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APPROXIMATE MODEL FOR VEHICLE INSPECTION ESTIMATION USING DEEP LEARNING NEURAL NETWORKS

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ABSTRACT

Periodic revisions of a vehicle are of vital importance to preserve the useful life of the mechanical and/or electrical parts, and thus, reduce the probability that the driver suffers an impasse during a trip. These revisions are performed in specialized laboratories that hold the vehicle for a few days; depending on the number of requests that are being attended at the time, so the driver must wait until there is availability for the attention of his vehicle. Although today there are specialized equipment that optimize the time it takes the technician to analyze the vehicle; these are expensive and difficult to access for a conventional driver who requires a quick test of your vehicle before going out to drive. Therefore, this paper proposes an approximate model that allows the driver to estimate the current state of his vehicle, based on historical information collected from sensors in previous technical reviews. This model consists of a neural network that is responsible for reducing the information from the sensors to a representation that predicts operating parameters, such as the battery level charge, the oil level, the kilometers traveled or the level of O2 present in the exhaust during engine operation.

Keywords: *Deep Learning Neural Networks; Computer Learning; Optimization; Classification; Signal Processing.*

1. INTRODUCTION

The hierarchical classification of vehicles is made considering factors such as functionality, design, or performance. Within this classification we highlight the automobiles since they have changed the lifestyle of people during the development of their daily activities. The automobiles can have two or more wheels and have an engine; that is responsible for replacing animal or human traction by an automatic traction mechanism; composed of a set of electromechanical parts that give the user the ability to transform fuel into mechanical energy to move through their environment [1-3].

The set of electromechanical parts that make up an automobile is subject to normal wear associated with its operation and other external factors, such as temperature and humidity of the environment, the skill in handling by the driver; the surface where the vehicle has been driven and crashes or damage caused by other vehicles. With the passage of time, these factors cause the driver to have to perform periodic preventive or corrective maintenance; which can lead to a reduction in the useful life of the vehicle or some of its mechanical or electrical parts; an accident if a fault or breakdown is not detected in time, or the total loss of the vehicle [2-4].

To reduce the accident rate, drivers are encouraged to have their vehicles periodically serviced in specialized workshops that certify the correct operation of their vehicles. However, due to the large number of vehicles circulating on the streets (according to the RUNT in Colombia approximately 16,042,336 vehicles circulate) the capacity of these workshops is limited; which makes the driver must wait several days to perform a detailed review of your vehicle; and thus, determine if there is any failure that affects its operation or deteriorate itself. A partial solution to this limitation is a visual or routine inspection by the user; however, in many cases the user does not have the necessary equipment and experience to determine if there is any type of failure that affects the integrity of the vehicle [1-2, 5].

Although the equipment and techniques used by a specialized workshop to check a vehicle vary depending on the model and make, four (4) wheel vehicles are usually inspected in the same way. That is systems such as fuel and oil filters, the condition of the brakes, the quality of the gases emitted by the exhaust, the condition of the suspension, the condition of the engine, among others, are always checked. More specifically, in current vehicles can be analyzed using the control computer that is responsible for storing a history of failures and report through a code if any system fails. However, in vehicles that do not have a computer, an inspection is performed using specialized equipment that is connected to the vehicle in a non-invasive way [10, 13].

In both cases, a history is generated with the behavior of the sensors that monitor variables such as oil and fuel level, the quality of the gases emitted, the state of the brakes, among others. Due to the large amount of information obtained in these reports, the analysis of the vehicle is performed in specialized software that are owned by the brand. Therefore, this article proposes a partial solution to the limitation that users must perform a periodic inspection of a vehicle; through a model that estimates the behavior of the monitored variables; and thus, inform the user if there is a failure or not from the historical information collected in previous inspections. This contribution is presented in the following sections, which are organized as follows: section 2 describes how a periodic inspection is performed and its relationship with the model, section 3 presents the developed model, and section 4 presents the results obtained.

2. MATERIALS AND METHODS

The tools used to inspect vehicles provide the user with information of the different mechanisms that make up the motor vehicle; this information is usually reported in plain text files that are interpreted by specialized software. However, this topic is addressed in this section from the techniques that retrieve vehicle information from the information provided by the sensors.

