INSPECTING & COST EVALUATION OF PRE-OWNED CARS USING DEEP LEARNING

AASHAY PATEL[1], HRITVIK DEKATE[2], SAURABH SUMAN[3]

[1,2,3]*Student, Dept. of Electronics and Communication, PESIT, BANGALORE, India*

---***---

Abstract - *The World is moving towards automatization of all services. To make this possible Artificial intelligence has played an important role. However the phenomenon of Artificial Intelligence was coined in 1956 but the technology has grown to such an extent that there is a lot more to extract from it. One such service where the following can be used is in rating the performance and emission index of pre-owned cars as well as estimating its cost. This paper discusses how modern deep learning models can be used to achieve these services. The paper discusses how availability of On Board Diagnostic System with the use of various sensors can be used to make decisions on the performance of cars. This would mean an overall improvement in prediction of automobile performance,emission index and cost.*

Key Words: - Deep Learning, Deep Neural Networks, Sensors, Automobile, On Board Diagnostics

1. INTRODUCTION

In the last decade it has been seen that owning a car is not just a luxury but a necessity. However many prefer to buy a pre-owned car. The used car market is an ever-rising industry, which has almost doubled its market value in the last few years. With the enforcement of stricter environmental laws, customers don't just look at the cost and performance but also the environmental hazards it causes. Most of the customers who approach a seller are unaware of the cost determining factors.

Predicting the reasonable resale value of a car is not a simple task. Now in this paper we tried to predict the nearly accurate value of the used car based upon the performance as well as the emission standards. Hence simplifying the overall process of resale of pre-owned cars. The resale cost of used cars depends on a number of factors. The most important ones are usually the age of the car, mileage, horsepower, fuel economy, ABS technology, engine performance, comfort level. However with changing trends the relating impacts of each factor vary hence we also propose a robust cost determining (including performance and emission rating) model.

The proposed model predicts the price based upon the performance of the pre-owned cars by using the help of several devices such as OBD (more specifically OBD-II), sensors, CAN and various microcontrollers (ex- Arduino Uno, Raspberry Pi). OBD-II focuses on diagnosing the performance of a car's engine to check any errors in the car's engine components. OBD-II connects with DLC (Data link connector). In modern cars most of the problems with the vehicle can be detected by OBD-II. Next for measuring the emission index we MEMS sensors can be employed which are low-cost and highly accurate inertial sensors. All the collected sensor data is fed to a deep learning model to predict the performance index, emission index and cost.

2. PROBLEM STATEMENT

The car market has expanded, the segments of cars have also increased in the market. This gives rise to a more competitive as well as a progressive market. However due to high prices most users prefer to go for pre-owned cars. People expect a value for money at the end irrespective of the fact whether the car is new or used. The actual problem lies in accurate pricing of used cars. Conventional methodologies are not reliable. Therefore, based upon the condition of the cars we need a model that could predict the actual pricing. The need for environmentally friendly cars has grown. With stricter environmental policies on used cars, most conventional pricing systems lack this feature. We need a model that could predict the price of used cars based upon different parameters such as age of the car, mileage, horsepower, fuel economy, ABS technology, engine performance, maximum speed, mileage, emission index, comfort level etc. An automated approach of this process is a requirement for simplicity and elimination of illegitimate activities.

3. LITERATURE SURVEY

A literature survey was done in order to know about the existing methods for the price predictions. Some of them are listed below.

This paper [1] mainly focuses on the wide scope of modern as well as legacy Machine learning technologies in automobiles. The capabilities of Deep learning to emphasis ADAS (Advanced Driver Assistance System) solutions are highlighted. Sensing of vehicle dynamics, vehicle inspection/heath monitoring. The emerging technology of automated driving and data-driven product development have evolved due to modern powerful Deep learning models are key areas that are expected to get the most attention. This article gives a list of the recent advances. Also the challenges faced in developing the Deep Learning models for the above mentioned applications are highlighted. The solution for health monitoring of vehicles provided in this paper is with the use of visual inspection (computer vision) and using sensor data provided by the OEM and advanced algorithms.

The paper [2] explains how the use of neural networks can help predict the cost of pre-owned cars using neural networks. Since the data is not linearly separable the use of artificial neural networks are very beneficial. The need for pre-processing the data is very important since a large number of inputs are fed to the neural network. This can also improve the optimization process of the algorithm. The need for the implementation of a cost evaluation model using neural networks is highlighted.

