An Intelligent Risk Management Framework for Monitoring Vehicular Engine Health

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***Abstract*—The unwanted vehicular engine irregularities diminish vehicular competence, hinder productivity, waste time, and sluggish personal/national economic growth. Transportation sectors are essential infrastructures that require practical vulnerability assessment to avoid unexpected consequences through risk severity assessment. Artificial intelligence would be vital in the Industry 4.0 era to eliminate these issues for seamless activity and ultimate productivity. This article presents a risk management framework that includes an efficient decision model for monitoring and diagnosing vehicular engine health and condition in real-time using vulnerable components information and advanced techniques. To do this, we used the vulnerability identification frame to identify the vulnerable objects. We created a decision model that used an infrastructure vulnerability assessment model and sensor-actuator data to diagnose and categorise engine conditions as good, minor, moderate, or critical. We used machine learning and deep learning algorithms to assess the effectiveness of the risk management system's decision model. The stacked ensemble of the deep learning algorithm outperformed other standard machine learning and deep learning algorithms in providing 80.3% decision accuracy for the 80% training data and efficiently managing large amounts of data. Anticipating the proposed framework might assist the automotive sector in advancing with cutting-edge facilities that are up to date.**

***Index Terms*—VHMS, Vulnerable Components, Fault Diagnosis Model, IoV, Engine Health Management**

I. Introduction

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THE significance of artificial intelligence (AI) in various sectors is increasing outstandingly, particularly for predictive fault analysis and its interpretation utilising generated information of the existing system. The automotive industry is the most promising sector in globalisation, where AI assists in substantial progress for various objectives. The growth of AI and its benefits have attracted the attention of the automotive sector. Additionally, its usage in predictive analytics for vehicle fault diagnosis and maintenance is growing significantly due to vehicle complicated structures and some sensitive components. Moreover, the current vehicular condition can be perceived with maximum accuracy and predicts the probable faulty items using generated data [1], [2]. The twenty-first century is the age of technology; every second counts in this era. Nowadays, an essential task is to enhance productivity by making better use of that time.

AI ensures safe operation and significantly reduces maintenance time, maintenance expenses, and unplanned downtime in this scenario. For this reason, AI has received much attention in recent years for its success in monitoring mechanical items health utilising various sensors and viable algorithms like machine learning (ML), deep learning (DL), and so on [3]. The study found that the opportunities for AI in monitoring vehicle conditions are significant since the European Commission estimates that about 50% of transport vehicles will be increased in the next 20 years [2]. Thus, intelligent and sophisticated remote monitoring of vehicle health is a potential alternative that continually generates data from many vulnerable components. In this case, Vehicle-ad hoc networks (VANETs) are used in conjunction with the internet of things (IoT) to establish the Internet of Vehicles (IoV), which demonstrates high researcher expectations due to the enormous positive feature mentioned eloquently in prior work [4]. Because of the complicated vehicle structure and many additional features, a lot of relevant research was done over the last decade to build an effective predictive fault diagnosis system with minimal expenditures. A comprehensive study revealed several fault analysis and interpretation approaches, such as on-board diagnostics (OBD) and OBD II, were used to monitor the vehicle status [2]. In this situation, traditional diagnosis scanning equipment such as the ELM327 Bluetooth adapter or high-level diagnostic procedures are often required to interpret alerted Diagnostic Trouble Codes (DTCs), which might be difficult for users to understand. Moreover, this activity causes a burden on the vehicle owner, and only a few particular characteristics can be watched, even when sophisticated features become available daily. As a result, more user-friendly diagnostic systems are needed to be developed to address the difficulties perfectly. Ref. [2] has developed a remote health monitoring system for the vehicle based on sensor data from OBD II. However, the authors overlooked any influencing variables such as environmental factors that may affect the degraded health of the vehicle and failed to categorise the vehicle conditions according to the identified fault. Unlike a traditional data analysis system, an AI-enabled sophisticated and automated data analysis system is preferred [3]. Furthermore, while the vulnerability assessment approach is not implemented in the automotive industry, it has the potential to be used in this industry as critical infrastructure for reducing unexpected events such as unplanned maintenance, excessive maintenance expenses, traffic accidents, and so on [5]. It is undeniable that using an AI-enabled automotive health management system has enormous potential to handle a wide variety of vehicular difficulties. However, it is a large area that must be approached step by step to be competitive. The vehicular engine is the most sensitive item and needs to be brought under the surveillance system first to diagnose the fault smartly in the vehicular system.

The following are the main contributions of this article:

1. An AI-based vehicular engine health monitoring system (VEHMS) risk management framework is proposed to monitor real-time vehicular engine health.
2. Utilising vehicle engine vulnerable components/vulnerable points (VCs/VPs) and related risk variables to develop a VEHMS decision model.
3. A comprehensive experimental study is carried out in order to verify the efficiency of the proposed recommendations.
4. Using the proposition create future opportunities for the automotive sector to advance.

