic performance in urban streets, J. Acoust. Soc. Am. 123 (2008) 1439–1445, https://doi.org/10.1121/1.2828068.
[29] S.L. Li, Y.Q. Zhao, G.M. Wu, C.P. Shi, N. Jiang, B. Xu, Multiparameter-based separation method for acoustic emission of in-service prestressed hollow slab tire-road noise signals, Appl. Acoust. 218 (2024). https://doi.org/ARTN 109895 10.1016/j.apacoust.2024.109895.
[30] M. Bueno, J. Luong, U. Viñuela, F. Terán, S.E. Paje, Pavement temperature influence on close proximity tire/road noise, Appl. Acoust. 72 (2011) 829–835, https://doi.org/10.1016/j.apacoust.2011.05.005.
[31] T. Li, Influencing parameters on tire–pavement interaction noise: Review, experiments, and design considerations, Designs 2 (2018) 38.
[32] X.L. Jia, L. Zhou, H.B. Huang, J. Pang, L. Yang, H.R. Karimi, Improving Electric Vehicle Structural-Borne Noise Based on Convolutional Neural Network-Support Vector Regression, Electronics 13 (2024). https://doi.org/ARTN 113 10.3390/electronics13010113.
[33] S.J. Hong, S.W. Park, S.W. Lee, Tire-Pavement Noise Prediction using Asphalt Pavement Texture, KSCE J. Civ. Eng. 22 (2018) 3358–3362, https://doi.org/10.1007/s12205-018-9501-3.
[34] A. Kamineni, V. Chowdary, Development of a Methodology to measure the In-Vehicle Noise Levels due to the Tire–Pavement Interaction, J. Inst. Eng. India Ser. A 101 (2020) 265–272.
[35] T.M. Jian Pang, Prediction and Analysis of Vehicle Interior Road Noise based on Mechanism and Data Series Modeling, Sound Vib. 58 (2024) 59–80. https://doi.org/10.32604/sv.2024.046247.
[36] V.F. Vázquez, M.E. Hidalgo, A.M. García-Hoz, A. Camara, F. Terán, A.M. Ruiz-Teran, S.E. Paje, Tire/road noise, texture, and vertical accelerations: Surface assessment of an urban road, Appl. Acoust. 160 (2020). https://doi.org/ARTN 107153 10.1016/j.apacoust.2019.107153.
[37] Y.Y. Yintao Wei, Analysis of coast-by noise of heavy truck tires, J. Traffic Transp. Eng. Engl. Ed. 3 (2016) 172–179.
[38] T. Li, Tire/road noise separation: tread pattern noise and road texture noise, in: Automot. Tire Noise Vib., Elsevier, 2020: pp. 7–26.
[39] G. De León, L.G. Del Pizzo, L. Teti, A. Moro, F. Bianco, L. Fredianelli, G. Licitra, Evaluation of tyre/road noise and texture interaction on rubberised and conventional pavements using CPX and profiling measurements, Road Mater. Pavement Des. 21 (2020) S91–S102, https://doi.org/10.1080/14680629.2020.1735493.
[40] F.G. Praticò, On the dependence of acoustic performance on pavement characteristics, Transp. Res. Part Transp. Environ. 29 (2014) 79–87, https://doi.org/10.1016/j.trd.2014.04.004.
[41] F. Holzmann, M. Bellino, R. Siegwart, H. Bubb, Predictive estimation of the road-tire friction coefficient, in, IEEE (2006) 885–890.
[42] M.R. Ganji, A. Ghelmani, A. Golroo, H. Sheikhzadeh, A Brief Review on the Application of Sound in Pavement monitoring and Comparison of Tire/Road Noise Processing Methods for Pavement Macrotexture Assessment, Arch. Comput. Methods Eng. 28 (2021) 2977–3000, https://doi.org/10.1007/s11831-020-09484-4.
[43] V.V. Saykin, Y.Y. Zhang, Y.H. Cao, M.L. Wang, J.G. McDaniel, Pavement Macrotexture monitoring through Sound Generated by a Tire-Pavement Interaction, J. Eng. Mech. 139 (2013) 264–271, https://doi.org/10.1061/(Asce)Em.1943-7889.0000485.
[44] R.J. Cao, Z. Leng, S.C. Hsu, W.T. Hung, Modelling of the pavement acoustic longevity in Hong Kong through machine learning techniques, Transp. Res. Part -Transp. Environ. 83 (2020). https://doi.org/ARTN 102366 10.1016/j.trd.2020.102366.
[45] M. Ohiduzzaman, O. Sirin, E. Kassem, Assessment of tire-pavement noise by using on-board sound intensity (OBSI) method in the State of Qatar, in: Bear. Capacity Roads Railw. Airfields, CRC Press, 2017: pp. 953–959.
[46] H. Wang, X. Zhang, S.C. Jiang, A Laboratory and Field Universal Estimation Method for Tire-Pavement Interaction Noise (TPIN) Based on 3D Image Technology, Sustainability 14 (2022). https://doi.org/ARTN 12066 10.3390/su141912066.
[47] G. De León, J. Cesbron, P. Klein, P. Leandri, M. Losa, Novel Methodology to Recover Road Surface Height Maps from Illuminated Scene through Convolutional Neural Networks, Sensors 22 (2022) 6603, https://doi.org/10.3390/s22176603.
[48] H. Edwin, Evaluating tire-pavement noise utilizing the on-board sound intensity method, Graduate School-New Brunswick (2013).
[49] V.F. Vázquez, J. Luong, M. Bueno, F. Terán, S.E. Paje, Assessment of an action against environmental noise: Acoustic durability of a pavement surface with crumb rubber, Sci. Total Environ. 542 (2016) 223–230, https://doi.org/10.1016/j.scitotenv.2015.10.102.
[50] S.E. Paje, J. Luong, V.F. Vázquez, M. Bueno, R. Miró, Road pavement rehabilitation using a binder with a high content of crumb rubber: Influence on noise reduction, Constr. Build. Mater. 47 (2013) 789–798, https://doi.org/10.1016/j.conbuildmat.2013.05.008.
[51] M. Bueno, J. Luong, F. Terán, U. Viñuela, V.F. Vázquez, S.E. Paje, Noise Reduction Properties of an Experimental Bituminous Slurry with Crumb Rubber Incorporated by the Dry Process, Coatings 4 (2014) 602–613, https://doi.org/10.3390/coatings4030602.
[52] J. Masino, M.J. Foitzik, M. Frey, F. Gauterin, Pavement type and wear condition classification from tire cavity acoustic measurements with artificial neural networks, J. Acoust. Soc. Am. 141 (2017) 4220–4229, https://doi.org/10.1121/1.4983757.
[53] H.X. Li, R. Nyirandayisabye, Q.M. Dong, R. Niyirora, T. Hakuzweyezu, I.A. Zardari, F. Nkinahamira, Crack damage prediction of asphalt pavement based on tire noise: A comparison of machine learning algorithms, Constr. Build. Mater. 414 (2024). https://doi.org/ARTN 134867 10.1016/j.conbuildmat.2024.134867.
