Original Article: Detection Framework For Overheating In Vehicle Engine Using Naïve Bayes Classifier

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ABSTRACT

Using sensors and actuators as engine control mechanisms brings technical complexity to rule-based approach to diagnosis as it is difficult to establish a complete association between sensor data and the symptoms. Diagnostic evaluation of critical components in vehicle engines has only gained little attention, whereas the interdependent nature of sensors and propeller requires continuous monitoring for stability and temperature control. In this study, the Bayesian probability approach was used to provide intelligence logic with mathematical formulation for detecting overheating in vehicle engines; by providing the architectural design of the proposed system.

The proposed framework was implemented using Microsoft Visual Basic.NET with integrated ActiveX Data Object (VB ADO) to experiment with the model for performance evaluation. Its usability testing and computational pattern were carried out with comparative analysis. Therefore, this study recommended that the problem domain for automobile diagnosis should be explicit about inculcating all engine-related problems other than overheating.

Introduction

Intelligent systems are increasingly essential in applying computational intelligence technology to modern societal situations. Computers that model the decision-making process of a human expert in a particular field of practice are increasing, and further research is in progress. The development of a particular machine exhibits features associated with human expertise, such as the learning process, logical reasoning, and problem-solving (Muhammed, 2017). Automobile technology has advanced over the years as vehicle specifications change rapidly due to environmental and economic factors. This

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development has its drawbacks, one of which is the general difficulty experienced by drivers and mechanics in diagnosing vehicle problems or handling automobile failures and malfunctions. The most common kind of expert system is a computer program with a set of rules that analyzes information the system's user-supplied about a particular class of problems and recommends one or more courses of user action. Intelligent systems can also provide computational analysis of the problem. The principle of thermodynamics has proved that a functioning engine could, at times, develop one fault or the other, and there is a need to detect such a fault to repair or rectify it. Meanwhile, detecting vehicle faults remains tedious, especially for inexperienced motorists, drivers, and even automobile technicians, commonly called 'mechanics' (Ekong et al., 2011) [1-4].

Identifying faults in case of vehicle breakdown is not easy, especially for inexperienced mechanics or drivers, as it requires a lot of expertise in diagnosing the fault. Vehicle problem detection is a set of diagnostic procedures that necessitates the deployment of human expertise or machine; such diagnosis requires high technical expert skills possessed by experienced mechanics. A successful diagnosis of car faults is predicated on an individual's expertise. It is, however, almost impossible to always have handy human expertise whenever a car develops fault as they are typically scarce; when such human expertise is available, it may come untimely or sometimes expensive. Meanwhile, the dependence on the experts could be reduced if such expertise is captured, documented, and retrievable via a computer program. Considerable efforts have been geared at developing and implementing expert systems, which is a primary application of artificial intelligence in mechanics and automobiles.

Despite the complexity of cognitive emulation of human diagnostic reasoning, which is a significant challenge in implementing computer-based programs for diagnostic advice, a broad and critical view revealed that diagnosis remains the primary application of ES. The expert system has, however, since developed into serving the dual function of diagnosis and treatment. A vehicle-related diagnostic system will serve car users and mechanics or automobile technicians alike by providing a recommended procedure to fix specific types of problems. Quite a number of sensors and actuators involved in the engine control system are not easy to handle with the use of a rule-based approach because it is almost impossible to ultimately establish the association between the sensor's data and symptoms (Angeli, 2010).

However, laudable efforts have been recorded in designing, developing, and deploying intelligent systems for troubleshooting vehicle problems. Much attention has been given to implementing expert systems for diagnosing general vehicle failure using a fuzzy and rule-based approach, yet with a drawback due to the complexity of unstructured data and the digital nature of the sensor/actuator. Consequently, the Bayesian model for troubleshooting specific components and monitoring the critical part of the vehicle engine has only gained little attention. In contrast, the interdependent nature of the engine, sensor, and propeller requires continuous monitoring for technical stability and temperature control, hence this study.

Related Literature

Diagnostic systems are used in applications where the computational processes for the problem do not exist or are poorly defined, but computational principles are available (Kukucka, 2010). Intelligent systems are used in consultation since it shows a quick diagnosis and description of the obtained results, which is helpful to the user or professional. The expert system allows the user to interact with a computer to solve a particular problem. This is possible because an intelligent system can store heuristic knowledge (Patra *et al*., 2010). The use of intelligent systems in vehicle troubleshooting is still rare, and their primary function is to become a tool for a human expert. Expert systems are rapidly being accepted for use by a non-expert to solve problems when human costly is expensive, untimely, or unavailable.

Deepa and Packiavathy (2012) provide an augmented reality framework that presents users with a pleasant experience through user-friendly and interesting input /output activities.

It was an Automobile Maintenance Information System (AR-MIS) based on the approach of service-based architecture. The AR-MIS involves two essential components, the automobile maintenance information system and three-dimensional resources access systems.

