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Weightless Neural Network-Based Fault Diagnosis in Suspension System

Vehicle suspension systems play a critical role in ensuring passenger comfort and safety. Detecting faults in these systems is vital for maintaining safety, performance, and cost-effectiveness. Traditional inspection methods have limitations, such as visual checks, bounce tests, and alignment assessments. This study explores Wilkie, Stonham, and Aleksander Recognition Device (WiSARD), a weightless neural network (WNN), for suspension fault diagnosis. A WNN model is employed to classify suspension system faults using sensor data. The dataset includes both normal and faulty conditions to train the model. The study assesses WiSARD under various fault conditions, including strut damage, mount failure, worn-out components, and low wheel pressure. Comparative evaluations demonstrate that the approach outperforms other classification techniques, achieving an impressive 95.63% accuracy with a rapid 0.05-second computation time for test data. This WNN-based method proves superior in detecting suspension faults and holds potential as a candidate for real-time vehicle fault diagnosis systems.

Keywords: *Fault diagnosis, Suspension system, Weightless Neural Network, Machine learning, classification*

1. INTRODUCTION

Suspension is a critical component of any car design as it plays a vital role in ensuring the safety, comfort, and handling of the vehicle [1]. The importance of suspension lies in the following key factors: (i) Safety: The suspension system ensures safety by keeping the wheels in contact with the road, thereby improving grip and traction, resulting in reduced chances of accidents while braking, accelerating, or turning; (ii) comfort: passengers are provided with more comfortable ride by absorbing shocks and vibrations from the road without which every bump on the road would be felt in the cabin leading to a distressing and uncomfortable driving experience; (iii) handling: good handling and stability of the car requires good suspension which is achieved by keeping the car level during turns and preventing excessive body roll thus allowing for better control and responsiveness; (iv) longevity: well-maintained suspension system can also extend the life of other car components such as tires and brakes by reducing wear and tear resulting in savings on repairs and replacements over time. The malfunction of a car suspension system can have severe repercussions on its safety and functionality [2]. Various indications of suspension failure include uneven tire wear, a rough or bumpy ride, excessive body roll while turning, and compromised handling and responsiveness [3].

Neglecting suspension maintenance can result in decreased braking, acceleration performance, longer stopping distance, and impaired driving control. Additionally, worn-out suspension components may damage other car parts, such as the tires and wheel alignment, exacerbating the issue. Therefore, it is crucial to ensure that the suspension system is functioning correctly to provide a secure and comfortable driving experience. Numerous research studies have explored the condition monitoring of semi-active and active suspension systems [4]. One study examines a clustering-based fault detection and monitoring method for automobile suspension systems that use only accelerator sensors located at four points [5]. The method is purely data-driven and capable of serving as an online tool without prior knowledge of the suspension model or fault features. The method's effectiveness is demonstrated through an experiment on an automobile suspension benchmark. The proposed approach represents a significant improvement over existing techniques in terms of simplicity, efficiency, and effectiveness in detecting and monitoring faults. Another study states the importance of continuous monitoring of the suspension system in railway vehicles, particularly with the advent of high-speed trains [6].

It presents a hybrid model approach for predicting faulty regimes in the suspension system based on vehicle acceleration data, parameter estimation, and a supervised machine learning model. The model accurately predicted faulty components with an 84.4% accuracy rate for both primary and secondary suspension systems. Furthermore, a fault detection and diagnosis method for automobile suspension systems based on mathematical models was carried out in [7]. Various techniques have been proposed to estimate unknown parameters of these models, including system identification and the local linear model tree (LOLIMOT) approach. LOLIMOT, which combines neural networks and physical models, has been used to

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generate parity equations for fault detection and diagnosis in suspension systems. Researchers use parameter estimation and LOLIMOT-generated parity equations to detect and diagnose faults in a suspension system that proved to be effective in simulated tests. Numerous studies have explored the use of machine learning and deep learning weighted neural networks for fault diagnosis. Li et al. researched a deep learning-based approach to diagnose faults in a vehicle sus–pension system using a convolutional neural network (CNN). The approach was found to be highly accurate, achieving a 95.5% success rate in detecting suspension system faults [8].

In another study, Sun et al. [9] compared the performance of machine learning and deep learning algorithms in diagnosing faults in suspension systems. The study employed support vector machines (SVM), K-nearest neighbor (KNN), random forest (RF), CNN, and long short-term memory (LSTM) models, with the deep learning models exhibiting superior accuracy and robustness in fault detection compared to the machine learning models. Weightless neural networks, such as the Wilkie, Stonham, and Aleksander Recognition Device (WiSARD) network, present a unique and innovative approach to fault diagnosis as compared to conventional weighted neural networks [10]. In contrast to weighted networks, weightless networks do not rely on complex weight matrices and instead make decisions based solely on the number of bits set to 1 in the input data. This approach offers several advantages, including faster processing times, lower memory requirements, and greater robustness to noisy and missing data. Moreover, weightless networks have demonstrated high accuracy in fault diagnosis tasks, making them a promising area of research for future applications. Although limited research has been conducted on the use of weightless neural networks for fault diagnosis, this paper emphasizes their potential usefulness in fault detection. This research study focuses on fault diagnosis utilizing WNNs, which represents a novel approach to this field. Previous studies have only been conducted by a limited number of researchers, which highlights the potential for further exploration and advancement in this area. By employing weightless neural networks, this research aims to contribute to the current knowledge in fault diagnosis and pave the way for more efficient and accurate diagnosis methods in the future.

Weightless neural networks, also known as neural gas networks or growing cell structures, present an alternative artificial neural network model that distinguishes itself from traditional neural networks in terms of operational methodology [11], [12]. WNNs do not rely on weights like their counterparts. Instead, binary connections are employed, allowing for a more efficient and faster learning process [13]. The ability to operate without weights makes WNNs useful in scarce or constantly changing data scenarios. WNNs are an emerging neural technology that differs from conventional networks. These networks consist of binary neurons and synapses, deviating from the conventional artificial neural networks that store weights and biases. Instead, WNNs rely on a simple activation signal of 1 or 0. This streamlined approach reduces complexity and minimizes memory requi–rements. Moreover, WNNs adopt a different approach to pattern recognition and exhibit real-time capacity to learn complex patterns. Their utilization spans various domains, including image processing, bio-inspired computing, and machine learning, where they find application in sensory perception, decision-making, and control. By eschewing the use of weights, WNNs facilitate the learning of relationships between inputs and outputs. The conceptual model of WNNs encompasses one or more layers of processing, with each cell fulfilling a specific function, such as clustering. These cells are arranged in an interconnected manner, ensuring efficient processing of input data.