[54] J. Alonso, J.M. López, I. Pavón, M. Recuero, C. Asensio, G. Arcas, A. Bravo, On-board wet road surface identification using tyre/road noise and support Vector Machines, Appl. Acoust. 76 (2014) 407–415, https://doi.org/10.1016/j.apacoust.2013.09.011.
[55] M. Kalliris, S. Kanarachos, R. Kotsakis, O. Haas, M. Blundell, Machine learning algorithms for wet road surface detection using acoustic measurements, in, IEEE (2019) 265–270.
[56] J. Masino, J. Pinay, M. Reischl, F. Gauterin, Road surface prediction from acoustical measurements in the tire cavity using support vector machine, Appl. Acoust. 125 (2017) 41–48, https://doi.org/10.1016/j.apacoust.2017.03.018.
[57] J. Masino, B. Wohnhas, M. Frey, F. Gauterin, Identification and prediction of road features and their contribution on tire road noise, WSEAS Trans. Syst. Control 12 (2017) 201–212.
[58] C. Ramos-Romero, C. Asensio, R. Moreno, G. de Arcas, Urban Road Surface Discrimination by Tire-Road Noise Analysis and Data Clustering, Sensors 22 (2022). https://doi.org/ARTN 9686 10.3390/s22249686.
[59] S.K. Lee, J. Yoo, C.H. Lee, K. An, Y.S. Yoon, J. Lee, G.H. Yeom, S.U. Hwang, Road type classification using deep learning for Tire-Pavement interaction noise data in autonomous driving vehicle, Appl. Acoust. 212 (2023). https://doi.org/ARTN 109597 10.1016/j.apacoust.2023.109597.
[60] J.K. Lee, B.K. Kim, H. Choi, S.I. Chang, Road-pavement classification by artificial neural network model based on tire-pavement noise and road-surface image, Appl. Acoust. 225 (2024) 110194, https://doi.org/10.1016/j.apacoust.2024.110194.
[61] S.K. Lee, H. Lee, J. Back, K. An, Y. Yoon, K. Yum, S. Kim, S.U. Hwang, Prediction of tire pattern noise in early design stage based on convolutional neural network, Appl. Acoust. 172 (2021). https://doi.org/ARTN 107617 10.1016/j.apacoust.2020.107617.
[62] T. Marin-Cudraz, E. Parizet, B.B. Perez, External tire noise: Determination of timbre parameters and unpleasantness factors, with a focus on truck tires, Appl. Acoust. 216 (2024). https://doi.org/ARTN 109765 10.1016/j.apacoust.2023.109765.
[63] E. Sabanovic, V. Zuraulis, O. Prentkovskis, V. Skrickij, Identification of Road-Surface Type using Deep Neural Networks for Friction Coefficient Estimation, Sensors 20 (2020).
[64] X. Yu, R. Dai, J. Zhang, Y. Yin, S. Li, P. Dai, H. Huang, Vehicle structural road noise prediction based on an improved Long Short-Term memory method, Sound Vib. 59 (2025) 2022. https://doi.org/10.59400/sv2022.
[65] Y. Ma, R. Dai, T. Liu, J. Liu, S. Yang, J. Wang, Research on Vehicle Road Noise Prediction based on AFW-LSTM, Machines 13 (2025) 425, https://doi.org/10.3390/machines13050425.
[66] Y. Yoon, H. Kim, S.K. Lee, J. Lee, S. Hwang, S. Ku, Tire–Road Friction Estimation and Classification Based on a CNN using Tire Acoustical Signals for Autonomous Driving Vehicles, in: Detroit, Michigan, United States, 2025: pp. 2025-01–8761. https://doi.org/10.4271/2025-01-8761.
[67] Y. Ma, R. Dai, T. Liu, M. Wang, Q. Ying, H. Huang, Physics-informed GRU model for vehicle road noise prediction: Integrating transfer path analysis and hybrid data, Sound Vib. 59 (2025) 3143. https://doi.org/10.59400/sv3143.
[68] P. Dai, R. Dai, Y. Yin, J. Wang, H. Huang, W. Ding, A Novel Empirical-Informed Neural Network Method for Vehicle Tire Noise Prediction, Machines 13 (2025) 911, https://doi.org/10.3390/machines13100911.
[69] Y. Ma, J. Wang, Z. Pan, H. Yi, S. Jia, H. Huang, Vehicle Wind Noise Prediction using Auto-Encoder-based Point Cloud Compression and GWO-ResNet, Machines 13 (2025) 920, https://doi.org/10.3390/machines13100920.
[70] H. Guo, Z. Yin, D. Cao, H. Chen, C. Lv, A Review of Estimation for Vehicle Tire-Road Interactions Toward Automated Driving, IEEE Trans. Syst. Man Cybern. Syst. 49 (2019) 14–30, https://doi.org/10.1109/TSMC.2018.2819500.
[71] S.L. Ling, F. Yu, D.Q. Sun, G.Q. Sun, L. Xu, A comprehensive review of tire-pavement noise: Generation mechanism, measurement methods, and quiet asphalt pavement, J. Clean. Prod. 287 (2021). https://doi.org/ARTN 125056 10.1016/j.jclepro.2020.125056.
[72] Y. Wang, J. Hu, F. Wang, H. Dong, Y. Yan, Y. Ren, C. Zhou, G. Yin, Tire Road Friction Coefficient Estimation: Review and Research Perspectives, Chin. J. Mech. Eng. 35 (2022) 6, https://doi.org/10.1186/s10033-021-00675-z.
[73] J. Leukel, L. Scheurer, V. Sugumaran, Machine learning models for predicting physical properties in asphalt road construction: a systematic review, Constr.

Build. Mater. 440 (2024) 137397, https://doi.org/10.1016/j.conbuildmat.2024.137397.
[74] D.M. Barbieri, B. Lou, Instrumentation and testing for road condition monitoring – a state-of-the-art review, NDT E Int. 146 (2024) 103161, https://doi.org/10.1016/j.ndteint.2024.103161.
[75] J. Kang, P. Tavassoti, M.N.A.R. Chaudhry, H. Baaj, M. Ghafurian, Artificial intelligence techniques for pavement performance prediction: a systematic review, Road Mater. Pavement Des. 26 (2025) 497–522, https://doi.org/10.1080/14680629.2024.2373222.
[76] J. Shang, A.A. Zhang, Z. Dong, H. Zhang, A. He, Automated pavement detection and artificial intelligence pavement image data processing technology, Autom. Constr. 168 (2024) 105797, https://doi.org/10.1016/j.autcon.2024.105797.
[77] D. Yang, D. Zhang, Y. Yuan, Z. Lei, B. Ding, L. Bo, Road terrain recognition based on tire noise for autonomous vehicle, Sci. Rep. 14 (2024) 30913, https://doi.org/10.1038/s41598-024-81666-7.
[78] P. Gautam, Y. Azizi, A. Chandy, Developing a Statistical Model to Predict Tire Noise at Different Speeds, SAE Int, J. Veh. Dyn. Stab. NVH 1 (2017) 198–203, https://doi.org/10.4271/2017-01-1507.