2.1. Inspection of a vehicle

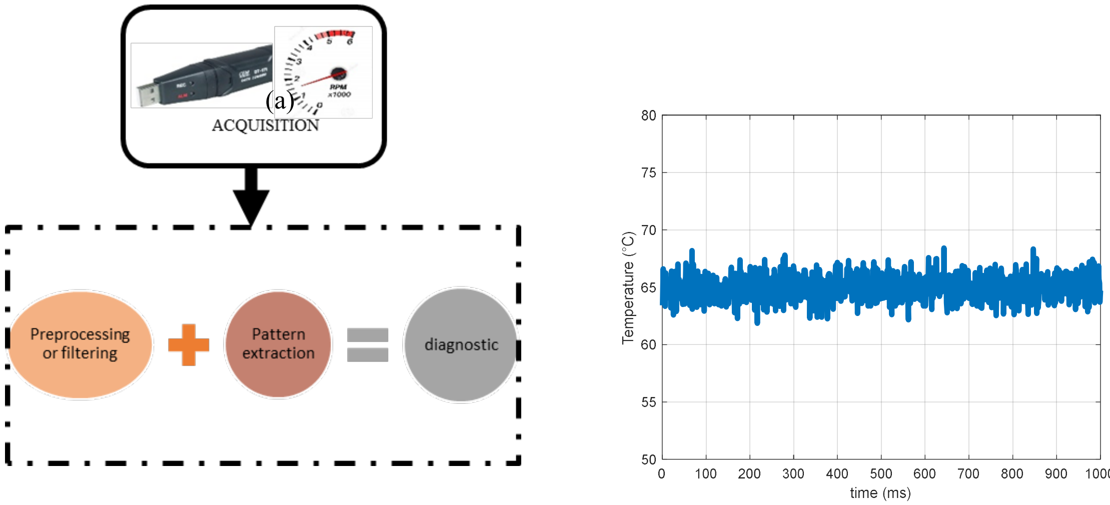
The inspection of a motor vehicle can be done in two ways. The first is a visual inspection where the user verifies that the oil levels are appropriate; the lights are working properly, the brake fluid level is appropriate, and that the surface of the wheels or chassis has no abnormalities that compromise the integrity of the vehicle. The second is the Technical Vehicle Inspection (TVI), which is a type of preventive maintenance in which a vehicle is periodically inspected by a certifying entity; which verifies compliance with safety factors and pollutant emissions in accordance with current regulations [6, 7].

There are different international standards and are governed by ISO/IEC 17020, which establishes the periodicity of technical reviews and the factors that must be considered to determine whether a vehicle meets a standard of performance or proper conditioning. These reviews normally check that the characteristics of the vehicle are the same as those reported in the registration certificate; the conditioning elements such as rearview mirrors, license plate, the condition of the body, floor, doors, locks and starting mechanism, signaling, and lighting, the efficiency of the braking system, steering performance, suspension and axle alignment, engine performance, the condition of the tires and the quality of the gases emitted during combustion [7-10].

TVIs are carried out with specialized and calibrated equipment including tachometers to check if the engine revs up correctly; carbon monoxide meters to determine the quality of the gases produced by the vehicle; thermometers to measure the operating temperature of the engine, feeler gauges to measure the thickness in the case of brake pad clearance measurement, distance meters to measure braking distance; chronometers to determine the reaction time of the safety systems, accelerometers to establish the effect of the activation of the safety systems on the passengers; lux meters to measure the luminance of the lights, alignment meters to verify the condition of the axles and suspension testers to verify the condition of the damping system. As can be seen, a large amount of information is generated by the sensors with relevant vehicle information, which is described in detail in the following section.

2.2. Reporting of motor vehicle information

The records of the vehicle's status information are presented in plain text files, which are generated using the vehicle's computer or external data loggers for sensors that are not part of it and are installed non-invasive (the sensors record at a frequency of approximately 50 Hz). Once the information of interest has been recorded for a certain time interval (5 to 10 minutes depending on the model of vehicle) the report goes to a specialized software that performs a validation of the systems that make up the vehicle; this validation then becomes a diagnosis to be interpreted by a specialist who dictates whether the recorded parameters are within a confidence interval [11].



(a) *(b)*

Figure 1: General diagram of the processing of a sensor reading in a vehicle by a data logger. a) Operation of the diagnostic application. b) Signal coming from the sensors.

Although the information techniques to generate a diagnosis manually and automatically have become widespread, its principle of operation is recording the information from a sensor, perform filtering that eliminates erroneous data or noise introduced during the acquisition of information; extract or compare patterns of behavior against others established as a standard by current regulations and finally generate a diagnosis of the system that has been evaluated [19], see Fig. 1.