Training WNNs involves a different approach compared to traditional neural networks. WNNs focus on the activation of concepts rather than the activation of individual neurons [14]. This means that instead of adjusting the weights of connections between neurons during training, the weights of concepts and their associations are adjusted. The training process entails presenting the network with input patterns and using a signal to modify the weights of the activated concepts. One notable advantage of weightless neural networks is their ability to learn from a few examples, making them particularly suitable for tasks such as classification and recognition. Despite their usefulness, weightless neural networks are an emerging technology that requires further research and development. The learning algo–rithms employed in weightless neural networks are de–signed to simulate the behavior of biological neurons and enable them to recognize patterns like the human brain. These networks find applications in scenarios where traditional neural networks may not be suitable, such as situations with highly variable input data or sig–nificant noise in the data. The learning algorithms used in weightless neural networks typically rely on exam–ples and can be trained to recognize complex patterns by exposing them to a large dataset. Overall, WNNs present an interesting and promising approach to sol–ving complex problems in various fields, including arti–ficial intelligence, machine learning, and data analysis.

However, as with any evolving technology, there are challenges and future directions that need to be considered. WNNs have the potential for diverse applications in the fields of machine learning and artificial intelligence. These networks can be utilized in pattern recognition tasks, including image classification, speech recognition, and natural language processing. They also offer solutions for prediction, forecasting, and decision-making problems.

WiSARD (Wilkie, Stonham, Aleksander Recog–nition Device) weightless neural networks are a type of neural network model that uses a binary pattern and logical rules to perform pattern recognition tasks, rather than numerical weights like traditional neural networks. WiSARD networks store neuron functions using lookup tables, allowing for a simple implementation and fast learning phase [15]. The WiSARD classifier is a fast algorithm that requires simple logical operations that are highly memory efficient since it only stores binary values in random access memory (RAM) cells. Overall, the WiSARD is a useful algorithm in the field of pattern recognition due to its speed and efficiency. The networks were originally designed for pattern recog–nition in image processing; however, they have been adapted for use in other areas of machine learning [16].

In one of the studies, researchers explored the capabilities of WiSARD, a weightless neural network that stores neuron functions using lookup tables instead of weights [17]. Initially intended for pattern recog–nition in image processing, the researchers introduced a new machine learning method called the WiSARD classifier, which transforms multivariable data into binary patterns for WiSARD input. The research paper's authors conducted a comprehensive experiment to assess the classification potential of WiSARD. They included the WiSARD classifier and eight other mac–hine learning methods in the experiment and evaluated their performance across seventy classification tasks. Statistical analysis, based on nonparametric tests, was used to compare the effectiveness of the WiSARD clas–sifier with other established machine learning libraries. The study found that the WiSARD classifier performed comparably well in classification tasks. The present study utilizes the WiSARD classifier, which offers mul–tiple advantages compared to conventional neural net–works [18]. The absence of weight updation, elimi–nation of model training, higher scalability, robustness, and low memory requirements are some takeaways of the WiSARD classifier. The following findings were inferred from the literature discussed above.

- The application of data-driven methods in the fault diagnosis domain is still in the primary stages of development.
- Studies carried out in suspension fault diagnosis were oriented towards detecting and identifying a single component like a ball joint, spring, or damper.
- Vibration-based measurement techniques were utilized widely among all measurement techniques for fault diagnosis.
- Suspension components like strut mount and lower arm bush faults were not explored.
- In collaboration with vibration measurements, mac–hine learning techniques proved to be effective in classifying various faults in numerous applications.
- Studies involving the diagnosis of multiple fault scenarios in suspension systems were limited.

1.1 Contribution of Study

1. A quarter-car model-like replication with a Mc–Pherson suspension system was fabricated for the pre–sent study to simulate the real-time working conditions of passenger cars.
2. A total of eight different suspension conditions, namely, low wheel pressure (LWP), externally damaged strut (STED), tie rod ball joint worn out (TRBJ), worn out strut (STWO), lower arm bush worn off (LABW), lower arm ball joint worn out (LABJ), strut mount fault (STMF) and good condition were considered in the study.
3. A piezoelectric accelerometer was used to collect the vibration signals for every condition of the suspension system.
4. Statistical features were extracted from the collected vibration signals while the J48 algorithm was used to select the most significant features that contribute towards classification.
5. The selected features were categorized into train test split ratio of 80%-20% that were further provided as input to the WiSARD classifier. Additionally, various hyperparameters of the WiSARD classifier were tuned to derive an optimal value that achieved maximum classification accuracy.

1.2 Novelty:

1. The paper specifically uses the WiSARD Weightless Neural Network for fault diagnosis, which does not require any weight updates and has been gaining popularity among weightless neural networks.
2. Eight test conditions of the suspension system were diagnosed accurately using the WiSARD classifier.
3. Several hyperparameters of the WiSARD classifier, such as bit number, bleach configuration, bleach flag, bleach step, map type, and tic number, were modified to determine the most optimal hyperparameters.
4. Optimal hyperparameters were determined, and the classification performance of the WiSARD classifier was assessed with various state-of-the-art techniques.

2. EXPERIMENTAL SETUP

The present experimental configuration simulates a quarter-car model that replicates the operational characteristics of the McPherson suspension system utilized in front-wheel drive automobiles. The research encompasses data collection using an accelerometer and a vibration sensor affixed to the control arm of the suspension system through adhesive mounting. The data acquisition process for distinct fault conditions necessitates the sequential substitution of the flawed components of the suspension system. Following data acquisition for the impaired states, vibration signals emanating from a properly functioning suspension system are procured [20]. The following section provides a detailed account of the experimental studies conducted concerning (a) fabrication of experimental setup, (b) faults of the suspension system considered in the study, and (c) data acquisition.

2.1 Fabrication of Experimental Setup

The setup comprises several components, including a frame, motor, wheel, drive shaft, idle roller, and loa–ding system. The fabricated test setup is shown in Figure 1. The suspension system of the Hyundai i10 was utilized in the fabrication of the test rig used in the present study.

The McPherson suspension system consists of a strut (damper in a coil spring), control arm (lower arm), tie rod, and knuckle. A quarter-car model test setup was designed and built to evaluate the condition of the suspension system on a uniform surface at a constant speed of 70 kmph.