Mostafa *et al*. (2012) implemented an intelligent diagnostic system that utilized qualitative and quantitative vehicle fault detection procedures. The combination of both provides reliability to the technical process and facilitates knowledge interaction and analysis. The system was named Vehicle Fault and Malfunction Diagnosis Assistance System (V FMDAS) and successfully implemented with real-time processing ability and validated with the basic diagnostic procedures that were found satisfactory.

An agent-based system has also helped mechanics diagnose vehicle faults (Salama et al., 2012). The Expert Diagnostic Information System for car failure and malfunction consists of a storage area, a graphical user interface, and the system module, which consists of reasoning specification, an inference engine knowledge base, and a user advisor. The system can capture facts from the domain expert, designer, external data sources, and system user and retains such expertise. Angeli (2010) explored the possibility that combining expert systems technology with other artificial intelligent methods or specific classical numerical methods adds more effectiveness to the diagnostic task.

Asabere and Kusi- Sarpong (2012) sought to deal with vehicle problems relating to sparking/starting the engine and the cooling systems of vehicles using the Mobile Vehicle Expert System (MVES). The system constitutes fifteen rule of thumb procedures that easily troubleshoot through a driver's mobile device anytime and anywhere through the initial diagnosis and further advice. A performance evaluation of the system reveals that it is self-evolving and instantly updates its expertise conveniently (Xiaofen *et al*., 2019).

A novel fault troubleshooting approach using a combination of Bayesian networks with multi-criteria decision analysis (MCDA) has been developed (Huang et al., 2014). The trio employed a Bayesian network to establish a fault diagnostic model for reasoning and calculating standard values of uncertain criteria like fault probability. MCDA is adopted to integrate the influence of the four criteria and compute the utility value of the actions in the troubleshooting step [5-7].

Materials and Method

The system prototype was created, which inculcates Naïve Bayes theorem for the inquiring posterior probability of overheating as a predictor in the vehicle engine to experiment with the model and to evaluate its experimental performance by measuring the nominal value of observed parameters and converting them to likelihood scale for classification. The goal is to subject its likelihood to prone components or determinant parameters with an assumption of independence among the predictors. The rapid prototyping approach is used as a process model because it makes it easy to build and experiment with the solution framework. The product model was also made available through structural representation, architecture, and formulation, thus;

Mathematical Formulation of Bayesian Model and Functional Logic

Naïve Bayes classifier is a machine learning model which needs prior training before the classification task. Hence, the training data contains several input signals or observations and the predictor clusters in which they are classified. For instance, the training set in table 1 contains the values of three parameters (T, H, P) and a predictor class (possible cause) in which various sequences of parameter values are grouped.

$$P(OverHx|vEng) = P(OverHx_1|vEng) + P(OverHx_2|vEng) + P(OverHx_n|vEng) \quad (3.1)$$

$P(OverHx_1|vEng)$ implies predictor OverHeating subjected to leakage radiator.

$P(OverHx_2|vEng)$ implies predictor OverHeating subjected to radiator choked up.

$P(OverHx_n|vEng)$ implies predictor OverHeating subjected to alternator belt.

Therefore, $P(vEng|OverHx) = P(OverHx|vEng) * P(vEng) / P(OverHx)$ (3.2)

The conditional probability of overheating in a vehicle engine is computed based on inverse probability called POSTERIOR by the probability distribution of parameters in observations subject to direct probability called PRIOR within the predictor class. The unseen sequence of values in observation parameters is aligned to one of the predictor classes to determine the class with the highest tendency.

Table 1 : Observation Parameters as Training Set

Temperature	Humidity	Pressure	Predictor Class	Overheating
High	Low	High	Burnt Gasket	True
High	Medium	High	Timing Chain	True
High	Low	Medium	Alternator /Fan Belt	True
High	Medium	Medium	Condensed Coolant	True
High	Low	High	Broken Water Pump	True
Medium	Medium	High	Radiator Choked up	True
Medium	Low	High	Coolant Blockage	True
Low	Medium	Medium	Undefined	False
Low	High	Low	Undefined	False

Bayesian model was provided to classify a set of observation data into one of the classes in the training set. The system must group this sequence of values into one of the predictor labels and yield a corresponding status. Accordingly, the experimental feature with the most significant numeric value and likelihood status must be selected for a probable outcome. The classifier needs to refer to the training data to compute every class's possible probability distribution based on the training set. To determine the possibility of the class FALSE, the classifier must check the number of data rows in which the TEMPERATURE scale equals LOW when the data row is classified as FALSE. There are two (2) data rows with this criterion, while seven (7) data rows in which the TEMPERATURE equals to or exceeds MEDIUM, and the data row is classified as TRUE. Therefore, the conditional possibility of TEMPERATURE equals LOW given FALSE equals to 2/9. The system computes all the conditional possibilities and discrete continuous data of monitoring sensors being continuously captured from the car's digital dashboard, as shown in table 2 and table 3.