There are techniques for automotive testing that are based on the information acquired by the embedded computer using the OBD (On-Board Diagnostics) protocol, which monitors the different systems in real-time and with external applications or devices continuous monitoring of the vehicle operation is performed. This computerized system is in the engine of the car and is developed by different manufacturers to control and monitor different aspects of the vehicle, which has proven to be very useful. However, independent repair shops cannot perform repairs or maintenance without the help of the manufacturers, since they require specialized software given by the manufacturer. Therefore, third-party applications have been developed that interpret vehicle information by taking the information delivered by the OBD protocol with a variant of this called OBD-II (The II indicates that it is a third-party standard) compatible with the free form SERIAL (RS-232) communication format [6, 7, 14].

Other specialized applications allow the user to study specific car systems in detail. On the one hand, those developed to automatically determine if the car's brake pedal is going to fail using the information acquired from the computer integrated into the engine. This application uses a monitoring algorithm that is responsible for the real-time monitoring of the sensors of the braking system. On the other hand, there are information systems based on SVM (support vector machines) that collect a large amount of information to try to predict a vehicle failure [12-14].

In all cases it is observed that the idea is to reduce human intervention to try to predict a vehicle failure; since the experience of each person is different and the interpretation of the information may be different in all cases. Therefore, this topic is still understudied for the construction of models or applications that allow the user to make accurate decisions regarding the information collected from the vehicle; either obtained through a TVI or the integrated engine computer. It is worth noting that the extraction or prediction of patterns in signals has been widely studied in other areas of knowledge; such as the interpretation of audio signals, image segmentation, pattern recognition in diagnostic images, or the variation of temperature in greenhouses [15-16].

This paper presents a supervised learning model based on a deep learning neural network (DLNN), in which the input and output parameters are specified to determine the behavior of the

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mechanisms that compose the vehicle and a possible failure. By definition, a DLNN is a variant of a conventional neural network whose representation allows the generation of models based on the behavior of biological neural synapses.

The models generated with a DLNN can be of two types: regression and classification. In the first case, mathematical expressions are generated with variable coefficients that are updated using algorithms for the correction of the margin of error at the output. In the second case, classification models group the information according to the characteristics of the labels that make up the training data set. In both cases, the shape of the resulting model is unknown because it is an object that is constructed according to the input information and the expected output [17-19].

Although the automatically generated DLNN model is unknown to the user, the topology or way of connection between neurons depends on some fixed variables such as: the number of neurons, the number of input and output layers, the number of hidden layers, the training algorithm, and the activation function. The number of input and output layers are defined by default when setting the training data set. The number of hidden layers can be fixed or variable depending on the training algorithm; because the more hidden layers, the more processing power of the computer is required. On the other hand, the activation function emulates the action potential generated when there are synapses between neurons; which is reflected in the DLNN by limiting the output values of each neuron through a mathematical function that represents this biological characteristic of the brain [17-19].

Although at present, there are no mechanisms to establish the form of the DLNN according to the problem to be solved; the mechanism adopted to determine which network configuration is the best is based on trial and error. That is, the user establishes several configurations of the DLNN and among them chooses the best one; or the one that, when estimating the output values, presents the smallest margin of error. Since this margin of error varies depending on the weights of each neuron and network topology; the training algorithm takes the training data set validates the behavior of the model during its execution. In each iteration of the training, the algorithm establishes the margin of error between the training data and the expected output; against those obtained when evaluating the model to modify the weights of the network [19].

The DLNN generated as a model during the execution of this work has the following characteristics: ten (10) inputs, one (1) output, 3200 neurons, 120 hidden layers. The initial weights of the hidden layers were assigned with a uniform distribution function, a sigmoid activation function and a training function; that corrects the margin of error a using the cosine function to compare the training data and those provided by the model incorporating the descending gradient technique. This function assumes the data sets as vectors (Training "A" and output or model "B") and estimates the angle between them (α from Eq. 1), whose coefficient changes between -1 and 1 whose similarity value establishes that the closer the angle is to the limits, the difference the margin of error is smaller.

$$\alpha = \cos(\theta) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \quad (1)$$

The DLNN training was performed on a sample set of 2500 records with 11 attributes (of which time and date were not considered for the DLNN training) recorded during several days from the embedded computer of a Mazda 3 vehicle. This set (Fig. 2) of samples was arranged as a list, where each of its components is filtered (Fig. 3b), segmented to classify with respect to fault type (Fig. 3c), and normalized (Fig. 3d), if any training sample cannot be segmented the component is assigned a default value of zero. Each record is assigned a fault code to determine its relationship to the vehicle condition; 0=Normal, 1=Low oil level, 2=High engine temperature, 3=Brake failure, 4=Airbag activated, 5=Faulty start, 6=Faulty tires, 7=Misaligned axles.