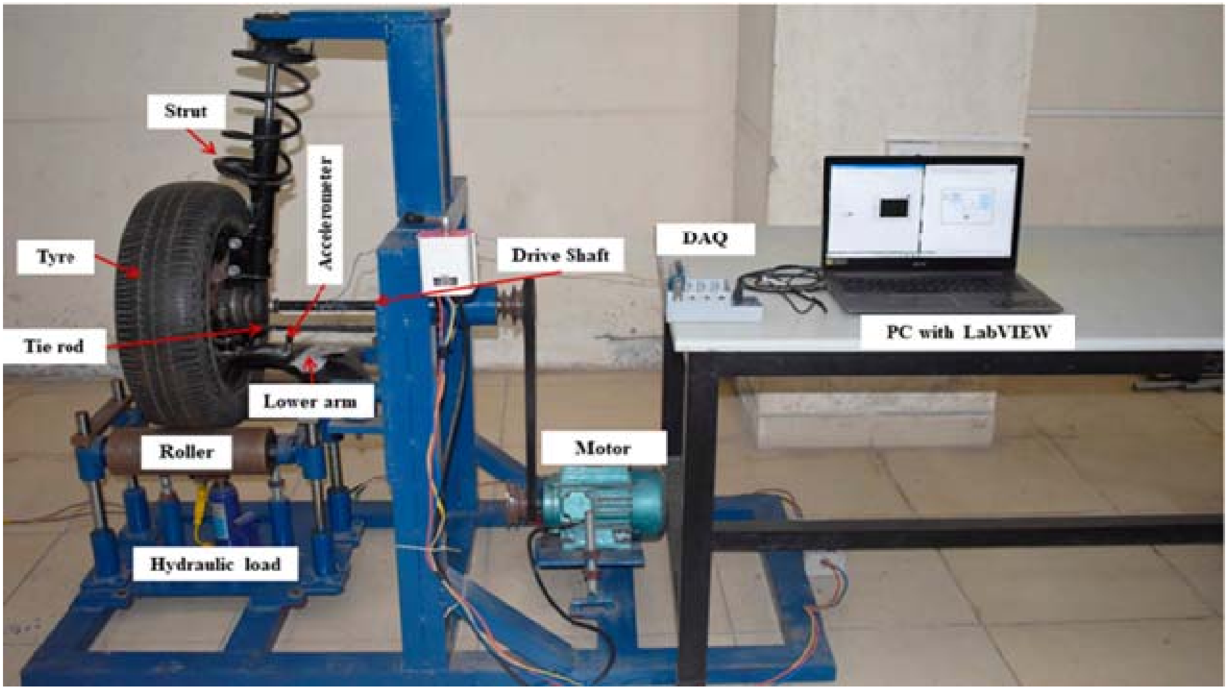

Figure 1. Fabricated test setup

The wheel runs over two supporting rollers with bearings that maintain constant speed by using the motor power (rotation force) through a belt drive and constant velocity (CV) joints. This minimizes the unwanted vibrations transmitted to the system. The load acting on the suspension is also controlled using a hydraulic system (jack) to adjust the height of the supporting rollers [21].

2.2 Faults in the Suspension System

The suspension system of a vehicle is critical in providing a comfortable ride and ensuring the safety and stability of the vehicle. Faults in the suspension system can lead to various problems that compromise these functions. In this research paper, some common faults (Figure 2) that occur in suspension systems were identified and discussed below [21]. It is essential to perform regular maintenance and inspections to identify and address these faults early. This practice helps prevent further damage to the suspension system, thereby ensuring safety and comfort for the occupants.

(i) Worn or damaged shock absorbers/dampers: These components are responsible for dampening the shocks and vibrations generated by the road. Worn/ damaged shock absorbers can lead to excessive bouncing, reduced vehicle stability, and poor handling.

(ii) Broken or worn springs: These springs provide the necessary support and cushioning for the vehicle's weight. If worn or broken, they can cause the vehicle to sag or bottom out, leading to poor ride quality and compromised handling.

(iii) Control arm bush: The control arm bush provides a pivot point between the suspension and the vehicle chassis. Worn or damaged bush can lead to uneven tire wear, poor handling, and reduced stability.

(iv) Loose or worn ball joints: These joints connect the steering knuckle to the control arm and allow the suspension to move up and down while steering. Loose or worn ball joints can cause noise, uneven tire wear, poor handling, and even steering problems.

(v) Bent or damaged steering components can cause the vehicle to pull to one side, leading to poor handling and reduced stability.

3. METHODOLOGY

The detection of faults in the suspension system is critical in ensuring the safe and reliable operation of a vehicle. In recent years, the use of WiSARD (Wilkie, Stonham, Aleksander Recognition Device) weightless neural networks has been utilized in fault diagnosis applications. This approach is based on the analysis of vibration sig–nals generated by the suspension system, which are processed and classified by the WiSARD (Wilkie, Stonham, Aleksander Recongition Device) weightless neural networks has been utilized in fault diagnosis classifier. Figure 3 shows the proposed methodology.

In the proposed methodology, the first step involves obtaining vibration data from the suspension system using an accelerometer sensor. The data is collected from the fabricated test rig, which is further preprocessed to extract relevant features.

- Subsequently, descriptive statistical features such as mean, mode, range, sum, count, kurtosis, skew–ness, standard deviation, median, standard error, etc., were extracted from the collected signals.
- Furthermore, feature selection was applied to reduce the dimensionality of the feature space by selecting the most relevant features for fault detection. This process reduces the complexity of the WiSARD network, thereby improving the accu–racy of the classification and reducing the computational cost. The J48 decision tree algorithm was selected for data extraction.