Table 2: Sample Data Captured From Digital Dashboard

Temperature (°C)	Humidity (%)	Pressure (mbar)
71	23	988.5
68	25	987
66	27	986.5
64	29	985
62	31	984.5

Table 3: Nominal scale for observation parameters/training set

Parameter	Low	Medium	High
Temperature	0-39	40-59	60-100
Humidity	0-49	50-79	80-100
Pressure	0-400	401-799	800-1000

The proposed system was experimented with to ascertain that results correspond with the expected output, ensuring the quality of service in terms of accessibility, usability, scalability, and acceptability due to relatively reduced cost. The generality of a diagnostic system for overheating detection in vehicle engines was also considered during the evaluation; its functional mechanism is flexible enough to accommodate specific domains of expertise or tailored towards a specific portion of the vehicle engine [8-10].

Results and Discussion

Having developed a software application to implement the proposed model, the diagnostic system focused on overheating detection was carefully tested for integration, usability, and functional prototyping to experiment with Naïve Bayes Model (NBM). After that, its performance was compared with existing models/methods for diagnosing automobile engines through primitive metrics for product and process. There are several existing systems being developed in the problem domain with different methodologies and integration parameters, thus; its functional scope is quite dynamic because it can handle enormous datasets promptly, unlike Asabere and Kusi-Sarpong (2012) that operates on a conventional rule-based approach which is only goal-driven and so generalized. Its implementation allows possible experimentation with the model, contrary to Salama et al. (2012), which was established as a position study without validation for reasoning specification. Though it produces similar results to Xiaofen *et al*. (2019) in rational inference, the program size by LOC parameter is not too long or large like Huang *et al*. (2014). In the same vein, the required space for working memory, which makes its algorithm faster for pre-processing and feature selection, just as in Olanloye (2014), backward chaining for an unseen sequence of parameters leads to predictor class.

Results of various operations involving input, processing, and output tasks are conveyed in the performance report, having carried out testing as depicted in Figures 1 to 4.

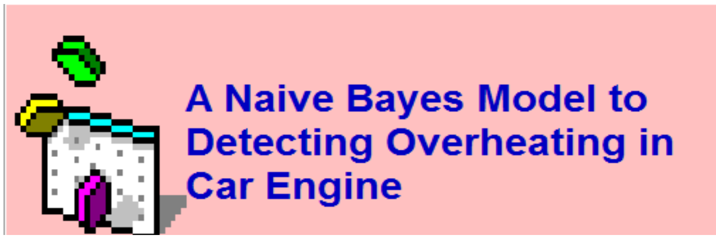

Figure 1: Splash Screen of the Prototype for Detection System

Figure 2: Login Screen of the Prototype for Detection System

Username and password are supplied as login credentials of the user; password characters could be made visible if the user is not sure of the set of characters being entered. However, privacy consciousness should be ensured to avoid shoulder surf attacks for impersonating the registered user on the system.

Figure 3: Main dashboard.

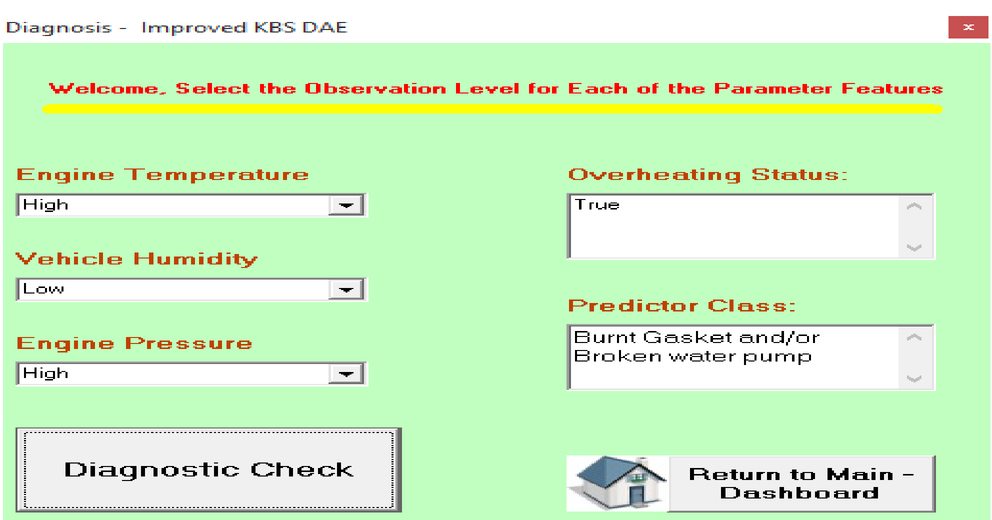

Figure 4: Diagnostic module for detection routine.

Conclusion

This proposed system is helpful to intermediate mechanics or automobile technicians to provide decision support, diagnostic report, and corrective measures. Using this system, loss of clients' patronage and income shortage due to lack of expertise, especially in the current knowledge economy, can be averted. This diagnostic system may allow mechanics to do more work in less time, bringing more income and gain through increased productivity. The application of intelligent systems in automobiles is exciting and has created considerable importance for diagnostic systems. The proposed system can help automobile technicians and motorists with decision support and corrective guidance.

The system constitutes components of intelligent fault diagnosis for the vehicle engine. Mechanics and motorists carried out the initial performance evaluation of the proposed system.

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