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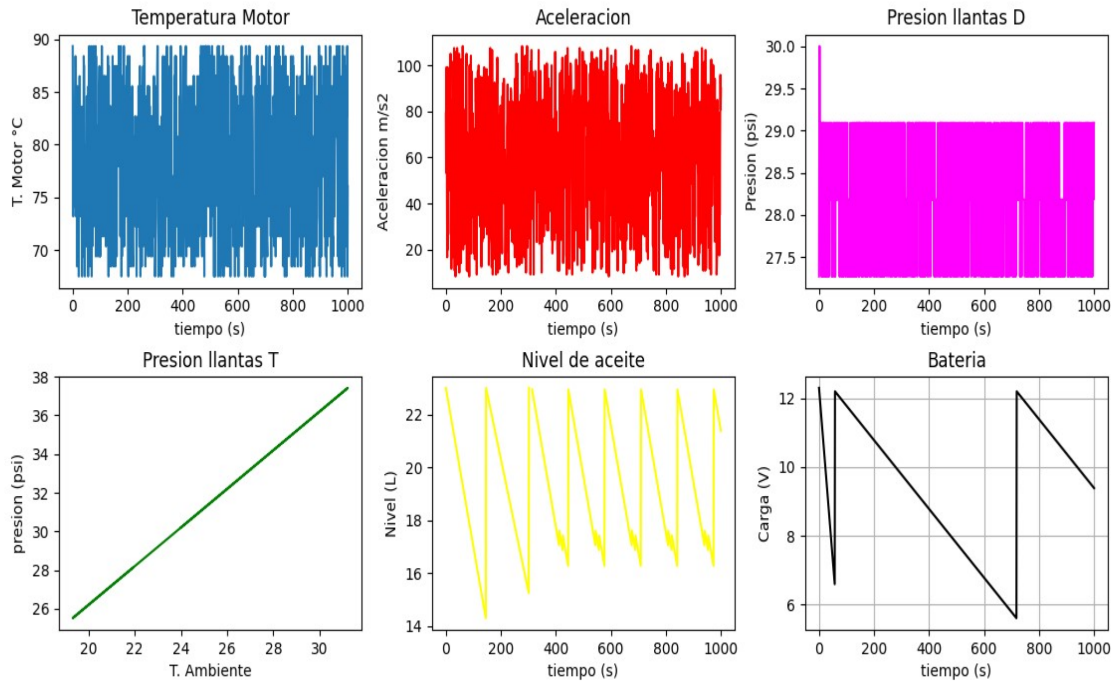
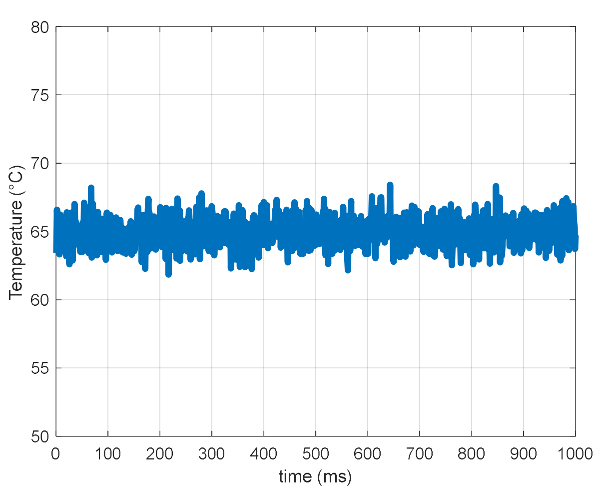


(a)