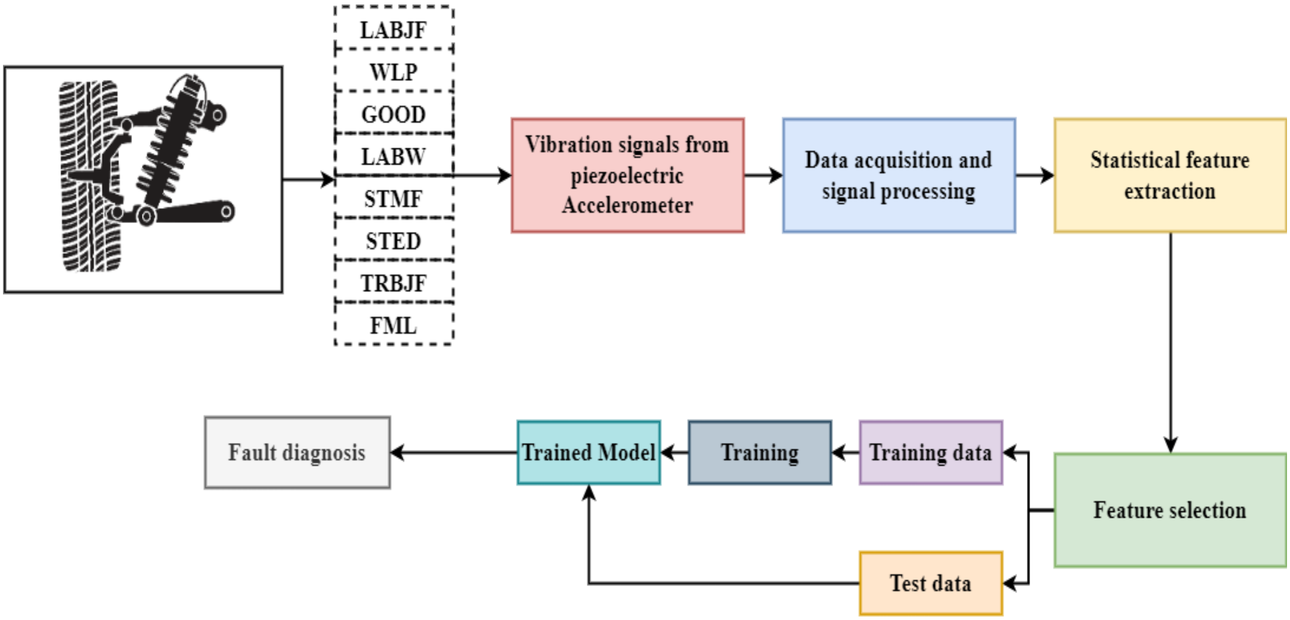

Figure 2. Suspension faults (a) strut mount failure, (b) strut external damage, (c) lower arm bush worn out, (d) lower arm ball joint fault, (e) strut worn out, and (f) low tire pressure.

Figure 3. Proposed methodologies for suspension fault diagnosis

- The selection of the contributing features, the collected dataset, is split into training and test datasets. The training data is fed as input to the WiSARD classifier for training with the corresponding fault labels. During training, the network learns to associate the vibration signals with the corresponding faults. The trained WiSARD network is then tested with the test data created. The performance of the network is evaluated using performance metrics.

3.1 Acquisition

Vibration signals were acquired using a piezoelectric accelerometer (NI-PCB 352C03) with a frequency range of 0.5–10,000 Hz and sensitivity of 10.26 mV/g, which was placed on the control arm of the suspension system using an adhesive mounting technique. To collect and convert the analog signal values into digital form, a data acquisition system (DAQ) was used. The output from the accelerometer was fed into the NI9234 DAQ through a USB chassis, and the data collection was performed using the NI LabVIEW software. To simulate different fault scenarios, various faulty components in the suspension system were replaced in a controlled manner without altering specific parameters such as the spring rate or damping coefficient.

The resulting data was then recorded using the sensors and preprocessed to remove any noise or outliers. The collected data was transformed into a suitable format and split as training and test data.

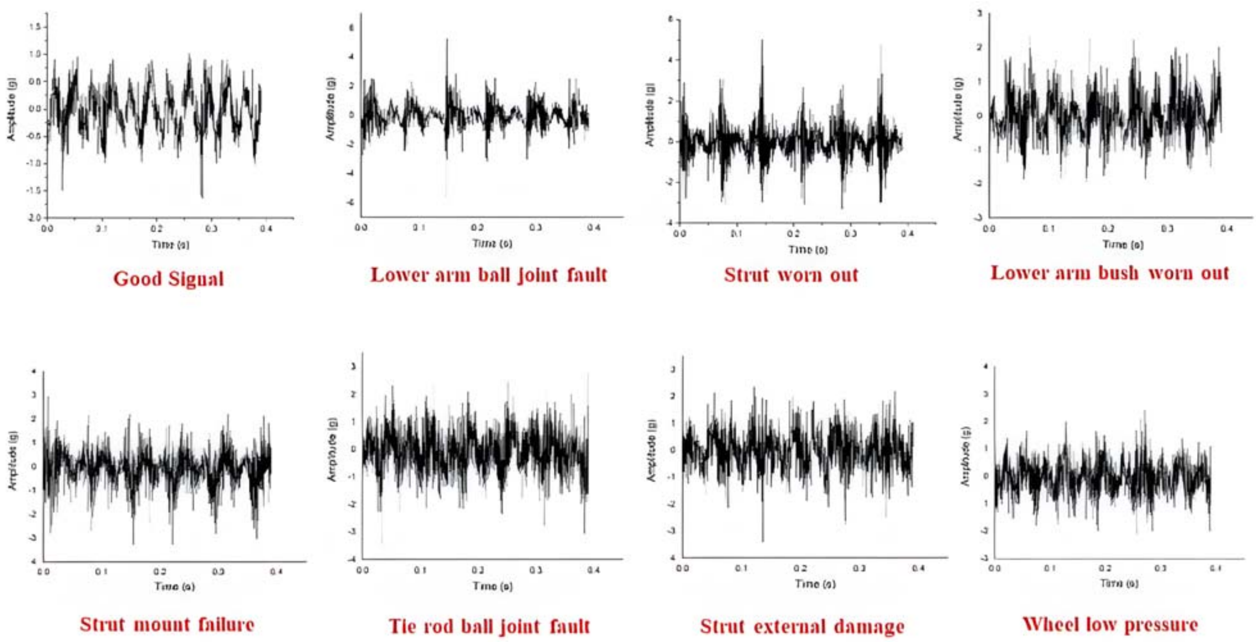

Figure 4. Sample of vibration plots of suspension conditions

Training data was fed as input to the WNN for the classifier training, while test data was supplied to evaluate the classifier performance. During the data acquisition process, a sampling frequency of 25 kHz was used with a sample length of 10,000 steps and 100 instances of data for no Load (0 psi) condition. Fig 4 illustrates the vibration plots corresponding to each of the eight distinct conditions. The graph is derived from good and faulty signals collected across 2000 samples at a frequency of 25,000 Hz. The vibration signal exhibits distinct variations for each specific fault condition. For instance, in the case of good, TRBJF, and LWP conditions, the vibration amplitude continuously fluctuates throughout the sample. In contrast, for other faults, the vibration amplitude rapidly fluctuates, reaches saturation, and then exhibits significant variations towards the end. Furthermore, each fault condition showcases a unique pattern corresponding to its specific fault type. These variations and distinctive fault patterns empower machine learning algorithms to classify faults efficiently using the extracted features.

