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Research Article

PREDICTIVE MAINTENANCE APPROACH FOR AUTOMOBILES

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ABSTRACT

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With the increasing demand for vehicles, predictive maintenance has gained more importance in the automobile industry. It has become however difficult to detect and recover the failure in-advance in vehicle due to the low scaled availability of sensors. However due to the advancements in the automobile industry, it has become very feasible to analyze and process the data i.e. the sensor data.Machine Learning techniques is used for prediction of failure. In this paper, we have presented an approach towards the fault prediction of the sub-systems of the vehicle. Sensorial data is collected while the bike is on the move. Now the data collected from the bike will be collected on both the conditions i.e. In normal condition when the bike is running efficiently and in the faulty condition, which is when a failure in a particular sub-system has occurred. The collected data is first sent to the android application via Bluetooth which further transmits the data onto the local server machine for the pre-processing and the analysis purpose. Various interesting patterns/outcomes are learned using the classifiers. These patterns are used to predict 2 possible outcomes i.e. 1.Root cause of failure 2. Time of failure. The root cause of failure can be predicted using the classification model and the possible time of failure can be predicted using the Regression model. These patterns can be later used to predict and detect the failures of other bikes which show identical behaviours. The ultimate goal of the approach is on increasing the vehicle's up-time.

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INTRODUCTION

80% of the vehicle shut downs are due to mechanical failures of these components which can cause their degradation and results in unplanned shut down. A faulty engine most commonly brings a mileage drop as an early indication or a damaged frame will induce cavitation which may cause vibration and degradation of the bearings and coupling faults. Break damage is generally due leakage of oil of due to the overtime damage and other components are among the causes of accidents with serious consequences for the safety of you and your vehicle as well as the environment or the other people if these events are not detected in time they will increase and lead to the destruction of the equipment and the failure of your motorcycle it is commonly accepted that repairing faulty equipment is 50% more expensive than preventing a failure an incident on this equipment will always entail costly repairs security risks and loss of time what if you could detect these events early with 'OUR' predictive maintenance solutions you're able to diagnose these causes of failures simply and inexpensively the detection of these events as soon as they appear will allow you to plan an intervention by limiting the costs and avoiding a full vehicle shutdown you can also quickly comply with changes necessary to keep you safe and your vehicle running, switching from a reactive mode to a predictive mode will allow you to increase the availability of your motorcycle while reducing your maintenance budget other heavy vehicle like Volvo TRUCKS have already set up some sort monitoring solutions for significant and measureable gains.

All subsystem consists of an actuator and sensors. These sensors and actuator are controlled by the Engine Control Unit (ECU). In order to communicate with the ECU, a high-level protocol is needed. One of such protocol is the OBD2. The OBD (On-Board Diagnostic) framework allows the owner to gain access over the data about the current condition of the different sub-systems of the automobile. The condition of the vehicle is evaluated using two parameters, diagnostics process and prognostic process. Diagnostic is associated with the current state of the vehicle's subsystem whereas, prognostic is associated with the future state of the subsystem .Prognostic data comes with serious challenges when it copes with onboard data. The development cost of this on-board data is limited and hence the number of sensors on vehicles is also limited. When the vehicle is moving, the sensor produces thousands of signals which is sent to the application

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continuously via wireless network which in our case is with Bluetooth. As the complexity of the automobile is increasing, the automobile industries are now moving towards automated data analysis. With the increasing trend in the android applications and reduced cost of wireless network, it is now feasible to analyze the data from vehicles for predictions of faults and failures.

This paper proposes an approach towards the use of sensorial data along with an android application as an UI to the user and the use of local machine for processing the data and performing various Machine Learning Algorithms for prediction of faults that will occur in future in your vehicle.

Related Work

A General Prognostic Tracking Algorithm for Predictive Maintenance [1]

The general prognostic tracking algorithm we come to know that from the taken predicted states one can estimate the future failure hazard, probability of survival and objective methodology. As in the paper several examples of features that provide an objective metric of machinery health are mentioned. For a user-prescribed threshold a feature is in a load environment and for a specific PHM goal, the dynamics can be estimated with a Kalman lter and the remaining time until the threshold is passed can be estimated. Example results are shown for crack growth on a tensioned steel band but this technique can be used on fatigue process with predictable growth.