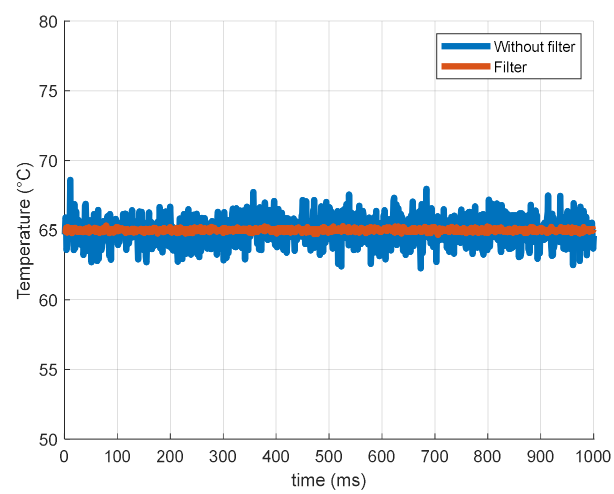
	A	B	C	D	E	F	G	H	I	J	K
1	id	time	temp	aceleration	presion 1	presion 2	level	batter	odomett	tempA	Fail
2	1	11:01:00 a. m.	87,4547	51,667	29,091	30,21	22,998	12,3	1	24,01	0
3	2	11:02:00 a. m.	84,60076	79,167	29	30,31	22,938	12,2	2	24,11	0
4	3	11:03:00 a. m.	81,74682	14,167	30	30,41	22,878	12,1	3	24,21	0
5	4	11:04:00 a. m.	78,89288	89,167	29,091	30,51	22,818	12	4	24,31	1
6	5	11:05:00 a. m.	76,03894	35	29,5455	30,61	22,758	11,9	5	24,41	3
7	6	11:06:00 a. m.	81,004	71,667	29,6455	30,71	22,698	11,8	6	24,51	3
8	7	11:07:00 a. m.	85,96906	26,667	29,7455	30,81	22,638	11,7	7	24,61	1
9	8	11:08:00 a. m.	79,76412	82,5	29,8455	30,91	22,578	11,6	8	24,71	3
10	9	11:09:00 a. m.	79,14418	55	29,9455	31,01	22,518	11,5	9	24,81	2

(b)

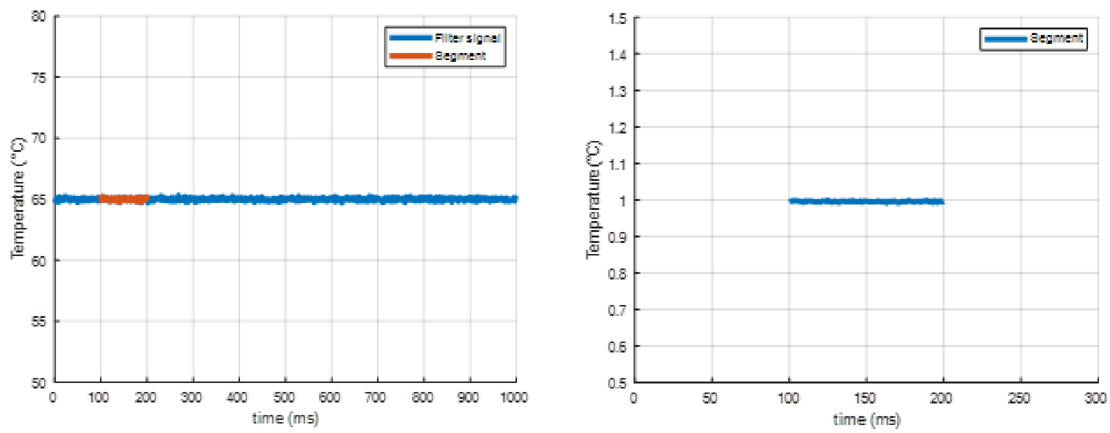
Figure 2: Segment of the report generated with the vehicle scanner. a) Behavior of attributes over time. b) Segment of the database used for training



(a)



(b)



(c) (d)

Figure 3: Classification of an attribute by assigning the detected fault. a) original attribute. b) Attribute filtered. c) Classified attribute. d) Normalized attribute

In some cases, the sensors are mixed with noise and its variability is large, so, during the implementation we chose to design low-pass filters to remove as much noise that may have the attribute before training, in this case, is a filter with cutoff frequency at 100Hz that removes excess excessive measurements and thus reduces the overtraining of the DLNN (see Fig. 4). It is worth noting that the filtered data replaces the original data to build a new database.