[79] A.A.M. Shubber, R.H.A. Al-Rubaee, M.H. Taher, Prediction models for distress noise generated due to tire-pavement surface interaction, IOP Conf. Ser.: Mater. Sci. Eng. 737 (2020) 012127, https://doi.org/10.1088/1757-899X/737/1/012127.
[80] A. Ongel, E. Kohler, J. Harvey, Principal Components Regression of Onboard Sound Intensity Levels, J. Transp. Eng. 134 (2008) 459–466, https://doi.org/10.1061/(ASCE)0733-947X(2008)134:11(459).
[81] J. Pinay, H.-J. Unrau, F. Gauterin, Prediction of Close-Proximity Tire-Road Noise from Tire Cavity Noise measurements using a statistical approach, Appl. Acoust. 141 (2018) 293–300, https://doi.org/10.1016/j.apacoust.2018.07.023.
[82] J. Cesbron, F. Anfosso-Lédée, D. Duhamel, H. Ping Yin, D. Le Houédec, Experimental study of tyre/road contact forces in rolling conditions for noise prediction, J. Sound Vib. 320 (2009) 125–144. https://doi.org/10.1016/j.jsv.2008.07.018.
[83] L. Rapino, L. Liu, A. Dinosio, F. Ripamonti, R. Corradi, S. Baro, Processing of tyre data for rolling noise prediction through a statistical modelling approach, Mech. Syst. Signal Process. 188 (2023) 110042, https://doi.org/10.1016/j.ymssp.2022.110042.
[84] L. Spies, T. Li, R. Burdisso, C. Sandu, An artificial neural network (ANN) approach to model Tire-Pavement interaction noise (TPIN) based on tire noise separation, Appl. Acoust. 206 (2023) 109294, https://doi.org/10.1016/j.apacoust.2023.109294.
[85] T. Li, R. Burdisso, C. Sandu, The effects of tread patterns on tire pavement interaction noise, in: INTER-NOISE NOISE-CON Congr. Conf. Proc., Institute of Noise Control Engineering, 2016: pp. 208–219.
[86] T. Li, R. Burdisso, C. Sandu, An Artificial Neural Network Model to Predict Tread Pattern-Related Tire Noise, In (2017:), https://doi.org/10.4271/2017-01-1904.
[87] Y. Che, W.X. Xiao, L.J. Chen, Z.C. Huang, GA-BP Neural Network based Tire Noise Prediction, Adv. Mater. Res. 443–444 (2012) 65–70, https://doi.org/10.4028/www.scientific.net/AMR.443-444.65.
[88] T. Lee, C. Chun, S.-K. Ryu, Detection of Road-Surface Anomalies using a Smartphone Camera and Accelerometer, Sensors 21 (2021) 561, https://doi.org/10.3390/s21020561.
[89] J.-T. Chiu, F.-Y. Tu, Application of a pattern recognition technique to the prediction of tire noise, J. Sound Vib. 350 (2015) 30–40, https://doi.org/10.1016/j.jsv.2015.04.013.
[90] S. Mohammadi, A. Ohadi, M. Irannejad-Parizi, A comprehensive study on statistical prediction and reduction of tire/road noise, J. Vib. Control 28 (2022) 2487–2501, https://doi.org/10.1177/10775463211013184.
[91] G. Dubois, J. Cesbron, H.P. Yin, F. Anfosso-Lédée, D. Duhamel, Statistical estimation of low frequency tyre/road noise from numerical contact forces, Appl. Acoust. 74 (2013) 1085–1093, https://doi.org/10.1016/j.apacoust.2013.03.011.
[92] H. Huang, Y. Wang, J. Wu, W. Ding, J. Pang, Prediction and optimization of pure electric vehicle tire/road structure-borne noise based on knowledge graph and multi-task ResNet, Expert Syst. Appl. 255 (2024) 124536, https://doi.org/10.1016/j.eswa.2024.124536.
[93] H. Liu, J. Zhang, P. Guo, F. Bi, H. Yu, G. Ni, Sound quality prediction for engine-radiated noise, Mech. Syst. Signal Process. 56–57 (2015) 277–287, https://doi.org/10.1016/j.ymssp.2014.10.005.
[94] J. Yao, Y. Xiang, S. Qian, S. Wang, S. Wu, Noise source identification of diesel engine based on variational mode decomposition and robust independent component analysis, Appl. Acoust. 116 (2017) 184–194, https://doi.org/10.1016/j.apacoust.2016.09.026.
[95] L. Liang, S. Chen, P. Li, The evaluation of vehicle interior impact noise inducing by speed bumps based on multi-features combination and support vector machine, Appl. Acoust. 163 (2020) 107212, https://doi.org/10.1016/j.apacoust.2020.107212.
[96] Y. Nakajima, Advanced Tire Mechanics, Springer Singapore, Singapore (2019), https://doi.org/10.1007/978-981-13-5799-2.
[97] J. Cheer, S.J. Elliott, Multichannel control systems for the attenuation of interior road noise in vehicles, Mech. Syst. Signal Process. 60–61 (2015) 753–769, https://doi.org/10.1016/j.ymssp.2015.01.008.
[98] X. Huang, H. Huang, J. Wu, M. Yang, W. Ding, Sound quality prediction and improving of vehicle interior noise based on deep convolutional neural networks, Expert Syst. Appl. 160 (2020) 113657, https://doi.org/10.1016/j.eswa.2020.113657.
[99] J. Jiang, Y. Li, Review of active noise control techniques with emphasis on sound quality enhancement, Appl. Acoust. 136 (2018) 139–148, https://doi.org/10.1016/j.apacoust.2018.02.021.
[100] P. Mohan, V.N. Padmanabhan, R. Ramjee, Nericell: rich monitoring of road and traffic conditions using mobile smartphones, in: Proc. 6th ACM Conf. Embed. Netw. Sens. Syst., ACM, Raleigh NC USA, 2008: pp. 323–336. https://doi.org/10.1145/1460412.1460444.
[101] D.R. Balcombe, P. Crowther, Practical development problems in achieving 74dB (a) for cars, Proc.-Inst. Acoust. 15 (1993) 49.
[102] S. Gade, P. Rasmussen, N. Taylor, Passy measurements vs. STSF passby simulations, in: Inter-Noise 96 Noise Control 25 Years Liverp. 30 July-2 August 1996, 1996: pp. 3087–3092.
[103] R.B. GmbH, BOSCH Automotive Handbook, Robert Bosch (2004). https://books.google.de/books?id=VmvsjBDgRaoC.
[104] M.E. Braun, S.J. Walsh, J.L. Horner, R. Chuter, Noise source characteristics in the ISO 362 vehicle pass-by noise test: Literature review, Appl. Acoust. 74 (2013) 1241–1265, https://doi.org/10.1016/j.apacoust.2013.04.005.
[105] J.A. Ejsmont, U. Sandberg, S. Taryma, Influence of tread pattern on tire/road noise, SAE Trans. 632–640 (1984).
[106] D.B. Thrasher, R.F. Miller, R.G. Bauman, Effect of Pavement Texture on Tire/Pavement Interaction Noise, in: 1976: p. 762011. https://doi.org/10.4271/762011.