An IoT Based Predictive Connected Car Maintenance Approach [2]

In this paper we come to know about the connected car as it says that the Connected car concept is getting lots of attraction now a days. It has a multiple benefits of from which Predictive Car Maintenance is the one, the paper talks about what predictive car maintenance is and how those problems can be solved. MQTT, a popular protocol for IoT is also discussed. A simulation of connected car sending sensors data to the cloud is also discussed. Finally, cost saving of a predictive car maintenance system over a traditional periodic car maintenance system is shown. This paper concluded by sharing of some of the challenges in implementing predictive maintenance of connected cars.

Practical Machine Learning Solution for Increasing Profit in a Car Repair Service [3]

This paper gives you different approaches for predicting a car repair service. The application is implemented for iPad and stores records of the performed reparations by previous clients. The proposed solution computes the costs of maintenance, generates a number of promotional packages and offers a sales simulation for proposed packages with a certain discount and sale rise. The classical Apriori algorithm is used for data processing.

Frequency-Inverse Document Frequency and Random Forest for modern aircraft maintenance systems, corrective maintenance is executed by maintenance technicians on ground using the real-time condition monitoring data during the night. . In this paper, a predictive model is proposed to predict faults with high priority in advance by exploring the historical data of aircraft maintenance systems, and preventive maintenance can be carried out based on the prediction results of the model. Prediction of faults with different priorities in this paper are formulated as a binary classification problem.

Fuel Efficiency Modelling and Prediction for Automotive Vehicles: A Data- Driven Approach Studies are mainly concerned with fuel efficiency modelling and prediction for common automobiles based on an informative vehicle database[4].

The problem of fuel efficiency analysis and prediction for everyday vehicles has been investigated. MII was used to determine the characteristics that significantly affect fuel economy. k-means clustering and SVM were applied for data clustering and classification, respectively. Five regression techniques have been exploited for fuel efficiency prediction, of which the prediction results obtained by QR and PLS were satisfactory, and were considered to be good candidates for fuel efficiency prediction.

Applied Iot: Car monitoring system using IBM BlueMix in this paper, the IoT car monitoring system is implemented using IBM BlueMix cloud applications [5]

The data monitored is transmitted by Bluetooth to IBM BlueMix cloud using smartphone internet connection so that the vehicle can be stored on the cloud database. For example the vehicle speed it can be see when a car is speeding up or slowing down.Further this system is to develop a full IoT car monitoring and supervising system such that the car driver can be supervised so he can drive the car in an efficient way.

Cloud –Based Driver Monitoring and Vehicle Diagnostic with OBD2 Telematics

In this paper he system consists of an OBD(On Board Diagnostics) port to Bluetooth dongle, a mobile app running on a smart phone and cloud based backend .They present a cloud-based vehicular data acquisition and analytics system for real time driver behaviour monitoring, trip analysis and vehicle diagnostics.

Predictive Maintenance

Automobile is a complex machine comprising of both hardware and software so the maintenance of these machines is very challenging. The conventional maintenance techniques are reactive and results in loss of money as well as reduces the lifespan of the vehicles. As a result, Predictive maintenance is required to overcome these issues. In India there has been enormous increase in the number of vehicles in the past 20 years. So we will require effective strategies to maintain the performance of the vehicle. In automobile industry, three types of maintenance is been performed, Preventive Maintenance, Corrective Maintenance and Predictive Maintenance. Preventive Maintenance is performed before fault has occurred and is the most common maintenance practice in the vehicle industry. In this type of maintenance vehicle parts are upgraded occasionally irrespective to its damage or not. As a result, some parts would be replaced even if there is no need for them to be changed thus increasing the overall cost of the maintenance to earn profits whereas, Corrective Maintenance is been performed after the damaged has occurred i.e. when we give our vehicle for servicing. Hence the part of the subsystem

that needs to be replaced which results in unavailability of the vehicle for a period of time. In contrast to this, in Predictive Maintenance, condition of the automobile is been analyzed to predict the probability of failure .Automobile has a very complex electro-mechanic structure comprising of various subsystems.