Finally, when building the database, the DLNN is trained with 70% of the available information and the remaining 30% was used as validation data to corroborate the performance of the model, which is represented in Algorithm 1 and complemented with the information presented in the following section.

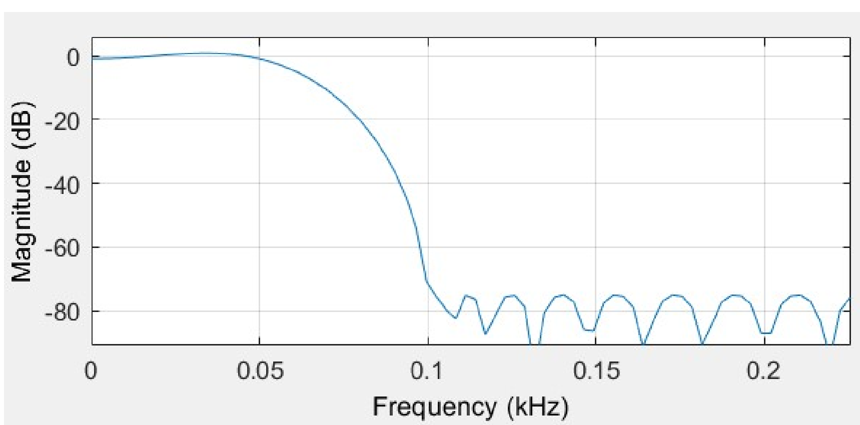


Figure 4: Filter applied to each attribute.

Algorithm 1. Functioning of the DLNN Training Algorithm

```
Create_DLNN function ()
    File ← Import data from the embedded computer.
    Arrangement 1 ← File complete (Disconnect the embedded
```

```
computer from the PC).
  For i < length (Array 1) do
          If Array 1 [i] ¡= null then
         Database [i] ← Filter Attribute (Array 1)
      Otherwise
         Database [i] ← Fill record with zero ()
  Input Attributes ← Segment (Database)
  Input Attributes ← Normalize (Input Attributes)
  Output attribute ← Take attribute Failure (Database)
  DN←Define DLNN
  Training data ← [Input Attributes, Output Attribute].
  Training data ← Training data (Select 70%)
  Validation Data ← Training data (Select 30%)
  DN←Train DN (Training data)
  DN←Validate DN (Validation data)
  Export DN

Main Function ()
  DN ← Import trained model
  FN ← Import integrated computer log
  FN ← Filter, segment and normalize (FN)
  SA ← Evaluate using the DN (FN)
  Publish ("The bug is:" SA)
```

3. IMPLEMENTATION

The application presented in this work was performed by connecting a Zumitek ELM 327 reference vehicle scanner via WIFI to a computer and generating the plain text files with the manufacturer's application, then using the KERAS and TensorFlow libraries of PYTHON 3.7 in the Anaconda interpreter in its version 4 of SPYDER and tested on a computer with an Intel® inside CORE^TM i3 processor and 8Gb of RAM. In addition, four (4) implementations of Algorithm 1 with different configurations of the DLNN (Table 1) were performed to choose the best one (reported in the previous numeral). In all cases, a selection of records from the database was made for training and validation in a stochastic way, the results of which are presented in the following section.

Table 1: DLNN test configurations.

DESCRIPTION	*DLNN SETTINGS*			
	DLNN 1	*DLNN 2*	*DLNN 3*	*DLNN 4*
Number of neurons	3200	1600	3200	2000
Activation function	Sigmoid	Sigmoid	Sigmoid	Exponential
Algorithm for assigning initial values to weights	Random with uniform distribution	Random with uniform distribution	Random with uniform distribution	Random with normal distribution
Number of hidden layers	120	120	60	240
Optimizing algorithm	Nadam	Nadam	Nadam	Adagrad
Strategy for estimating error	Downward gradient	Downward gradient	Downward gradient	Mean square error

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4. RESULTS AND DISCUSSION

As mentioned, four (4) different configurations of the DLNN were made from 100% of the records in the database; 70% were trained and the remaining 30% were validated. During the training and model building phase, the graph shown in Fig. 5 was produced, which groups together the curves that show the reduction in the margin of error between the expected value (vehicle failure) and the given value (model output).

Once the training of the networks was finished, another experiment was carried out, which consisted of generating 10 reports of the car with a failure of 100 records each (the duration of each test was one minute) that were not used during training or validation, and another 10 by selecting random segments from the training database to measure the margin of error in each configuration of the DLNN; and determine whether the proposed technique can predict failures from the information generated in other instants of time (see Table 2). Finally, the results obtained during the performance of these experiments are discussed in detail in the next section.