In paper [3] Data (ex- make, model, volume of cylinder, mileage, paint color, manual/automatic) was collected initially from different daily newspapers. After that sorting was done for the data that had sufficient information. The system proposed different techniques like Multiple linear regression in which a factor was computed that was used for consideration. K-Nearest Neighbours is a machine learning technique in which the new data is compared to all the existing records in order to locate the best match. Naïve Bayes in which two experiments were conducted, in first original data was used and in second numerical attributes were used. Decision tree was implemented. Outcomes of all these were compared in order to find out the best possible performance. Price computation was done based upon the performance. The weakness of above mentioned models is the difficulty to handle output classes with numeric values. Hence the price had to be classified into classes which introduced further grounds for inaccuracies. Hence advanced algorithms like artificial neural networks can perform better.

The car performance can be analyzed using various factors but major are acceleration capability, automated braking system (ABS), mileage and vibration absorbing capability.
The paper [4] proposes the calculation of acceleration capability using engine performance curve, in this Dynamometer is used to determine engine power and then simulate engine performance curve from the details of car specification like maximum power, maximum torque and engine speed. After simulating, they performed the car acceleration capability performance using a contour plot between car acceleration and engine speed at each gear position.

This paper [5] explains about the measurement of ABS (Automated Braking System). In this paper two circuits are designed to validate the results of a simulation tool for predicting ABS performance, one circuit was used to measure the braking distance and velocity distribution and other one is for measuring the longitudinal acceleration of the vehicle. Test runs are done on vehicles and all the data is saved in a SD card with time-stamped using built-in RTC. This data was processed using the two algorithms proposed and the results are obtained, this result is used to determine the ABS performance.

Gameiro da Silva in his paper [6] has focused on vibration based comfort measurement of vehicles. In this article the main techniques related to comfort evaluation in passenger vehicles were described. But we will be mainly focusing on the comfort level measurement according to vibration produced in the cars. The comfort level is determined using an index called SEAT and is the ratio of disturbance recognized by the passenger when seating on the seat at rest and the disturbance that would have been felt if the seat was rigid in the frequency range of interest. The sensors used are accelerometer e.g. piezoelectric inductive etc. Some signal modification is needed before analyzing like amplification, averaging and many more.

Kozawa in his paper [7] has also done some similar kind of work. In his paper a portable ride comfort meter was developed which gives an index called Vibration Number (VN) as a measure of vibration comfort of passengers, the index is calculated using multiple regression analysis. The index scale is in the range of 0 to 100. Only 3 vibration inputs were taken into account (vertical vibration of the seat, lateral vibration at the back and vertical vibration at the feet). The VN is calculated using formula $VN = 18 \log_{10}(k_1 10^{a1} + k_2 10^{a2} + k_3 10^{a3}) - 20$, where kn is undisclosed axis multiplying factors.

Juniastel in his paper [8] has shown that vehicle exhaust content level can be measured by applying a combination of several sensors. In this research, a tool to detect vehicle combustion system condition based on vehicle exhaust content level has been designed. The measurement results of EGD are not only displayed on PC but also passed on through Bluetooth HC-05 so it can be seen by Smartphone device. The EGD system as proposed consists of three sensors: TGS-2201, MG-811 and TGS-262. Arduino, Bluetooth and gas sensor testing were done to examine EGD performance. The results obtained were compared with the standard gas analyzer. The comparison results of emission of carbon dioxide (CO_2), Hydrocarbon (HC) and oxygen (O_2) shows that exhaust gas emission produced by pertamax (PTM) fuel are less than pertalite (PTL) and premium (PRM).

This paper [9] proposed measurement of engine performance of motor vehicles using a diagnostic tool (such as OBD-II which provides real time data in addition to a standardized series of diagnostic trouble codes). The conduction of two free acceleration measurements and the total reduced moment of inertia are calculated for the shaft of the roller. All of this process is naturally controlled and calculated with the aid of adequately elaborated measuring software and the end result will be external characteristics curve of torque and performance defined by exact value.

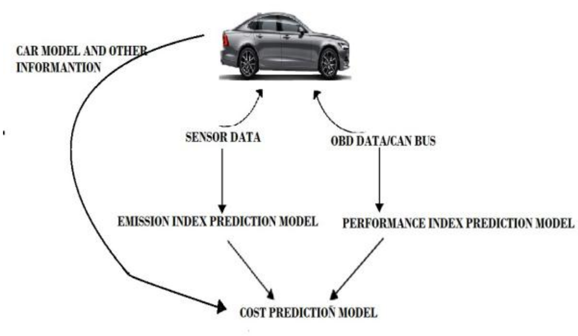
[10]The paper proposes on determining the condition of the cars using OBD-II protocol. OBD-II uses a standardized digital communications port to get the real time data which helps the technician to diagnose the problem easily. OBD-II scanner is connected to the OBD-II 16 pin connector. The system works by continuously sending electrical signals through the OBD scanner as a feedback to the vehicle's ECU. These are responsible to detect air/fuel volume so the ECU can precisely determine the accurate mixture in real-time. The OBD scanner is a tool to diagnose problems on the vehicle's electrical and emission systems. When a failure is detected, the ECU stores faulty code in memory so that it can be read by the scanner. OBD-II defines parameters that can be monitored and assigned a code to each PID. Several subsystem interaction modes are also set by the OBD-II standard to offer a straight-forward interaction with the vehicle's systems, such as the heating and ventilation systems, transmission system, and engine/chassis system, thus allowing for more accurate diagnosis depending on functionality.