3.2 Feature Extraction

In this study, each fault condition exhibits a distinct and unique pattern oriented to that particular fault. These variations and unique fault patterns are instrumental in enabling machine learning algorithms to accurately classify and differentiate among different faults aided by the extracted features. The study focuses on extracting. various statistical features from the vibrational signals, including mean, median, mode, standard deviation, sample variance, standard error, skewness, kurtosis, minimum, maximum, sum, range, and count. The collected data is processed and organized to enhance readers' understanding of the underlying characteristics of vibration signals [24]. Subsequently, the statistical information is consolidated, and specific features are extracted and stored in a comma-separated value (CSV) data file, allowing easy accessibility for further analysis. These extracted features serve as crucial input for training machine learning models, enabling them to detect and identify faults within the suspension system automatically. By leveraging these techniques, machine learning models can effectively learn and recognize the distinct patterns associated with different faults, facilitating automated fault detection in suspension systems.

3.3 Feature Selection

Feature selection is the process of selecting the most relevant features from a larger set of features in a dataset to improve the accuracy and interpretability of machine learning models by reducing the number of irrelevant or redundant features [25]. There are different feature selection algorithms like J48, recursive feature elimination, and random forest. Among them, J48 is considered an important algorithm due to its simple design and accurate rule generation. J48 is a well-known feature selection algorithm that accounts for several benefits [26]. Firstly, it employs a decision tree method to create a model that depicts the possible consequences of different decisions. This tree-like structure can be easily interpreted and understood, which makes it simpler for researchers to extract valuable insights from the model. Secondly, J48 uses a greedy approach to pick the most informative features at each decision tree node that is effective and can handle large datasets with numerous features. Thirdly, J48 has been extensively tested and proven to be effective in enhancing classification accuracy in various applications. Overall, J48 is a reliable and effective feature selection algorithm that is widely used by researchers and professionals in diverse fields.

To perform feature selection in the J48 algorithm, the first step is to construct a decision tree using all the available features. Next, the importance or relevance of each feature is determined by computing the information gain or gain ratio obtained from the decision tree. This measure indicates the extent to which each feature contributes to reducing the entropy or disorder of the data. Based on these scores, the algorithm sorts the features in descending order of importance and selects the top ‘k’ features. The value of ‘k’ can be chosen based on a predefined threshold cross-validation. Finally, the J48 algorithm constructs a new decision tree using only the selected features and evaluates its performance on a test set. The benefit of feature selection is that it improves the efficiency and accuracy of the classification task by focusing only on the most informative attributes and avoiding irrelevant features that may decrease performance. However, selecting features can lead to a reduction in interpretability and information loss if important features are ignored. Therefore, choosing the right set of features is important to balance the accuracy and complexity of the model. Fig 5 depicts the decision tree generated for fault detection in the suspension system.

3.4 Feature Classification using WiSARD

The WiSARD (Wilkie, Stonham, Aleksander Recog–nition Device) classifier is a machine learning algorithm often used for pattern recognition tasks. It is developed to overcome the limitations of conventional classifiers, such as the perceptron and nearest neighbor contrast to other standard classifiers that work on fixed input data. WiSARD uses a mapping of the input feature space to a set of values random access memory (RAM) cells. Each RAM cell signifies a specific input feature attribute.

The binary values stored in the RAM cells are used to decide about the input being classified. The WiSARD classifier is a fast algorithm as it only requires simple logical operations. It also showcases high memory efficiency since only binary values are stored in RAM cells. Overall, the WiSARD is a useful algorithm in the field of pattern due to its speed and efficiency. The basic architecture consists of a set of random weights that are used to split the input into partitions. From there, the output of each partition is processed and fed into the final decision layer that determines the classification of the input. The size and number of partitions can be adjusted to optimize performance for datasets. Overall, the WiSARD architecture is designed to be scalable, efficient, and effective for a wide range of applications.

The first stage of the WiSARD classifier procedure involves the preprocessing of the input data. This crucial step is undertaken to prepare the data for subsequent classification operations. During the preprocessing stage, the input data is transformed into a format that is more suitable for analysis and classification purposes. The specific preprocessing techniques employed may vary depending on the nature of the input data. It may encompass operations such as feature scaling and normalization. Normalization ensures that all input data is converted into a consistent format, while feature scaling guarantees that all features have similar ranges. Additionally, feature selection may be performed to choose a subset of input features that will be utilized for the classification task. Once the preprocessing stage is completed, the WiSARD classifier commences the classification process, where it categorizes the input data into one of several possible categories. The following steps take place while the WiSARD classifier is working.

(a) Encoding-Binarization: Encoding-Binarization is a widely employed technique in various machine learning algorithms, including the WiSARD classifier, that plays a crucial role in enhancing the efficiency and accuracy of data processing. This technique involves the conversion of input data into a binary format wherein each feature is represented by a binary digit (0 or 1). By simplifying the data in this manner, it becomes easier for the algorithm to process and classify it effectively.