[107] B. Zhu, D. Hu, F. Liao, J. Chen, B. Su, J. Wu, Y. Wang, A Fast Approach to Optimize Tread Pattern Shape for Tire Noise Reduction, Appl. Sci. 13 (2023) 10256, https://doi.org/10.3390/app131810256.
[108] S.-K. Lee, H. Lee, J. Back, K. An, Y. Yoon, K. Yum, S. Kim, S.-U. Hwang, Prediction of tire pattern noise in early design stage based on convolutional neural network, Appl. Acoust. 172 (2021) 107617, https://doi.org/10.1016/j.apacoust.2020.107617.
[109] M. Li, W. Van Keulen, M. Van De Ven, A. Molenaar, G. Tang, Investigation on material properties and surface characteristics related to tyre–road noise for thin layer surfacings, Constr. Build. Mater. 59 (2014) 62–71, https://doi.org/10.1016/j.conbuildmat.2014.02.050.
[110] K.-Y. Ho, W.-T. Hung, C.-F. Ng, Y.-K. Lam, R. Leung, E. Kam, The effects of road surface and tyre deterioration on tyre/road noise emission, Appl. Acoust. 74 (2013) 921–925, https://doi.org/10.1016/j.apacoust.2013.01.010.
[111] J. Bohatkiewicz, M. Hałucha, M.K. Dębiński, M. Jukowski, Z. Tabor, Investigation of Acoustic Properties of Different Types of Low-Noise Road Surfacers under In Situ and Laboratory Conditions, Materials 15 (2022) 480, https://doi.org/10.3390/ma15020480.
[112] K. Ismayilov, K. Karimova, A. Azimov, U. Raxmatov, Comparative analysis of noise levels available on simple and rubber granule asphalt-concrete coating roads, IOP Conf. Ser.: Earth Environ. Sci 1142 (2023) 012038, https://doi.org/10.1088/1755-1315/1142/1/012038.
[113] P. Kindt, F. De Coninck, P. Sas, W. Desmet, Analysis of Tire/Road Noise Caused by Road Impact Excitations, in: 2007: pp. 2007-01–2248. https://doi.org/10.4271/2007-01-2248.
[114] U. Sandberg, Road traffic noise—The influence of the road surface and its characterization, Appl. Acoust. 21 (1987) 97–118, https://doi.org/10.1016/0003-682X(87)90004-1.
[115] M.A. Staiano, Influence of pavement type and aggregate size on tire-pavement noise generation, Noise Control Eng. J. 69 (2021) 162–172, https://doi.org/10.3397/1/376916.
[116] L.G. Del Pizzo, L. Teti, A. Moro, F. Bianco, L. Fredianelli, G. Licitra, Influence of texture on tyre road noise spectra in rubberized pavements, Appl. Acoust. 159 (2020) 107080, https://doi.org/10.1016/j.apacoust.2019.107080.
[117] P.S. Els, M.J. Stallmann, T.R. Botha, A.G. Guthrie, K.R.S. Wright, K. Augsburg, K. Höpping, V. Bernius, C. Sandu, E. Jimenez, Comparison of Tire Footprint Measurement Techniques, in: Vol. 3 18th Int. Conf. Adv. Veh. Technol. 13th Int. Conf. Des. Educ. 9th Front. Biomed. Devices, American Society of Mechanical Engineers, Charlotte, North Carolina, USA, 2016: p. V003T01A027. https://doi.org/10.1115/DETC2016-59944.
[118] E. Ascari, M. Cerchiai, L. Fredianelli, G. Licitra, Statistical Pass-by for Unattended Road Traffic Noise Measurement in an Urban Environment, Sensors 22 (2022) 8767, https://doi.org/10.3390/s22228767.
[119] R. Moreno, F. Bianco, S. Carpita, A. Monticelli, L. Fredianelli, G. Licitra, Adjusted Controlled Pass-by (CPB) Method for Urban Road Traffic Noise Assessment, Sustainability 15 (2023) 5340, https://doi.org/10.3390/su15065340.
[120] S. Dallasta, L. Rapino, F. Ripamonti, S. Baro, R. Corradi, Prediction of coast-by tyre/road noise based on equivalent monopoles synthesised from indoor tests, Appl. Acoust. 241 (2026) 111033, https://doi.org/10.1016/j.apacoust.2025.111033.
[121] W. Gardziejczyk, M. Motylewicz, P. Gierasimiuk, R. Ziolkowski, D. Grzyb, Noisiness of road surfaces in Poland according to the Statistical Pass-by method, Transp. Res. Part Transp. Environ. 148 (2025) 104996, https://doi.org/10.1016/j.trd.2025.104996.
[122] G. Licitra, M. Bernardini, R. Moreno, F. Bianco, L. Fredianelli, CNOSSOS-EU coefficients for electric vehicle noise emission, Appl. Acoust. 211 (2023) 109511, https://doi.org/10.1016/j.apacoust.2023.109511.
[123] B. Radhika, V. Pannala, S. Singh, S. Sundar, K.P. Biligiri, Time-Frequency analysis of acoustic signals from tyre-pavement interaction, J. Acoust. Soc. Am. 151 (2022) 370–386, https://doi.org/10.1121/10.0009269.
[124] C. Ramos-Romero, P. León-Ríos, B.M. Al-Hadithi, L. Sigcha, G. De Arcas, C. Asensio, Identification and mapping of asphalt surface deterioration by tyre-pavement interaction noise measurement, Measurement 146 (2019) 718–727, https://doi.org/10.1016/j.measurement.2019.06.034.

[125] J. Cesbron, P. Klein, Correlation between tyre/road noise levels measured by the Coast-by and the Close-ProXimity methods, Appl. Acoust. 126 (2017) 36–46, https://doi.org/10.1016/j.apacoust.2017.05.005.
[126] M.-Q. Tran, H.-P. Doan, V.Q. Vu, L.T. Vu, Machine learning and IoT-based approach for tool condition monitoring: a review and future prospects, Measurement 207 (2023) 112351, https://doi.org/10.1016/j.measurement.2022.112351.
[127] L. Gabrielli, L. Ambrosini, F. Vesperini, V. Bruschi, S. Squartini, L. Cattani, Processing Acoustic Data with Siamese Neural Networks for Enhanced Road Roughness Classification, in: 2019 Int. Jt. Conf. Neural Netw. IJCNN, IEEE, Budapest, Hungary, 2019: pp. 1–7. https://doi.org/10.1109/ijcnn.2019.8852108.
[128] I. Abdic, L. Fridman, D.E. Brown, W. Angell, B. Reimer, E. Marchi, B. Schuller, Detecting road surface wetness from audio: A deep learning approach, in: 2016 23rd Int. Conf. Pattern Recognit. ICPR, IEEE, Cancun, 2016. https://doi.org/10.1109/icpr.2016.7900169.
[129] Kensuke Hayashi, Seiichi Shin, Road type estimation by wavelet analysis of running tire sound, in: 2008 Int. Conf. Wavelet Anal. Pattern Recognit., IEEE, Hong Kong, China, 2008: pp. 650–653. https://doi.org/10.1109/ICWAPR.2008.4635859.
