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Vehicle Diagnostics Systems and Intelligent Failure Prediction

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ABSTRACT

Increase in demand of automotives has led to large scale development of the automobile sector. High vehicular population does eventually lead to high failure rate and negligence of obvious symptoms of faults and shortcomings in machinery. Traditional diagnosis involves cause and action approach, wherein the curative actions and repairs on the vehicle are done only upon failure and not beforehand as no system exists in order to take preventive measures. For now, preventive measures are taken only as a part of regular maintenance and care. Current On-Board Diagnostics devices which indicate breakdown of the parts and were considered state-of-the-art gadgets, but with recent developments a need has risen to upgrade and to take preventive measures rather than taking action and repair after breakdown on the vehicle. This issue can be resolved by implementing Internet Of Things (IOT) devices and Deep Learning Models to predict failures beforehand and avoid any breakdown. The idea is to nip in the bud the failure cause in order to prevent any mishap and potentially save unnecessary expenses. Models are trained with the help of past datasets and vehicular test results which indicate threshold values which will then indicate failure of the specified parts momentarily if no action is taken upon the indication by the system. The system consists of an OBD device which will feed data into a remote server, which, upon running the given algorithm on received data will dynamically update the provided dashboard with warning indications and messages of the failure thresholds

Keywords *— Vehicle Diagnostics, Sensor Fusion, Predictive Analytics and Deep Learning*

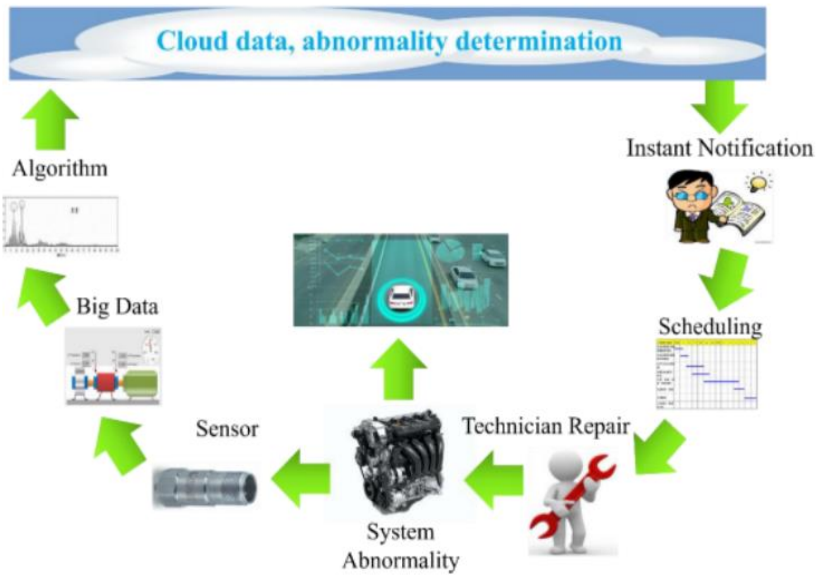
I. INTRODUCTION

Transport is one of the most important fields in the Global Economy. To ensure passenger safety, modern vehicles are equipped with multiple safety features being airbags, Anti-lock–brakes (ABS), Traction Control, Electronic Stability Control. Coping up with newer innovations in the IT industry, the transportation industry as well has adapted the use of computer assisted technologies in order to ensure leisure and safety as well as assistance systems. To name a few of the Intelligent Systems in the recent times of the automotive industry, Brake Assist, Forward-Collision Warning (FCW), Automatic Emergency Braking (AEB), Pedestrian Detection, Cruise Control, BlindSpot Warning, Backup Camera and Parking Assists, as well as Tire-Pressure Monitors and Telematics. The vehicle systems are always in motion and are in contact with each other under motion. This results in wear and tear along with other issues such as overheating, hyperpressure and metal fatigue. These faults however were being monitored by various sensors present in the car.

The output and communication of the sensors with the person however is still unpredictable. With these sensor technology's fault diagnosis mainly depends on either of the two conditions: whether a specific part is working or damaged. No threshold condition was conveyed by the present system. This significantly affects the health of vehicles. Prediction of failure or fatal damage can be done with the help of threshold values picked up by the sensors. The sensors convey the observed values to the computing element in the system and any prediction regarding the vehicle either positive or negative is conveyed to the user. In recent years implementation of IOT in vehicles, now being called together as IOV, has piqued the interest of experts in failure prediction resulting in it being a highly researched topic. Abnormal Diagnosis indicated by the implemented system and the prediction model in the early stages of failure will help to avoid or effectively reduce traffic accidents and collisions as well as threats to the lives of pedestrians, passersby, and property.