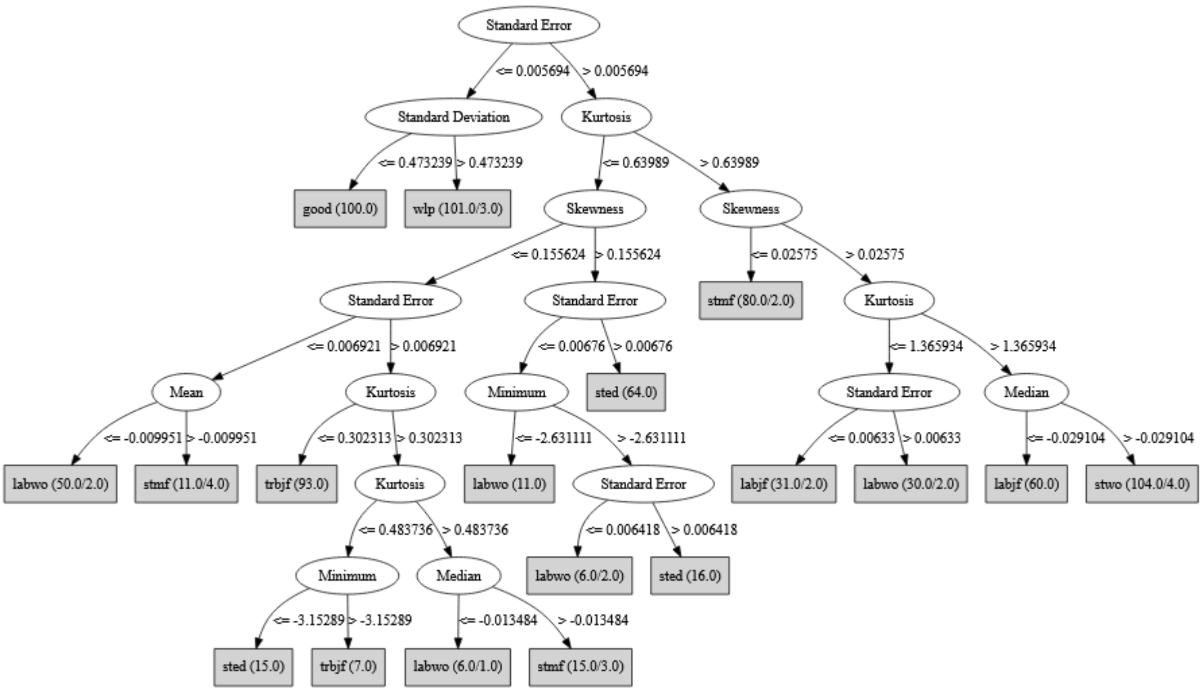

Figure 5. J48 decision tree derive

(b) Creating the address space: Building the WiSARD classifier involves a crucial step known as creating the address space. This address space is essentially a matrix consisting of binary values that serve to represent the locations of the WiSARD memory cells. The size of this address space is determined by two factors: the number of features present in the dataset and the number of bits allocated to each feature. Corresponding to each memory cell within the WiSARD network, there exists a unique address within the address space. To construct the address space, the WiSARD classifier identifies all distinct features within the dataset and assigns each feature a distinct binary code. The designated code then becomes the feature address within the address space. The resulting binary matrix is subsequently utilized to ascertain which memory cells will be activated in response to a given input. An advantageous aspect of this process is that the creation of the address space is automated, facilitating the effective training and usage of the WiSARD classifier. The address space will perform two major operations, namely, random subspace projection and discriminative learning, before predicting the final outputs.

(c) Predictions: It plays a pivotal role in the WiSARD classifier, constituting an indispensable component of the model. Once the training process is completed using the input data, the WiSARD classifier adapts across the acquired patterns to generate predictions for novel and previously unseen data. This classifier selectively iden–tifies the output neuron exhibiting the highest level of activity as the corresponding class. This distinctive approach contributes significantly to the classifier's ability to produce precise predictions even when the input data is characterized by noise or incompleteness. Notably, the WiSARD classifier also possesses the capacity to address multiclass classification problems encompassing multiple output classes. Consequently, the WiSARD classifier emerges as a formidable tool capa–ble of delivering accurate and robust predictions, the–reby proving its efficacy across a diverse range of machine-learning tasks. The major tasks performed through the WiSARD classifier are presented as follows.

(d) Classification Process: The classification process is considered the fundamental core of any machine learning algorithm that involves the crucial task of categorizing input data into various possible classes or categories. Specifically, the WiSARD Classifier utilizes a distinctive approach wherein the classification process relies on a set of randomly generated patterns referred to as "discriminators." These discriminators are systema–tically compared against the input data to identify the discriminator that most closely corresponds to the input. The WiSARD classifier successfully assigns the input to its respective class by identifying the best matching discriminator. This iterative process is repeated for each input data point until all the data points have been effectively classified. Due to its ability to handle substantial amounts of data rapidly and accurately, the WiSARD classifier emerges as a powerful tool for diverse tasks such as recognition and speech processing.

(e) Decision Rules: The WiSARD Classifier is an effective classification method that utilizes decision rules to classify input data. These decision rules are generated through a learning process where the classifier is trained on a labeled dataset. Each decision rule is represented as a string that corresponds to a specific classification. During the classification process, the classifier applies these decision rules to the input data concurrently, and the class with the greatest number of active rules is chosen as the final classi–fication. The utilization of decision rules in the WiSARD classifier offers a swift and efficient approach to classification. The classifier compares the input data to binary values instead of performing intricate com–putations on the data to perform classification. Conse–quently, the WiSARD classifier's reliance on decision rules makes it particularly well-suited for tasks involving high-dimensional data or large datasets

4. HYPERPARAMETERS IN WISARD

Hyperparameters are predefined settings that resear–chers employ to govern the behavior and performance of machine learning algorithms. Hyperparameters play an instrumental role in improving the overall model performance, generalization ability, and training time. Choosing suitable values for hyperparameters is critical as it greatly influences the model's capacity to learn from the available data [26]. The adjustment of hyper–parameters enables fine-tuning of the classifier, resul–ting in improved performance. By identifying optimal values for hyperparameters, such as the number of RAMs or discrimination threshold, the classifier can enhance its accuracy, precision, and recall. Through modifications in hyperparameters, the classifier can adapt and acquire specific patterns inherent to the given dataset, ultimately leading to enhanced performance. Additionally, hyperparameters play a crucial role in preventing the classifier from either overfitting or underfitting the data, thus ensuring optimal model training [27]. WiSARD classifier performance can be assessed through the variation in hyperparameters, including bit number, bleach confidence, bleach flag, map type, and tic number.

5. RESULTS AND DISCUSSIONS

The current study aims to evaluate the effectiveness of the proposed WNN model (WiSARD) in detecting fa–ults within a suspension system. The evaluation was conducted under eight distinct test conditions, as outlined in the provided data. The performance of the WiSARD network was assessed through the varying hyperpa–rameters, including bit number, bleach confidence, bleach flag, map type, and tic number. The primary objective of this study is to train the model to attain the highest possible accuracy in fault detection within suspension systems. The experiments' results demonstrate the proposed solution's efficacy and po–tential application for real-time scenarios. The overall dataset was split into training and test sets with a split ratio of 80%-20%. The validation was performed using the training set that underwent a ten-fold cross-validation.

5.1 Impact of Changing ‘Bit Number’

This parameter determines the number of RAMs used in the classifier. Increasing the number of RAMs can enhance the model's capacity to learn complex patterns; however, it may also increase computational requi–rements. Table 1 presents a detailed analysis of the effects of varying the 'bit number' on various classi–fication statistics. The results obtained in Table 1 signify that the value of test accuracy varies with chan–ging bit number. However, the highest classification accuracy of 95.63% was obtained for 32-bit numbers. Thus, the value of the bit number 32 was selected as the optimal value that was fixed and passed on to the next set of hyperparameter experimentation.

Table 1. Performance of WiSARD classifier by varying bit number

Bit number	Training Set Accuracy (%)	Cross Validation Accuracy (%)	Test Set Accuracy (%)
4	97.81	90.37	91.25
8	99.98	92.87	93.75
16	100.00	93.75	94.37
32	100.00	93.37	95.63

5.2 Impact of Changing ‘Bleach Confidence’

Bleaching is an effective technique employed in the WiSARD classifier to mitigate the issue of overfitting. This approach involves randomly resetting a specific fraction of RAMs during the training process. The bleaching factor determines the extent to which the bleaching process is applied. Table 2 comprehensively examines the impact of altering the 'bleach confidence' on diverse classification statistics. The obtained results in Table 2 indicate that a bleach confidence value of 0.95 exhibited exceptional performance, leading to mi–nimal errors. Based on these findings, a bleach confidence of 0.95 is highly effective in achieving accurate and reliable classification outcomes.