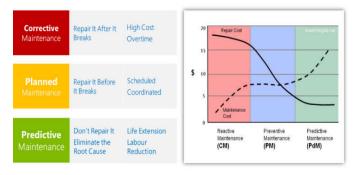


Fig 1 Three Types of Maintenance

METHODOLOGY

Client Server Architecture

Client/server architecture is a computing model in which the server hosts, delivers and manages most of the resources and services to be consumed by the client. This type of architecture has one or more client computers connected to a central server over a network or internet connection. This system shares computing resources. The server houses and provides highend, computing-intensive services to the client on demand. Client/server architecture works when the client computer sends a resource or process request to the server over the network connection, which is then processed and delivered to the client.

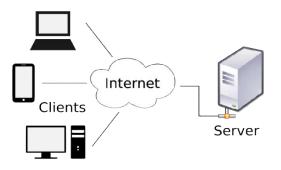
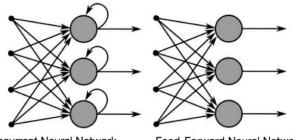


Fig 2 Client Server Architecture

Recurrent Neural Network(RNN)

Recurrent Neural Networks (RNN) are a powerful and robust type of neural networks and belong to the most promising algorithms out there at the moment because they are the only ones with an internal memory. This is because it is the first algorithm that remembers its input, due to an internal memory, which makes it perfectly suited for Machine Learning problems that involve sequential data. Because of their internal memory, RNNs are able to remember important things about the input they received, which enables them to be very precise in predicting what's coming next. This is the reason why they are the preferred algorithm for sequential data like time series, speech, text, financial data, audio, video, weather and much more because they can form a much deeper understanding of a sequence and its context, compared to other algorithms. Recurrent Neural Networks produce predictive results in sequential data that other algorithms cannot.



Recurrent Neural Network

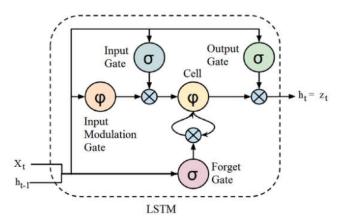
Feed-Forward Neural Network

Figure 6.1: RNN vs ANN

Long Short Term Memory (LSTM)

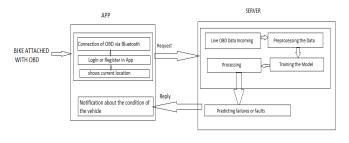
Long Short-Term Memory (LSTM) networks are an extension for recurrent neural networks, which basically extends their memory. Therefore it is well suited to learn from important experiences that have very long time lags in between. The units of an LSTM are used as building units for the layers of a RNN, which is then often called an LSTM network. LSTMs enable RNNs to remember their inputs over a long period of time. This is because LSTMs contain their information in a memory, that is much like the memory of a computer because the LSTM can read, write and delete information from its memory. This memory can be seen as a gated cell, where gated means that the cell decides whether or not to store or delete information (e.g if it opens the gates or not), based on the importance it assigns to the information. The assigning of importance happens through weights, which are also learned by the algorithm.

In an LSTM you have three gates: input, forget and output gate. These gates determine whether or not to let new input in (input gate), delete the information because it isnt important (forget gate) or to let it impact the output at the current time step (output gate). You can see an illustration of a RNN with its three gates below:



Proposed System

The proposed system follows client server architecture. Client is simply the application .OBD is connected to App via Bluetooth . Login id is provided to the user which is unique for each user. Once the login is created the user gets its current location .Server does the pre-processing of the incoming real time data from OBD. The pre-processing means cleaning of data that contains noise, empty fields. We than divide the data i.e split the data for training and testing the data. Train model needs a specific algorithm that is used to train the model. In our case we have used LSTM .After all it does prediction from the data which is trained. And the reply is send to the user on the app letting him know the condition of the vehicle.