This paper [11] focuses on selection of key parameters for vehicle operations and employing sensors for their retrieval. The values are obtained using the OBD-II protocol and they are related with the vehicle operation and the fuel consumption. Selected parameters can be retrieved through the CAN bus. This paper proposes to retrieve values during vehicle movement. A Mini Bluetooth scanner (Elm 327) is connected to the vehicle; it retrieves the values of the parameters and communicates through Bluetooth with an interface. Retrieved speed and RPM measurements were compared, since both dashboard and the OBD-II monitor showed the same values, the results have been consistent and the diagnostic protocol worked as expected. Calculations regarding Fuel consumption were the same as manufacturer values. It has been verified that random starts and stops require massive fuel consumption whereas normal driving without aggressive acceleration requires minimum fuel consumption.

The objective of this paper [12] is to develop a methodology to calculate in real-time the energy and environmental impact of spark ignition and diesel vehicles using an OBD and dynamometer chassis. An OBD scanner is connected to the vehicle's ECU and several parameters such as rpm, vehicle speed, engine load, lambda sensor voltage, catalyst temperature, intake airflow, pressure and temperature are obtained. Fuel Consumption can be evaluated from OBD data directly from a parameter (PID) of SAEJ1979 standard. Lambda value and power for spark ignition vehicles is directly obtained from the OBD acquisition tool. In a developed calibration procedure 3 tests on a dynamometer chassis were done: the maximum power curves, the curve at idle and a curve at fixed rpm varying the engine load. All the vehicles showed that the difference between measurements was not more than 4% so this methodology can be adopted to calculate the power and consumption of vehicles during their real use.

4. ARCHITECTURE

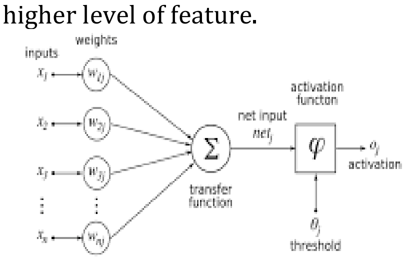
The system consisting of various sensor data is fed as input to a feed-forward deep learning model. The system consists of models for prediction of Emission index, Performance index and Cost of pre-owned cars.



PROPOSED MODEL DESCRIPTION

5. DEEP LEARNING:

Deep learning also known as deep structured learning is a subset of machine learning methods based on artificial neural networks. They use a layered architecture for computation. Deep Learning can be supervised, semi-supervised or unsupervised. After each layer the model extracts a higher level of feature.



The sensor data is fed as input to the model (x for image reference). The features are linearly transformed using different layers each consisting of weighted adder followed by an activation function. At each level of the neural network features at a higher level are obtained. Thus as the neural network propagates in forward direction, at the last level the final value is predicted. To train the model, the predicted value is compared with the test data and the error is calculated (in this case Ordinary least squares error). Now the model propagates in a backward direction. Using optimization techniques such as gradient descent or Adam optimizer, the new weights and bias are calculated at each level of the model and replaced.

Since input data can be categorical (example the car model name or make) this data has to be encoded using techniques such as One Hot Encoding. To avoid overfitting and converge optimization techniques faster, the input data is normalized. To avoid overfitting of the model regularization is done. This technique reduces the model complexity and increases accuracy on the testing dataset.

6. ON BOARD DIAGNOSTICS AND SENSORS

On-board diagnostics (OBD) is used in automobiles and used for vehicle's self-diagnostic and reporting capability. OBD-II uses a digital communications port to get the real time data.

OBD-II scanner is connected to the vehicle's ECU through OBD-II 16 pin connector. The system works by continuously sending electrical signals through the OBD scanner as a feedback to the vehicles' ECU (electronic control unit). These are responsible to detect air/fuel volume, Real-time parameters: RPM, speed, pedal position, spark advance, intake airflow rate, coolant temperature, engine load, etc. When a failure is detected, the ECU stores faulty code in memory so that it can be read by the scanner. OBD-II system uses 2 types of codes. Diagnostic Trouble Code (DTC): to describe an issue and Parameter ID (PID): to require data from the ECU.