Table 2. Performance of WISARD classifier by varying bleach confidence

Bleach confidence	Training Set Accuracy (%)	Cross Validation Accuracy (%)	Test Set Accuracy (%)
0.60	100.00	93.13	95.63
0.70	100.00	94.00	93.13
0.80	100.00	93.25	94.37
0.90	100.00	92.63	95.62
0.95	100.00	94.25	96.25

5.3 Impact of Changing ‘Bleach Flag’

This hyperparameter involves randomly resetting a fraction of RAMs to reduce overfitting. The bleach flag, when set to "True" or "1," indicates that bleaching is enabled and will be applied during training. Conversely, when set to "False" or "0," it signifies that bleaching is disabled, and RAMs will not be reset during training. The bleach flag provides flexibility to selectively turn the bleaching process on or off based on the specific requirements or characteristics of the problem being addressed. Table 3 shows the impact of changing the bleach flag parameter. The obtained results indicate that a bleach flag with FALSE achieved the maximum test accuracy of 94.38%.

Table 3. Performance of WISARD classifier by varying bleach flag

Bleach flag	Training Set Accuracy (%)	Cross Validation Accuracy (%)	Test Set Accuracy (%)
TRUE	54.21	37.25	45.00
FALSE	100.00	93.63	94.38

5.4 Impact of Changing ‘Bleach Step’

The decay rate of active bits during the bleaching process is controlled by the parameter known as the 'bleach step'. A higher value assigned to the 'bleach step' results in a faster decay and a more rapid reduction in bit activity. The effects of altering the 'bleach step' parameter on various classification statistics have been thoroughly examined and documented in Table 4. This analysis provides valuable insights into the relationship between the 'bleach step' and the performance of the classification system. Hence, based on the information presented in the table, the selection made was a bleaching step with a value of 2.

Table 4. Performance of WISARD classifier by varying bleach step

Bleach step	Training Set Accuracy (%)	Cross Validation Accuracy (%)	Test Set Accuracy (%)
1	99.84	93.25	95.00
2	100.00	93.13	95.24
5	100.00	93.50	94.17
10	100.00	93.00	94.37

5.5 Impact of ‘Map Type’

The hyperparameter 'map type' plays a pivotal role in determining the mapping scheme employed within the WiSARD classifier. This parameter essentially governs the allocation of input features to distinct RAM con–tained within the classifier. The 'map type' hyper–parameter encompasses a range of choices for struc–turing the input data, including one-hot encoding and binary encoding. The judicious selection of an app–ropriate 'map type' enables researchers to enhance the classifier efficacy in accurately capturing and proces–sing information derived from the input features. Table 5 demonstrates a substantial variance in accuracy when employing the RANDOM map-type hyperparameter. The maximum test accuracy of 94.38% was obtained with the RANDOM map type.

Table 5. Performance of WISARD classifier by varying map type

Map type	Training Set Accuracy (%)	Cross Validation Accuracy (%)	Test Set Accuracy (%)
RANDOM	100.00	92.75	94.38
LINEAR	99.84	78.25	72.50

5.6 Impact of ‘Tic Number’

The 'tic number' parameter controls the frequency at which the classifier processes each training instance during the training process. To evaluate its effect, different values of 'tic number' (1, 10, 20, 50, 100, and 256) were tested. Table 6 presents a detailed analysis of the impact of adjusting the 'tic number' parameter on different classification statistics. The results, as pre–sented in Table 6, infer that when each training instance was processed 256 times, the classifier performed exceptionally well with an accuracy of 95.00%.

Table 6. Performance of WISARD classifier by varying tic number

Tic number	Training Set Accuracy (%)	Cross Validation Accuracy (%)	Test Set Accuracy (%)
1	13.28	13.13	12.50
10	91.09	77.75	76.87
20	95.78	83.38	80.62
50	99.53	90.75	93.75
100	99.53	92.50	93.13
256	100.00	93.88	95.00

5.7 Optimal Hyperparameter Selection

Table 7 presents the optimal hyperparameter selection based on the experiments carried out in the afore–mentioned sections. The model performance with the optimal hyperparameter settings was evaluated with the aid of the confusion matrix represented in Fig 6.

Table 7. Optimal hyperparameters for the WIZARD classifier

Hyperparameter	Configuration
Bits	32
Bleach Confidence	0.95
Bleach Flag	FALSE
Bleach Step	2
Map Type	RANDOM
Tic Number	256

A confusion matrix is a table used to evaluate the performance of a classification algorithm. The matrix summarizes the predictions made by the algorithm on a set of test data, comparing the predicted labels with the true labels [28]. The matrix represents a multiclass classification that separates faulty and non-faulty sus–pension systems, respectively [29]. According to the matrix in Fig 6, the model demonstrated a high level of accuracy in classifying instances by correctly identifying 153 out of 160 instances. However, the model also mis–classified 7 instances, indicating some errors in its classi–fication process. While the overall performance appears to be relatively good, the misclassifications suggest that further analysis and fine-tuning may be necessary to improve the model's accuracy and minimize false posi–tives or negatives. Fig 6 illustrates the overall perfor–mance of the model. Notably, the model exhibited a re–markably short testing time of just 0.05 seconds, representing a potential applicability in real-time fault diagnosis systems. The study emphasized the significance of employing the WiSARD classifier with 32 bits and 256 tics, as this configuration led to accurate classi–fication. Moreover, the study successfully demonstrated the effectiveness of the proposed fault diagnosis method that utilizes the WiSARD classifier.

Table 8 provides a comprehensive overview of the detailed accuracy measures for eight distinct classes. The depicted metrics include TP (True Positive Rate), FP (False Positive Rate), Precision, Recall, F-measures, MCC (Matthews Correlation Coefficient), ROC Area (Receiver Operating Characteristic Area), and PRC Area (Precision-Recall Curve Area). The representation allows for a thorough assessment of the performance of each class across these key evaluation criteria.