PROPOSED SYSTEM

It uses OBD-II protocol and an Android app as the device of mediation. In addition, it comes with a set of complex analyses to perform reckless driving detection, driving anomaly detection, vehicle sensor failure prediction, high-fuel consumption and high-coolant temperature alert generation and trip detail summarization. The analyses are performed both in real time as well throughout a long period of time. While some of these analyses are performed within the app, more complex and resource consuming ones are performed in the back end. The results of these analyses are made visible through two interfaces. The drivers themselves are able to get the results through the Android app in the form of notifications. Alerts generated both in the backend as well as the app due to undesirable situations are sent to the drivers. Also results of long term analyses are displayed through a web interface. The web interface enables stake holders such as organizations insurance companies and fleet vehicle management systems and authorities to view results of a desired set of people.

Implementation

The Application is made on Android Platform of Android Studio .The App contains the login and register page which assigns unique id for a user. This data is stored in the database on firebase for authentication of the user which has already registered.

LOGIN ?
 Enter Email ID
Enter User name
Enter Vechical Number
REGISTER

Fig 6 Login or Register

After successfully performing the above task , you see a screen that displays google map showing users current location.



Fig 7 Users Current Location

In Menu Button you have different options like connect, history and setting . History gives user the past details of his ride. Connect option is to do final agreement to the connection of the OBD connected in vehicle to the application.

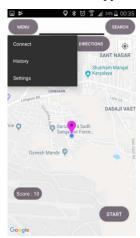


Fig 8 Options in Menu

Vehicle Simulation

The flow of data starts from the car engine to the smartphone. Therefore, the system needs to beconnected and communicating with the PCM (Powertrain Control Module) throughout project.

Since this is not a practical situation, the first component that was developed was a simulator to simulate the PCM.The simulator consists of two components as follows.

CSV Reader52

The actual datasets that were collected from various sources were stored in .csv files where eachtrip is stored as a separate file. The simulator is developed with the capability of reading a given.csv file. The user interface of the simulator

Not connected	ULATOR
enter no between	
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S3:	S4:
S5:	S6:
S7:	S8:
S9:	S10:
S11:	S12:
S13:	S14:
S15:	S16:
S17:	S18:
S19:	S20:
S21:	

Fig 9 UI of Simulator

Communicator

Communicator acts as a vehicle where an OBD2 adapter is connected. Once the CSV Reader reads a line in the file, it is separated into single data values. Each of these data values are sent via Bluetooth to the Android App upon request using the OBD2 protocol. The communicator supports both OBD 2 and AT command requests by the app.

The model is trained using Long Short term memory algorithm of recurrent neural network(RNN).We have used Keras. In order to train LSTM on our data, we need to convert data into the shape accepted by the LSTM. We have pre-processed our data and have converted it into the desired format. now is the time to create our LSTM. The LSTM model that we are going to create will be a sequential model with multiple layers. We will add some LSTM layers to our model for predict.

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Fig 10 Different Models Train

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Fig 11 Accuracy of different Types of Regression

RESULTS

We have successfully implemented the project of predictive maintenance for automobiles by training RNN (Recurrent Neural Network) .We have used LSTM as it had the highest accuracy of all the types. With the help of Keras library the processing is gained some help . An the final output of the probability of failure that may occur in the vehicle will be notified to the user through the notification in the mobile.

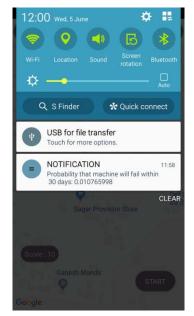


Fig 12 Final Probability of Prediction

CONCLUSIONS

Thus the predictive maintenance of vehicles will surely stop getting your vehicle from completely getting damaged as well giving user prior notification about the failure so that the user don't face any kind of problem .The cost of maintenance is reduced than the regular way of vehicle maintenance allowing the user to get knowledge about what fault has occurred rather than been fooled by the mechanic. Hence our proposed system can be used for prediction of failures.

Acknowledgment

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