[130] A. Gupta, S. Gowda, A. Tiwari, A.K. Gupta, XGBoost-SHAP framework for asphalt pavement condition evaluation, Constr. Build. Mater. 426 (2024) 136182, https://doi.org/10.1016/j.conbuildmat.2024.136182.
[131] B. Peng, Y. Bi, B. Xue, M. Zhang, S. Wan, A Survey on Fault Diagnosis of Rolling Bearings, Algorithms 15 (2022) 347, https://doi.org/10.3390/a15100347.
[132] J.P. Paulo, J.L.B. Coelho, M.A.T. Figueiredo, Statistical classification of road pavements using near field vehicle rolling noise measurements, J. Acoust. Soc. Am. 128 (2010) 1747–1754, https://doi.org/10.1121/1.3466870.
[133] S. Mohammadi, A. Ohadi, Introducing a procedure for predicting and reducing tire/road noise using a fast-computing hybrid model, J. Acoust. Soc. Am. 151 (2022) 1895–1912, https://doi.org/10.1121/10.0009751.
[134] J. David, T. De Pessemier, L. Dekoninck, B. De Coensel, W. Joseph, D. Botteldooren, L. Martens, Detection of road pavement quality using statistical clustering methods, J. Intell. Inf. Syst. 54 (2020) 483–499, https://doi.org/10.1007/s10844-019-00570-z.
[135] Z. Wang, J. Zhan, C. Duan, X. Guan, Z. Zhong, Z. Cao, Road Surface Recognition Based on Vision and Tire Noise, in: 2021 5th CAA Int. Conf. Veh. Control Intell. CVCI, IEEE, Tianjin, China, 2021: pp. 1–5. https://doi.org/10.1109/CVCI54083.2021.9661199.
[136] W. Van Hauwermeiren, K. Filipan, D. Botteldooren, B. De Coensel, Opportunistic monitoring of pavements for noise labeling and mitigation with machine learning, Transp. Res. Part Transp. Environ. 90 (2021) 102636, https://doi.org/10.1016/j.trd.2020.102636.
[137] T. Pradhan, P. Nimkar, K. Jhajharia, Machine Learning and Deep Learning for Big Data Analysis:, in: D. Darwish (Ed.), Adv. Bus. Inf. Syst. Anal., IGI Global, 2024: pp. 209–240. https://doi.org/10.4018/979-8-3693-0413-6.ch008.
[138] M. Bahri, F. Salutari, A. Putina, M. Sozio, AutoML: state of the art with a focus on anomaly detection, challenges, and research directions, Int. J. Data Sci. Anal. 14 (2022) 113–126, https://doi.org/10.1007/s41060-022-00309-0.
[139] F. Mohr, M. Wever, E. Hüllermeier, ML-Plan: Automated machine learning via hierarchical planning, Mach. Learn. 107 (2018) 1495–1515, https://doi.org/10.1007/s10994-018-5735-z.
[140] A. Alsharef, K. Aggarwal, M. Sonia, A.M. Kumar, Review of ML and AutoML Solutions to Forecast Time-Series Data, Arch. Comput. Methods Eng. 29 (2022) 5297–5311, https://doi.org/10.1007/s11831-022-09765-0.
[141] M. Feurer, K. Eggensperger, S. Falkner, M. Lindauer, F. Hutter, Practical automated machine learning for the automl challenge 2018, in: Int. Workshop Autom. Mach. Learn. ICML, 2018: pp. 1189–1232.
[142] S.K. Karmaker ("Santu"), Md.M. Hassan, M.J. Smith, L. Xu, C. Zhai, K. Veeramachaneni, AutoML to Date and Beyond: Challenges and Opportunities, ACM Comput. Surv. 54 (2022) 1–36. https://doi.org/10.1145/3470918.
[143] L. Cui, Y. Chen, J. Deng, Z. Han, A novel attLSTM framework combining the attention mechanism and bidirectional LSTM for demand forecasting, Expert Syst. Appl. 254 (2024) 124409, https://doi.org/10.1016/j.eswa.2024.124409.
[144] Z. Han, J. Zhao, H. Leung, K.F. Ma, W. Wang, A Review of Deep Learning Models for Time Series Prediction, IEEE Sens. J. 21 (2021) 7833–7848, https://doi.org/10.1109/JSEN.2019.2923982.
[145] Y. Hua, Z. Zhao, R. Li, X. Chen, Z. Liu, H. Zhang, Deep Learning with Long Short-Term memory for Time Series Prediction, IEEE Commun. Mag. 57 (2019) 114–119, https://doi.org/10.1109/MCOM.2019.1800155.
[146] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436–444, https://doi.org/10.1038/nature14539.
[147] S. Hochreiter, J. Schmidhuber, Long Short-Term memory, Neural Comput. 9 (1997) 1735–1780, https://doi.org/10.1162/neco.1997.9.8.1735.
[148] https://medium.com/@rebeen.jaff/what-is-lstm-introduction-to-long-short-term-memory-66bd3855b9ce, (n.d.).
[149] X. Huang, Q. Li, Y. Tai, Z. Chen, J. Liu, J. Shi, W. Liu, Time series forecasting for hourly photovoltaic power using conditional generative adversarial network and Bi-LSTM, Energy 246 (2022) 123403, https://doi.org/10.1016/j.energy.2022.123403.
[150] M. Schuster, K.K. Paliwal, Bidirectional recurrent neural networks, IEEE Trans. Signal Process. 45 (1997) 2673–2681, https://doi.org/10.1109/78.650093.
[151] A. Aziz Sharfuddin, Md. Nafis Tihami, Md. Saiful Islam, A Deep Recurrent Neural Network with BiLSTM model for Sentiment Classification, in: 2018 Int. Conf. Bangla Speech Lang. Process. ICBSLP, IEEE, Sylhet, 2018: pp. 1–4. https://doi.org/10.1109/ICBSLP.2018.8554396.
[152] H. Kang, S. Yang, J. Huang, J. Oh, Time Series Prediction of Wastewater Flow Rate by Bidirectional LSTM Deep Learning, Int. J. Control Autom. Syst. 18 (2020) 3023–3030, https://doi.org/10.1007/s12555-019-0984-6.
[153] S.-L. Shen, P.G. Atangana Njock, A. Zhou, H.-M. Lyu, Dynamic prediction of jet grouted column diameter in soft soil using Bi-LSTM deep learning, Acta Geotech. 16 (2021) 303–315, https://doi.org/10.1007/s11440-020-01005-8.
[154] P.T. Yamak, L. Yujian, P.K. Gadosey, A Comparison between ARIMA, LSTM, and GRU for Time Series Forecasting, in: Proc. 2019 2nd Int. Conf. Algorithms Comput. Artif. Intell., ACM, Sanya China, 2019: pp. 49–55. https://doi.org/10.1145/3377713.3377722.
[155] X. Li, X. Ma, F. Xiao, F. Wang, S. Zhang, Application of Gated Recurrent Unit (GRU) Neural Network for Smart batch Production Prediction, Energies 13 (2020) 6121, https://doi.org/10.3390/en13226121.