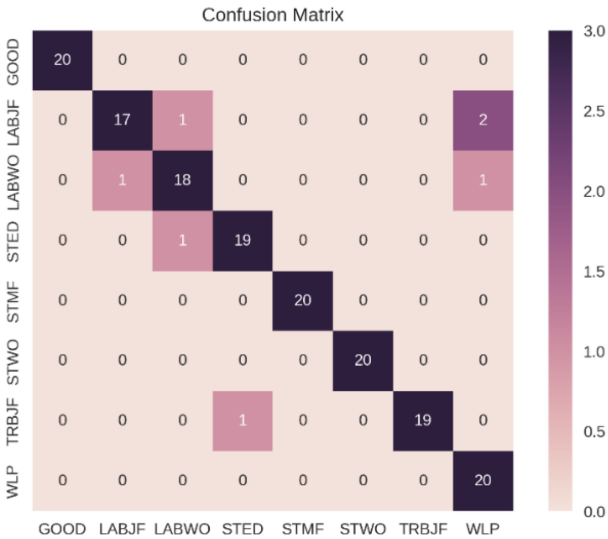

Figure 6. Confusion matrix of WiSARD classifier with opti–mal hyperparameters

5.8 Comparison with other studies

The performance of the proposed WiSARD classifier is compared and evaluated with various state-of-the-art techniques. Table 9 represents the performance comparison that details the classification accuracy achieved over the years. Based on the observations, one can suggest that the proposed WiSARD classifier outclasses the state-of-the-art works.

Table 8. Performance metrics comparison of WISARD classifier for optimal hyperparameters

PRC Area	ROC Area	MCC	F1 Score	Recall	Precision	FP Rate	TP Rate	Class
1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	GOOD
0.68	0.95	0.88	0.89	0.85	0.94	0.00	0.85	LABJF
0.79	0.94	0.88	0.90	0.90	0.90	0.01	0.90	LABWO
0.91	0.98	0.94	0.95	0.95	0.95	0.00	0.95	STED
0.96	0.99	1.00	1.00	1.00	1.00	0.00	1.00	STMF
1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	STWO
0.96	0.99	0.97	0.97	0.95	1.00	0.00	0.95	TRBJF
0.94	0.99	0.92	0.93	1.00	0.87	0.02	1.00	WLP
0.90	0.98	0.95	0.95	0.95	0.95	0.00	0.95	**WA**

WA-Weighted average

Table 9. Performance comparison with various state-of-the-art methods

State-of-the-art methods	Classification Accuracy (%)	References
K Nearest Neighbour	89.40	[30]
Naïve Bayes	90.60	[30]
Support Vector Machines	92.50	[31]
BayesNet	94.50	[32]
Expert system production rule	95.00	[33]
Fuzzy neural network	95.00	[34]
WiSARD (Proposed)	95.63	

6. CONCLUSION

The current study presents a novel method for diagnosing faults in suspension systems through the use of WNNs. Suspension systems are crucial for ensuring the safety and comfort of passengers in vehicles. However, due to wear and tear, the internal components of suspension systems may develop faults over time, endangering vehicle and passenger safety. Using an accelerometer installed in the fabricated test rig, the proposed approach uses a WNN model to classify suspension system faults based on vibration signals obtained for each suspension condition. The collected vibration signals were preprocessed, and descriptive statistical features were extracted. The commendable features that elevate classification performance were selected using the J48 decision tree algorithm. The selected features were split into training and test datasets with which the WiSARD classifier was trained and evaluated. Additionally, the study compares the performance of the proposed method with that of other classification techniques, including weighted neural networks.

The results show that the WNN-based approach outperforms these techniques, successfully detecting faults in the suspension system. The proposed method achieves a classification accuracy of 95.63%. This approach has the potential to be used in real-time fault diagnosis systems for vehicles, thereby enhancing their safety and reliability.

Eight different conditions, including strut external damage, strut mount failure, ball joint wear, control arm bush wear, control arm ball joint wear, strut wear, low wheel pressure, and good condition, were considered. WNN can successfully identify faults even in the absence of weights.

In summary, this research work proposes a novel approach for diagnosing faults in suspension systems using WNN and demonstrates its superiority over other classification techniques, with potential implications for improving the safety and performance of suspension systems in vehicles. As a future scope, one can do the following: (i) the experiments carried out in the study were performed under laboratory conditions with a quarter-car model. The proposed method and model accuracy may differ. As a future work, implementation in real-time can be of greater significance. (ii) numerous other families of classifiers can be experimented with and analyzed along with various hyperparameter tuning.

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ABBREVIATIONS

WiSARD	Wilkie, Stonham, and Aleksander Recognition Device
WNN	Weightless neural network
LOLIMOT	Local linear model tree
CNN	Convolutional neural network
SVM	Support vector machines
KNN	K nearest neighbor
RF	Random forest
LSTM	Long short-term memory
RAM	Random access memory
LWP	Low wheel pressure
STED	Externally damaged strut
TRBJ	Tie rod ball joint worn out
STWO	Worn out strut

LABW	Lower arm bush has worn off
LABJ	Lower arm ball joint worn out
STMF	Strut mount fault
CV	Constant velocity
DAQ	Data acquisition system
CSV	Comma separated value
TP	True positive
FP	False positive
MCC	Mathews correlation coefficient
ROC	Receiver operating characteristic
PRC	Precision recall curve

NOMENCLATURE

mV/g	Milli volt per acceleration due to gravity
Hz	Hertz
kHz	Kilo hertz
kmph	Kilometer per hour
%	percentage

ДИЈАГНОСТИКА КВАРОВА ЗАСНОВАНА НА БЕСТЕЖИНСКОЈ НЕУРОНСКОЈ МРЕЖИ У СИСТЕМУ ВЕШАЊА

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Системи вешања возила играју кључну улогу у обезбеђивању удобности и безбедности путника. Откривање кварова у овим системима је од виталног значаја за одржавање безбедности, перформанси и исплативости. Традиционалне методе инспекције имају ограничења, као што су визуелне провере, тестови одбијања и процене поравнања. Ова студија истражује Вилки, Стонхам и Александер Уређај за Препознавање (ВиСАРД), бестежинску неуронску мрежу (ВНН), за дијагнозу квара суспензије. ВНН модел се користи за класификацију грешака система ослањања користећи податке сензора. Скуп података укључује нормалне и неисправне услове за обуку модела. Студија процењује ВиСАРД под различитим условима квара, укључујући оштећење подупирача, квар носача, истрошене компоненте и низак притисак на точковима. Компаративне процене показују да приступ надмашује друге технике класификације, постижући импресивних 95,63% тачности са брзим временом израчунавања тестних података од 0,05 секунди. Ова метода заснована на ВНН доказује се супериорном у откривању кварова на суспензији и има потенцијал као кандидата за системе за дијагностику грешака возила у реалном времену.