The remaining sections of the paper are organised as follows: Section II describes the related works, whereas Section III presents the proposed VEHMS risk management framework and the research methods. Then, the results and discussion are described eloquently in Section IV. Finally, in Section V, the conclusions are provided along with a contributing remark.

II. Related Works

The most hotly debated topic among researchers and automotive engineers is developing an effective predictive fault diagnostic system for vehicles using AI. Because it has the potential to enhance the automotive industry and lower maintenance costs, improve vehicle durability, and ensure a safe and enjoyable ride. In this situation, a data-driven approach predictive fault diagnosis system is more efficient and adaptable than a model-based and knowledge-based fault diagnostic system. As a result, substantial attention has been drawn to vehicle engine health management systems [6]. However, the transportation industry is facing substantial challenges in increasing the rate of accidents and maintenance costs. These challenges are primarily the result of the vehicle users irresponsibility and their failure to recognise and address internal vehicular problems (such as unexpected vehicle repair and replacement of parts). Researchers are implementing a variety of monitoring features and facilities in the vehicle regularly to reduce these concerns. The Society of Automotive Engineers developed a system called OBD-II to diagnose and monitor various aspects of a vehicle, including the anti-lock braking system, exhaust manifold, airbag, powertrain (including transmission and chassis), catalyst efficiency, longitude and latitude, speed, coolant temperature, and many other issues [2]. Beyond that, researchers recommended additional monitoring features, such as driver activity monitoring systems in real-time driving situations, intelligent traffic management, and so on [7]. As a result of these activities and the growing interest in minimising traffic accidents and maintenance costs, researchers are increasing their efforts to perform further research into real-time monitoring of vehicle fitness, especially engine's vulnerable items, known as VEHMS. A vital consideration in this instance is the development of a flexible, long-lasting, and secure communication network for vehicles, which is also being realised, and the upgrading of the VEHMS is becoming more widespread and sophisticated. VEHMS sensors and Internet of Things technologies developed another model based on the Fuzzy inference method [8]. This system provided remotely real-time information about battery health, engine health, emitted gas properties versus fuel quantity, battery voltage, mileage, and emitted hydrocarbons by the engine. Shafi et al. [2] developed a remote health monitoring and prognostic maintenance system to monitor the vehicle using artificial intelligence and Internet of Things technologies in conjunction with the engine control unit (ECU). ML techniques were applied in this situation, and several researchers used DL algorithms for data analysis to obtain accurate and instant VEHMS reports from massive data [3]. Furthermore, it is strengthened by Wi-Fi, LTE-V, 5G, and IoV to communicate and deliver vehicle structural health information to remote stakeholders. On the other hand, vulnerability is a significant concern in the automobile industry, and it is described as the susceptibility to harm that has numerical values through a mathematical expression. It is commonly used to assess the severity of a loss and indicate potential implications in the future. Although the vulnerability assessment system has a wide range of application possibilities, it is only employed in a small number of industries such as software applications, food systems, supply chain [9], climate, landslide issues, aircraft, nuclear power plants [10]. So, implementing this matter in the transportation sector as a vital infrastructure may reduce the risk severity [5]; however, unfortunately, its application dissemination has not been as effective as it could have been. As a result, the vulnerability assessment might facilitate the development of an advanced decision model for diagnosing vehicular engine faults and prioritising maintenance requirements based on the functionality of sensible components and the impact of irregularities [4]. Although the vehicular engine is considered to be the heart of a vehicle, it has several critical components that are essential to its proper operation. Therefore, we presented an intelligent risk management framework for diagnosing real-time vehicle engine conditions remotely using a wireless network.

III. Methodology

A. Overview of VEHMS Risk Management Framework

Figure 1 represents an intelligent real-time risk management system for remotely monitoring vehicular engine health conditions to reduce unplanned downtime, unexpected maintenance, and expenditures, enhance vehicle performance, and raise public awareness. These include engine overheating concerns, coolant temperature, coolant level measurement, radiator fan, and pump motor terminal voltage monitoring utilising integrated sensors. For cylinder-piston and crankshaft issues, accelerometer sensors with the continuous wavelet transform analysis for signal's peak value over time, RMS, mean, Kurtosis, and Skewness are preferred [11]. Magnetic pickup and voltage sensors are used to detect engine misfires and starting failures simultaneously using engine output power [12] and voltage variation [13]. Furthermore, it is proposed to use an online sensor to continuously monitor the physio-chemical parameters of engine lubricating oil in real-time [14]. The decision processing and notification system, on the other hand, is divided into two stages, including data management and data analytics. The data management stage is the first and most important step in the proposed framework for collecting information from the deployed sensor at numerous locations. The sensors installed in the vehicle's engine are active during operation and collect data from the specified point for further processing.