To achieve this objective implementation of the proposed system should be approached as to build a physics-based model consisting of the physical and mechanical descriptions of the functioning of the vehicle. Data-based approaches are also to be considered as datasets are used to set threshold values along with the physical-mathematical model's correlation to the machinery in picture. Various chemical, electrical, mechanical properties of the considered components should be studied; this requires high-level domain knowledge. Application of statistical methods to predict, estimate, and optimize the average life of a system may be beneficial in certain specific situations related to the operation of mechanical components, such as the battery of an electric vehicle or gear train of an automobile.

Flow Chart:



II. COMPONENTS INVOLVED

Proposed IoT system employs an arsenal of components for seamless functioning and appropriate and accurate outputs. The requisites involve:

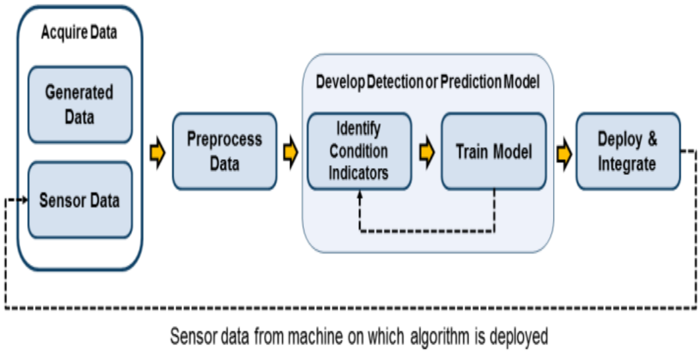
- On-Board Unit (OBU)
  - Vehicle ECU
  - OBD-II adaptor
  - GPS receiver and transmitter
  - Wireless Module
- Vehicle Diagnostics Server(VDS)
- Dashboard System

OBU or the On-Board Unit comprises the vehicle ECU, OBD-II adaptor, GPS receiver and transmitter and wireless modules, as previously mentioned.

The OBU is housed in the vehicle and acts as the on-ground reporting system, mainly collecting data and transmitting the same to Another remote system for analysis. ECU or the Electronic Control Unit of the vehicle helps to determine an overview of the electrical system and layout of the vehicle granting a deeper understanding of the vehicle systems. OBD-II adapter helps collect the output of sensors present in the car and provide the data to a remote server with the help of GPS and Wireless module. VDS or the Vehicle Diagnostics Server (VDS) can be dubbed as an online expert system which has a dataset of the observations from historical databases and tests along with algorithms and trained models to predict accurate results upon the reception of data from OBU and threshold value analysis The entire vehicle comprises various subsystems, The failure event may be significantly different. The cause of the failure may simply occur in the same subsystem.

The failure of explicit phenomenon can be judged as a subsystem failure, and is suitable for a rule-based inference engine which matches, selects and executes the selection rules for this process. However, a fault may fail to cover the number of subsystems. It usually does not have explicit symptoms and is suitable for use case-type inferences which store, identify, extract, and use similar examples and experiences to solve problems. Therefore, the proposed system will use rule-based and case-based simultaneously to design the expert system.

System Design



Beginning with data that describes the system in a range of healthy and faulty conditions, developing a detection model (for condition monitoring) or a prediction model (for prognostics) was essential. Developing such a model requires identifying appropriate condition indicators, and training a model to interpret them. That process is very likely to be iterative, as different condition indicators and different models until it proves to be the best model for application. Finally, deploying the algorithm and integration into the systems for machine monitoring, maintenance and repair. In failure prediction, the data will be monitored to attain details about the wheels to get the failure, the probability of failure is calculated to handle product quality on a factory at a certain time. In a lot of cases, failures occur due the environment changes; thus, the environmental worthiness was also measured. So those vehicles and their electronic hardware can be enhanced to withstand harsh conditions. To achieve better An enhancement environment stress analysis was carried out with boundary prediction.

III. REAL TIME MONITORING

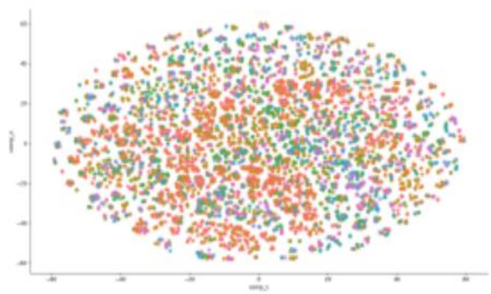
In real time monitoring instead of tracking vehicle location, the working status of the vehicle was monitored using a remote server or VDS. Any possibility of malfunction/failure is predicated on the system, the needed action is to be carried out immediately to avoid critical failures in real time.