[156] Y. Li, R. Sun, R. Horne, Deep Learning for Well Data History Analysis, in: Day 1 Mon Sept. 30 2019, SPE, Calgary, Alberta, Canada, 2019: p. D011S008R002. https://doi.org/10.2118/196011-MS.
[157] A. Tokgöz, G. Ünal, A RNN based time series approach for forecasting turkish electricity load, in: 2018 26th Signal Process. Commun. Appl. Conf. SIU, IEEE, Izmir, Turkey, 2018: pp. 1–4. https://doi.org/10.1109/SIU.2018.8404313.
[158] J. Wang, X. Li, J. Li, Q. Sun, H. Wang, NGCU: a New RNN Model for Time-Series Data Prediction, Big Data Res. 27 (2022) 100296, https://doi.org/10.1016/j.bdr.2021.100296.
[159] M.K. Mahadi, R. Rahad, M.A. Haque, M.M. Nishat, Gated recurrent unit (GRU)-based deep learning method for spectrum estimation and inverse modeling in plasmonic devices, Appl. Phys. A 130 (2024) 784, https://doi.org/10.1007/s00339-024-07956-z.
[160] H.C. Kilinc, S. Apak, F. Ozkan, M.E. Ergin, A. Yurtsever, Multimodal Fusion of Optimized GRU–LSTM with Self-attention Layer for Hydrological Time Series forecasting, Water Resour. Manag. (2024), https://doi.org/10.1007/s11269-024-03943-4.
[161] H. Balti, A. Ben Abbes, I.R. Farah, A Bi-GRU-based encoder–decoder framework for multivariate time series forecasting, Soft. Comput. 28 (2024) 6775–6786, https://doi.org/10.1007/s00500-023-09531-9.
[162] Z. Yang, Y. Tian, T. Zhou, Y. Zhu, P. Zhang, J. Chen, J. Li, Time-series deep survival prediction for hemodialysis patients using an attention-based Bi-GRU network, Comput. Methods Programs Biomed. 212 (2021) 106458, https://doi.org/10.1016/j.cmpb.2021.106458.
[163] S. Mekruksavanich, N. Hnoohom, A. Jitpattanakul, A Hybrid Deep Residual Network for Efficient Transitional activity Recognition based on Wearable Sensors, Appl. Sci. 12 (2022) 4988, https://doi.org/10.3390/app12104988.
[164] O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, D.J. Inman, A review of vibration-based damage detection in civil structures: from traditional methods to Machine Learning and Deep Learning applications, Mech. Syst. Signal Process. 147 (2021) 107077, https://doi.org/10.1016/j.ymssp.2020.107077.
[165] Y. Wang, R. Zou, F. Liu, L. Zhang, Q. Liu, A review of wind speed and wind power forecasting with deep neural networks, Appl. Energy 304 (2021) 117766, https://doi.org/10.1016/j.apenergy.2021.117766.
[166] X. Ye, Y. Cao, A. Liu, X. Wang, Y. Zhao, N. Hu, Parallel convolutional neural network toward high efficiency and robust structural damage identification, Struct. Health Monit. 22 (2023) 3805–3826, https://doi.org/10.1177/14759217231158786.
[167] T.B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D.M. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, D. Amodei, Language Models are Few-Shot Learners, (2020). https://doi.org/10.48550/ARXIV.2005.14165.
[168] H. Touvron, M. Cord, M. Douze, F. Massa, A. Sablayrolles, H. Jégou, Training data-efficient image transformers & distillation through attention, (2020). https://doi.org/10.48550/ARXIV.2012.12877.
[169] Y. Wang, H. Wu, J. Dong, Y. Liu, M. Long, J. Wang, Deep Time Series Models: A Comprehensive Survey and Benchmark, (2024). https://doi.org/10.48550/ARXIV.2407.13278.
[170] S. Li, X. Jin, Y. Xuan, X. Zhou, W. Chen, Y.-X. Wang, X. Yan, Enhancing the Locality and Breaking the Memory Bottleneck of Transformer on Time Series Forecasting, (2019). https://doi.org/10.48550/ARXIV.1907.00235.
[171] B. Lim, S.Ö. Arık, N. Loeff, T. Pfister, Temporal Fusion Transformers for interpretable multi-horizon time series forecasting, Int. J. Forecast. 37 (2021) 1748–1764, https://doi.org/10.1016/j.ijforecast.2021.03.012.
[172] A. Vaswani, Attention is all you need, Adv. Neural Inf. Process. Syst. (2017).
[173] B. Wu, L. Wang, Y.-R. Zeng, Interpretable wind speed prediction with multivariate time series and temporal fusion transformers, Energy 252 (2022) 123990, https://doi.org/10.1016/j.energy.2022.123990.
[174] Z. Yan, L. Yue, W. Luo, J. Sun, Real-time detection of road surface friction coefficient: a new framework integrating diffusion model and Transformer in Transformer algorithms, Alex. Eng. J. 113 (2025) 620–632, https://doi.org/10.1016/j.aej.2024.11.003.
[175] P. Lara-Benítez, L. Gallego-Ledesma, M. Carranza-García, J.M. Luna-Romera, Evaluation of the Transformer Architecture for Univariate Time Series Forecasting, in: E. Alba, G. Luque, F. Chicano, C. Cotta, D. Camacho, M. Ojeda-Aciego, S. Montes, A. Troncoso, J. Riquelme, R. Gil-Merino (Eds.), Adv. Artif. Intell., Springer International Publishing, Cham, 2021: pp. 106–115. https://doi.org/10.1007/978-3-030-85713-4_11.
[176] L. Yang, A. Shami, On hyperparameter optimization of machine learning algorithms: Theory and practice, Neurocomputing 415 (2020) 295–316, https://doi.org/10.1016/j.neucom.2020.07.061.

[177] B. Bischl, M. Binder, M. Lang, T. Pielok, J. Richter, S. Coors, J. Thomas, T. Ullmann, M. Becker, A. Boulesteix, D. Deng, M. Lindauer, Hyperparameter optimization: Foundations, algorithms, best practices, and open challenges, Wires Data Min. Knowl. Discov. 13 (2023) e1484.
[178] C. Bergmeir, J.M. Benítez, On the use of cross-validation for time series predictor evaluation, Inf. Sci. 191 (2012) 192–213, https://doi.org/10.1016/j.ins.2011.12.028.
[179] C. Bergmeir, R.J. Hyndman, B. Koo, A note on the validity of cross-validation for evaluating autoregressive time series prediction, Comput. Stat. Data Anal. 120 (2018) 70–83, https://doi.org/10.1016/j.csda.2017.11.003.
[180] N. Elshaboury, M.S. Yamany, S. Labi, O. Smadi, Enhancing local road pavement condition prediction using Bayesian-optimized ensemble machine learning and adaptive synthetic sampling technique, Int. J. Pavement Eng. 25 (2024) 2365957, https://doi.org/10.1080/10298436.2024.2365957.
[181] C. Liang, M. Hao, Y. Shen, H. Li, J. Fan, Tire noise prediction based on transfer learning and multi-modal fusion, Proc. Inst. Mech. Eng. Part J. Automob. Eng. (2025), https://doi.org/10.1177/09544070241232606.