MEMS are low-cost, and high accuracy inertial sensors and these are used to serve an extensive range of industrial applications. This sensor uses a chip-based technology namely micro-electro-mechanical-system. As we have seen in previous few years, the regulations have changed regarding pollution emission of vehicles for conserving global environment, this made us to think about another factor of price prediction that is gases emitted by the vehicles which is measured by MEMS gas air flow sensors. The more the gas or the pollution they emit the price is reduced according to that for this purpose the MEMS airflow sensor is used. These MEMS airflow sensor determine the flow rate and flow direction from the engine depending on the direction and flow rate.

Vibration sensor is very useful in the automotive sector, it is used mainly for vibration detection in engines and for the comfort of passenger vehicles. Vibrations can be measured using a velocity meter, MEMS accelerometer etc. but the MEMS accelerometer is best suited for our model because it is low-cost and has better durability. The real time data of car vibrations is captured using the sensor and analyzed using different techniques like STFT (Short-Time Fourier Transform).

EGD (Emission Gas Detector) is a tool for finding gas content in the vehicle exhaust level. Emission detector is placed inside the vehicle's exhaust system and the measurements are made by the EGD which is further displayed on the interface. It comprises of three sensors namely TGS-2201, MG-811 and TGS-262 with the help of which we can measure the contents of CO_2, CO, HC, NO_x in the exhaust system. Thus by knowing the contents of these gases, the index of an exhaust system can be rated.

7. CONCLUSION AND FUTURE WORK

To improve the cost prediction algorithm parameters such as inflation rate and market competition are considered attributes. Image processing can be used to identify dents and other flaws. Being a data driven model as data collection increases the model accuracy improves. A detailed report can be generated about the car and can be presented to the customers. Hence looking at the capabilities of the model it can resolve the problems as stated in the problem statement.

REFERENCES

[1] Singh, Kanwar & Arat, Mustafa." Deep Learning in the Automotive Industry: Recent Advances and Application Examples." (2019).

[2] W. Yansong, S. Gongqi and Z. Qiang, "New Model for Residual Value Prediction of the Used Car Based on BP Neural Network and Nonlinear Curve Fit," in *2014 Sixth International Conference on Measuring Technology and Mechatronics Automation*, Shanghai, China, 2011 pp. 682-685.

[3] Pudaruth, Sameerchand. (2014). Predicting the Price of Used Cars using Machine Learning Techniques. International Journal of Information & Computation Technology. 4. 753-764.

[4] Kuna Noppadol, Jarut. (2013). The Concept to Measure the Overall Car Performance. Journal of Science and Technology MSU. 34. 24-29. 10.14456/jscitech.2013.102.

[5] Khanse, Karan & Pierce, Eric & Ng, Michael & Taheri, Saied. (2015). Performance Measurement of Vehicle Antilock Braking Systems (ABS). 10.4271/2015-01-0591.

[6] Gameiro da Silva, Manuel. (2002). Measurements of comfort in vehicles. Measurement Science and Technology. 13. R41. 10.1088/0957-0233/13/6/201.

[7] Kozawa Y, Sugimoto G and Susuki Y 1986 A new ride comfort meter SAE Paper 860430.

[8] Rajagukguk, Juniastel & Pratiwi, Rani & Kaewnuam, Eakgapon. (2018). Emission Gas Detector (EGD) for Detecting Vehicle Exhaust Based on Combined Gas Sensors. Journal of Physics: Conference Series. 1120. 012020. 10.1088/1742-6596/1120/1/012020.

[9] Lakatos, István. (2013). Diagnostic Measurement for the Effective Performance of Motor Vehicles. Acta Polytechnica Hungarica. 10. 239-249.

[10] Abukhalil, Tamer & Al-Mahafzah, Harbi & Alksasbeh, Malek & Alqaralleh, Bassam. (2020). Fuel Consumption Using OBD-II and Support Vector

Machine Model. Journal of Robotics. 2020. 1-9. 10.1155/2020/9450178.

[11] Rimpas, Dimitrios & Papadakis, Andreas & Samarakou, Maria. (2019). OBD-II sensor diagnostics for monitoring vehicle operation and consumption. Energy Reports. 6. 10.1016/j.egyr.2019.10.018.

[12] Alessandrini, Adriano & Filippi, Francesco & Ortenzi, Fernando. (2012). Consumption calculation of vehicles using OBD data.

8. BIOGRAPHIES

AASHAY PATEL
BE 3rd year,
Dept. of Electronics and
Communication
PESIT BSC

HRITVIK DEKATE
BE 3rd year,
Dept. of Electronics and
Communication
PESIT BSC

SAURABH SUMAN
BE 3rd year,
Dept. of Electronics and
Communication
PESIT BSC