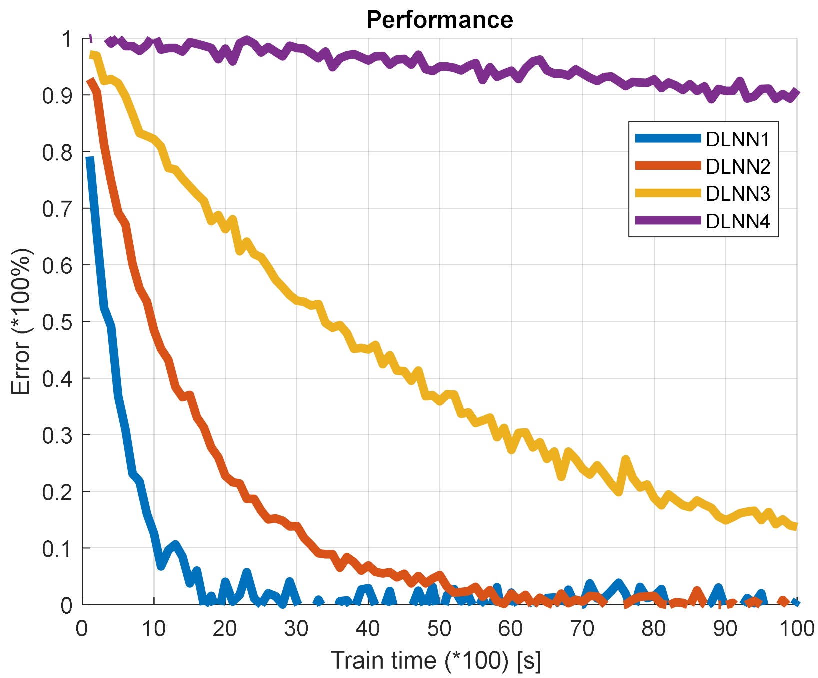

Fig. 5 Performance during DLNN training in its different configurations.

Table 2. Number of edges predicted by DLNN

	CONFIGURATION			
	DLNN 1	DLNN 2	DLNN 3	DLNN 4
KNOWN RECORDS				
PREDICTED	10	5	4	1
NOT PREDICTED	0	5	6	9
TOTAL	***10***	***10***	***10***	***10***
UNKNOWN RECORDS				
PREDICTED	9	2	1	0
NOT PREDICTED	1	8	9	10
TOTAL	***10***	***10***	***10***	***10***

5. CONCLUSIONS

Fig. 4 shows the behavior of the filter when applied on a database attribute and that it is possible to retrieve the sensor information without a trained classifier, i.e., although the filter does not predict the failure, it is possible to extract the values recorded by the sensor and know the state of the mechanism intuitively. Although the objective of the DLNN is to reduce the user intervention during the diagnosis of the fault in a vehicle. It is possible that an experienced user can intuitively interpret a possible fault with the clean and filtered information provided by the algorithm before the training of the network, since the normal operating ranges of the vehicle can be found in the manufacturer's manual.

Table 1 presents the different configurations of the DLNN, whose input attributes are arrays composed of multiple attributes conditioned and packaged as if they were one. That is, the DLNN supports multidimensional dimensions as input parameters considering that a dimensionality reduction must be made to the value of one; which facilitates the construction of a regression classifier because the number of neurons and links between them is reduced. Therefore, experiments were performed with multiple configurations of the DLNN as shown in Fig. 5 of which DLNNN 1 was the one with the best performance in reducing the convergence time; which shows that an appropriate configuration does not result in the uncontrolled increase of the number of hidden layers and neurons in the network.

Table 2 presents the results obtained by testing the DLNNs on data records taken at different time intervals, which allows us to highlight two features of the DLNNs. First, DLNNN 1 and 2 presented in Table 1 predict data even if they do not belong to the original training dataset with an error margin of less than 10%, indicating that these configurations can predict failures even if these data records have longer time intervals than those of the experiment. Secondly, DLNNN 3 and 4 of Table 1 do not have a satisfactory result because they have a margin of error greater than 90%, but it is possible that by increasing the training time these converge to a satisfactory result (projecting the graphs shown in Fig. 5).

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