[182] Q. Abbas, T. Ali, A.T. Asad, M. Aslam, Analyzing the impact of geosynthetic reinforcement on Sinkhole: a numerical investigation with Machine Learning approach, Eng. Fail. Anal. 157 (2024) 107915, https://doi.org/10.1016/j.engfailanal.2023.107915.
[183] Z. Cai, Q. Fan, R.S. Feris, N. Vasconcelos, A Unified Multi-scale Deep Convolutional Neural Network for Fast Object Detection, in: B. Leibe, J. Matas, N. Sebe, M. Welling (Eds.), Comput. Vis. – ECCV 2016, Springer International Publishing, Cham, 2016: pp. 354–370. https://doi.org/10.1007/978-3-319-46493-0_22.
[184] Z. Deng, B. Wang, Y. Xu, T. Xu, C. Liu, Z. Zhu, Multi-Scale Convolutional Neural Network with Time-Cognition for Multi-step Short-Term load forecasting, IEEE Access 7 (2019) 88058–88071, https://doi.org/10.1109/ACCESS.2019.2926137.
[185] J. Dolz, K. Gopinath, J. Yuan, H. Lombaert, C. Desrosiers, I. Ben Ayed, HyperDense-Net: A Hyper-Densely Connected CNN for Multi-Modal Image Segmentation, IEEE Trans. Med. Imaging 38 (2019) 1116–1126. https://doi.org/10.1109/TMI.2018.2878669.
[186] L.L. Filho, R. De Oliveira Werneck, M. Castro, P. Ribeiro Mendes Júnior, A. Lustosa, M. Zampieri, O. Linares, R. Moura, E. Morais, M. Amaral, S. Salavati, A. Loomba, A. Esmin, M. Gonçalves, D.J. Schiozer, A. Ferreira, A. Davólio, A. Rocha, A multi-modal approach for mixed-frequency time series forecasting, Neural Comput. Appl. 36 (2024) 21581–21605. https://doi.org/10.1007/s00521-024-10305-z.
[187] Z. Kong, C. Zhang, H. Lv, F. Xiong, Z. Fu, Multimodal Feature Extraction and Fusion Deep Neural Networks for Short-Term load forecasting, IEEE Access 8 (2020) 185373–185383, https://doi.org/10.1109/ACCESS.2020.3029828.
[188] M. Canizo, I. Triguero, A. Conde, E. Onieva, Multi-head CNN–RNN for multi-time series anomaly detection: an industrial case study, Neurocomputing 363 (2019) 246–260, https://doi.org/10.1016/j.neucom.2019.07.034.
[189] D. Gkoumas, S. Uprety, Dawei Song, Investigating non-classical correlations between decision fused multi-modal documents, (2018). https://doi.org/10.13140/RG.2.2.18856.42246.
[190] M. Aslam, J.-S. Kim, J. Jung, Multi-step ahead wind power forecasting based on dual-attention mechanism, Energy Rep. 9 (2023) 239–251, https://doi.org/10.1016/j.egyr.2022.11.167.
[191] A.H. Nielsen, A. Iosifidis, H. Karstoft, Forecasting large-scale circulation regimes using deformable convolutional neural networks and global spatiotemporal climate data, Sci. Rep. 12 (2022) 8395, https://doi.org/10.1038/s41598-022-12167-8.
[192] Z. Diao, X. Wang, D. Zhang, Y. Liu, K. Xie, S. He, Dynamic Spatial-Temporal Graph Convolutional Neural Networks for Traffic forecasting, Proc. AAAI Conf. Artif. Intell. 33 (2019) 890–897, https://doi.org/10.1609/aaai.v33i01.3301890.
[193] M. Zahid, F. Ahmed, N. Javaid, R.A. Abbasi, H.S. Zainab Kazmi, A. Javaid, M. Bilal, M. Akbar, M. Ilahi, Electricity Price and load forecasting using Enhanced Convolutional Neural Network and Enhanced support Vector Regression in Smart Grids, Electronics 8 (2019) 122, https://doi.org/10.3390/electronics8020122.
[194] J. Dai, H. Qi, Y. Xiong, Y. Li, G. Zhang, H. Hu, Y. Wei, Deformable Convolutional Networks, in: 2017 IEEE Int. Conf. Comput. Vis. ICCV, IEEE, Venice, 2017: pp. 764–773. https://doi.org/10.1109/ICCV.2017.89.
[195] K.M. Borgwardt, A. Gretton, M.J. Rasch, H.-P. Kriegel, B. Schölkopf, A.J. Smola, Integrating structured biological data by Kernel Maximum mean Discrepancy, Bioinformatics 22 (2006) e49–e57, https://doi.org/10.1093/bioinformatics/btl242.
[196] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets, Adv. Neural Inf. Process. Syst. 27 (2014).
[197] R.N.V.J. Mohan, B.H.V.S.R.K. Raju, V.C. Sekhar, T.V.K.P. Prasad, Algorithms in Advanced Artificial Intelligence, 1st ed., CRC Press, London, 2025. https://doi.org/10.1201/9781003641537.
[198] C. Lu, S. Li, Z. Lu, Building energy prediction using artificial neural networks: a literature survey, Energy Build. 262 (2022) 111718, https://doi.org/10.1016/j.enbuild.2021.111718.
[199] P. Kumari, D. Toshniwal, Deep learning models for solar irradiance forecasting: a comprehensive review, J. Clean. Prod. 318 (2021) 128566, https://doi.org/10.1016/j.jclepro.2021.128566.
[200] E. Brophy, Z. Wang, Q. She, T. Ward, Generative adversarial networks in time series: A survey and taxonomy, (2021). https://doi.org/10.48550/ARXIV.2107.11098.
[201] Y. Que, Y. Dai, X. Ji, A. Kwan Leung, Z. Chen, Z. Jiang, Y. Tang, Automatic classification of asphalt pavement cracks using a novel integrated generative adversarial networks and improved VGG model, Eng. Struct. (2023) 115406, https://doi.org/10.1016/j.engstruct.2022.115406.
[202] E. Brophy, Z. Wang, Q. She, T. Ward, Generative Adversarial Networks in Time Series: a Systematic Literature Review, ACM Comput. Surv. 55 (2023) 1–31, https://doi.org/10.1145/3559540.
[203] W. Xu, H. Peng, X. Zeng, F. Zhou, X. Tian, X. Peng, A hybrid modelling method for time series forecasting based on a linear regression model and deep learning, Appl. Intell. 49 (2019) 3002–3015, https://doi.org/10.1007/s10489-019-01426-3.
[204] Z. Hajirahimi, M. Khashei, Hybrid structures in time series modeling and forecasting: a review, Eng. Appl. Artif. Intell. 86 (2019) 83–106, https://doi.org/10.1016/j.engappai.2019.08.018.
[205] Y. Wu, From ensemble learning to deep ensemble learning: a case study on multi-indicator prediction of pavement performance, Appl. Soft Comput. 166 (2024) 112188, https://doi.org/10.1016/j.asoc.2024.112188.