IV. DIAGNOSTIC PROCESS AND SESSION GENERATION

Data acquisition is a critical process in the prediction systems. Data from the sensors is gathered and developed using the OBU and is then transferred to the VDS by the Wireless Module to be stored in the designated area. The diagnostic process starts when a vehicle with An unknown malfunction is connected to a VDS for fault detection purposes. The physical input by the sensors is then mapped with the symptoms of the problem.We only focus on the sessions, in which the faults were successfully identified. In other words, we discard every session, the fault of which has not been successfully determined.

V. DATA STRUCTURE AND MODEL TRAINING

The focus of the trained model should be mandated on successful identification of faults and Otherwise, all other sessions proving otherwise should be discarded. Retention of non-useful data will result in lowered accuracy and increased load on the diagnostic system and the model. The Diagnostic dataset was then generated by converting the extracted sessions into vectors. These vectors served as inputs for the Deep Learning Model. The traditional machine learning techniques are inefficient for processing this data and hence a better result is obtained to overcome these shortcomings and to redefine the model.



VI. ARCHITECTURE OF DL MODEL

The vehicle features and symptoms, which have been represented as vectors, are encoded in a boolean input tensor, where x i k {0, 1}, i[1, N], N2093. The fault type is given by gk where G is the total number of fault types and k is one of K sessions. The proposed learning method is based on a deep sequential 9 layer architecture, plus the standard input and output layers. The 9 layer architecture encompasses 3 repetitive blocks. Each block consists of 3 layers as follow:

1) A regular densely connected neural-network layer with a number of units, Ψ, can be arrived at:

$$\Psi = \delta/(\eta + \beta) * \lambda$$

Where: δ represents the number of tensors, η represents the number of fault types, β represents the length of the tensor and $1 \leq \lambda < 5$.

2) The activation function for the regular densely connected hidden Layer is a Rectifier Linear Unit . In general, this function can be arrived at:

$$f(x) = \max(0, x), \text{ s.t. } f(x) = \{x \in R|x > 0\}$$

x is the input to a neuron. This type of activation function works by thresholding values at 0, simply by giving the output of $f(x) = 0$ when the $x < 0$ and conversely, it outputs a linear function when $x > 0$.

3) A Dropout layer with a dropping rate equal to 20% for a good regularization and overfitting prevention.

Finally, the three blocks are connected to a dense Softmax layer for final classification. The model schema architecture is giving in Table I. As an optimiser function for our training model, ADAM method was utilized for stochastic optimisation of DNN parameters, which minimizes a categorical cross entropy function between the training and the predicted diagnostic tactic (x k→ y k) where k is a specific session.

VII. ESTIMATION OF INPUT RELEVANCE

Local Interpretable Model-agnostic Explanations(LIME) Model is used in developing the model to provide an interpretable and locally faithful explanation of predictions. This component is concerned with answering this question by supporting the diagnostic prediction with an understandable explanation, which provides more credibility to the diagnostic system. LIME gives some insights about the importance of every input with respect to the determined fault type, that is, a label that is locally isolated as a binary model. LIME makes use of complex equations in order to obtain robust and accurate results.

VIII. ADVANTAGES AND DISADVANTAGES

Advantages:

- Reduced downtime and a longer lifespan
- Reduced maintenance costs
- Improved safety
- Enhanced productivity

Disadvantages:

- Scheduling takes time
- Hardware cost might generate expensive system

IX. FUTURE SCOPE AND CONCLUSION

In the current era of 5G communication development, the IoV communication network is a crucial development focus. In recent years especially, the rapid development of unmanned vehicle technology has also strengthened the necessity for vehicle fault diagnosis. Immediate and adequate maintenance operations are critical to the operation of autonomous vehicles, as they can provide warnings and emergency proactive protective actions before failures occur, thereby minimizing the shocks caused by mechanical failures. To be able to warn of failures before they occur, predictive maintenance can be used, which is a preventative optimal maintenance strategy that predicts potential failures and takes immediate and appropriate maintenance actions This paper integrated CAN/OBD-II system, 3.5G mobile network, GPS, and expert system to develop an intelligent technology for real-time vehicle diagnostics and early fault estimation.This proposed system is comprised of on-board unit (OBU) module and vehicle Diagnostic Server (VDS).Constant communication among independent systems. The data obtained from the vehicle will be transmitted to the VDS wherein analysis of the data will be done and will be run through the Deep Learning models for detection of abnormal conditions and proximity to the threshold values. The VDS will then update the user dashboard regarding warnings of damage, malfunction, and suggested repair plans.

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