[206] Y. Wu, Q. Zhang, Y. Wang, X. Zhu, Advanced Hybrid CNN-GRU Model for IRI Prediction in Flexible Asphalt Pavements, J. Transp. Eng. Part B Pavements 151 (2025) 04025003, https://doi.org/10.1061/JPEODX.PVENG-1570.
[207] S. Bloemheuvel, J. Van Den Hoogen, D. Jozinović, A. Michelini, M. Atzmueller, Graph neural networks for multivariate time series regression with application to seismic data, Int. J. Data Sci. Anal. 16 (2023) 317–332, https://doi.org/10.1007/s41060-022-00349-6.
[208] Y. Cheng, D. Wang, P. Zhou, T. Zhang, A Survey of Model Compression and Acceleration for Deep Neural Networks, (2017). https://doi.org/10.48550/ARXIV.1710.09282.
[209] Y. Cheng, D. Wang, P. Zhou, T. Zhang, Model Compression and Acceleration for Deep Neural Networks: the Principles, Progress, and challenges, IEEE Signal Process Mag. 35 (2018) 126–136, https://doi.org/10.1109/MSP.2017.2765695.
[210] T. Gokmen, Y. Vlasov, Acceleration of Deep Neural Network Training with Resistive Cross-Point Devices: Design Considerations, Front. Neurosci. 10 (2016), https://doi.org/10.3389/fnins.2016.00333.
[211] A. Mishra, J.A. Latorre, J. Pool, D. Stosic, D. Stosic, G. Venkatesh, C. Yu, P. Micikevicius, A.S. Deep, Neural Netw. (2021). https://doi.org/10.48550/ARXIV.2104.08378.
[212] M. Pandey, M. Fernandez, F. Gentile, O. Isayev, A. Tropsha, A.C. Stern, A. Cherkasov, The transformational role of GPU computing and deep learning in drug discovery, Nat. Mach. Intell. 4 (2022) 211–221, https://doi.org/10.1038/s42256-022-00463-x.
[213] Y.-C. Zhou, M.-Q. Li, L.-B. Ji, Denoising Deep Autoencoder Gaussian Mixture Model and Its Application for Robust Nonlinear Industrial Process Monitoring, in: 2021 Int. Conf. Comput. Inf. Sci. Artif. Intell. CISAI, IEEE, Kunming, China, 2021: pp. 67–73. https://doi.org/10.1109/CISAI54367.2021.00021.
[214] E. Batzolis, E. Vrochidou, G.A. Papakostas, Machine Learning in Embedded Systems: Limitations, Solutions and Future Challenges, in: 2023 IEEE 13th Annu. Comput. Commun. Workshop Conf. CCWC, IEEE, Las Vegas, NV, USA, 2023: pp. 0345–0350. https://doi.org/10.1109/CCWC57344.2023.10099348.
[215] Y. Chen, B. Zheng, Z. Zhang, Q. Wang, C. Shen, Q. Zhang, Deep Learning on Mobile and embedded Devices: State-of-the-art, challenges, and Future Directions, ACM Comput. Surv. 53 (2021) 1–37, https://doi.org/10.1145/3398209.
[216] V. Sze, Y.-H. Chen, J. Emer, A. Suleiman, Z. Zhang, Hardware for machine learning: Challenges and opportunities, in: 2017 IEEE Cust. Integr. Circuits Conf. CICC, IEEE, Austin, TX, 2017: pp. 1–8. https://doi.org/10.1109/CICC.2017.7993626.
[217] R.M. Knabben, G. Trichês, E.F. Vergara, S.N.Y. Gerges, W. Van Keulen, Characterization of tire-road noise from Brazilian roads using the CPX trailer method, Appl. Acoust. 151 (2019) 206–214, https://doi.org/10.1016/j.apacoust.2019.03.013.
[218] L.G. Del Pizzo, F. Bianco, A. Moro, G. Schiaffino, G. Licitra, Relationship between tyre cavity noise and road surface characteristics on low-noise pavements, Transp. Res. Part Transp. Environ. 98 (2021) 102971, https://doi.org/10.1016/j.trd.2021.102971.
[219] C. Ramos-Romero, J. Cermeno, C. Asensio, Shifts detection in the road surface condition through tyre/road noise analysis and pattern recognition approach, In (2021).
[220] Y. Zhang, J.G. McDaniel, M.L. Wang, Pavement macrotexture estimation using principal component analysis of tire/road noise, in: H.F. Wu, T.-Y. Yu, A.L. Gyekenyesi, P.J. Shull (Eds.), SPIE Proc., SPIE, San Diego, California, USA, 2014. https://doi.org/10.1117/12.2045584.
[221] Y. Zhao, H.F. Wu, J.G. McDaniel, M.L. Wang, Evaluating road surface conditions using tire generated noise, in: T.Y. Yu, A.L. Gyekenyesi, P.J. Shull, A.A. Diaz, H.F. Wu, A.E. Aktan (Eds.), San Diego, California, USA, 2013: p. 869409. https://doi.org/10.1117/12.2012269.
[222] P. Boyraz, Acoustic road-type estimation for intelligent vehicle safety applications, Int. J. Veh. Saf. 7 (2014) 209, https://doi.org/10.1504/IJVS.2014.060167.
[223] ambrosini livio, gabrielli leonardo, vesperini fabio, squartini stefano, cattani luca, deep neural networks for road surface roughness classification from acoustic signals, J. Audio Eng. Soc. (2018).
[224] X. Chen, L.J. Chen, Analysis Tire Tread patterns Noise based on Wavelet Transform, Adv. Mater. Res. 823 (2013) 180–183, https://doi.org/10.4028/www.scientific.net/AMR.823.180.
[225] J.F. He, X.X. Jin, W.Y. Wang, Analysis of Tire Tread Pattern's Impact on Interior Vibration and Noise based on Wavelet Transform, Appl. Mech. Mater. 66–68 (2011) 1755–1761, https://doi.org/10.4028/www.scientific.net/AMM.66-68.1755.

[226] S.W. Hwang, J.H. Han, K.D. Sung, S.K. Lee, The Study of Tire Pattern Noise by using Wavelet Transform, Appl. Mech. Mater. 105–107 (2011) 267–270, https://doi.org/10.4028/www.scientific.net/AMM.105-107.267.
[227] S.-H. Park, Y.-H. Kim, Visualization of pass-by noise by means of moving frame acoustic holography, J. Acoust. Soc. Am. 110 (2001) 2326–2339, https://doi.org/10.1121/1.1404976.
[228] D. Dogan, Road-types classification using audio signal processing and SVM method, in: 2017 25th Signal Process. Commun. Appl. Conf. SIU, IEEE, Antalya, Turkey, 2017. https://doi.org/10.1109/siu.2017.7960154.
[229] Der-Hsien Shen, Chia-Ming Wu, Jia-Chong Du, Application of Grey Model to Predict Acoustical Properties and Tire/Road Noise on Asphalt Pavement, in: 2006 IEEE Intell. Transp. Syst. Conf., IEEE, Toronto, ON, Canada, 2006: pp. 175–180. https://doi.org/10.1109/ITSC.2006.1706738.