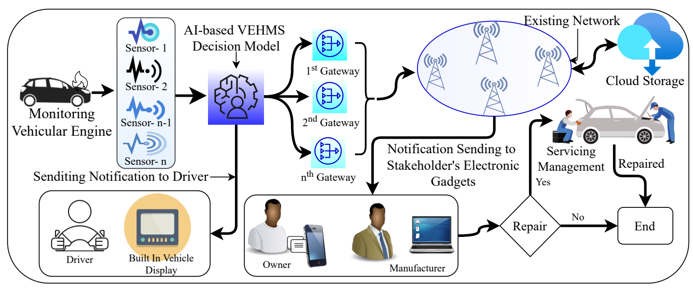


Figure 1: VEHMS risk management framework.

The sensor's data must be appropriately analysed to diagnose a malfunctioning car engine in real-time since it may dynamically accumulate a vast quantity of data. DL and ML algorithms are applied for comparing, scrutinising, and recognising more accurate outcomes of an AI-based VEHMS decision model. However, the multi-layer perceptron (MLP) deep learning technology shown in Figure 2 is used for the data analytic process, dynamic fault categorisation, and the vehicle engine notification system. Data is first pre-processed by tagging, investigating, and identifying features to develop an appropriate optimal model retrieved from the central data storage. Afterwards, the data are separated into two categories: training and validation data. Using a validation set in an MLP model, it is essential to evaluate the trained model is appropriate once the training process has been completed with satisfying results and adequate weight updates. Using edge cases inside the vehicle as part of the final model, based on the successful trained model with a satisfying result, is recommended.

B. VEHMS Risk Management Process

As a summary of the vehicle engine risk management system, the research overview is presented in Section III-A.

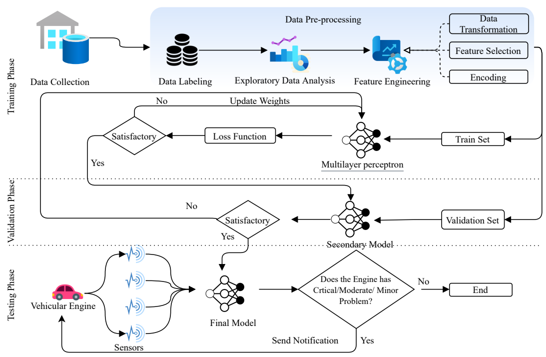


Figure 2: VEHMS decision model's data analytic process.

We divided the VEHMS risk management process into four phases (Figure 3) based on diagnosing vehicle engine faults, which will be covered in the following sections.

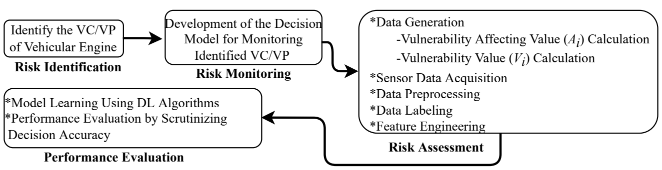


Figure 3: VEHMS Risk Management Process.

1) Risk Identification: Since not all engine components have the same impact on vehicle performance. To begin this investigation, we first identify VC/VP's on the framework for identifying vulnerable components, including the severity of damage and loss, potential problem, and functionality in the subsystem. Based on this, the following VC/VPs have been identified: crankshaft (V_1), engine overheating (V_2), cylinder-piston (V_3), engine starter (V_4), engine misfires (V_5), and engine lubricant (V_6).

2) Risk Monitoring: As stated in [15], we utilised the *Vulnerability Value* of the engine's VC/VP and sensor readings to develop a decision model for the VEHMS. Individual vulnerability values (VC/VP) and sensor reading are interrelated, and their product is referred to as the ***Severity Value***. Assuming $f(V)$ is vulnerability value function and $f(S)$ is sensor reading function, then VC/VP's Severity Value (SV) is defined as Equation (1).

$$SV_i = f(S) * f(V) \tag{1}$$

where, *i= 1,2,3,4,......* n^{th} VC/VP.

Now, from [16] using Infrastructure Vulnerability Assessment Model, $f(V)$ is the product of weightage function $f(W)$ and different impacts function of ***Vulnerability Affecting Value*** $f(A)$, which is expressed as Equation (2).

$$f(V) = f(A) * f(W) \tag{2}$$

From Equation (2), the uniform formula of ***Vulnerability Value*** is defined as Equation (3).

$$V_i = A_i * W_i \tag{3}$$

where, A_i is ***Vulnerability Affecting Value***, and W_i is ***Weightage*** of VC/VP as the ratio between the ***Relative Significance*** (RS_i) of desired VC/VP to all VC/VP ***Relative Significance*** ($\sum RS_i$). Many issues as intensifying factors of individual VC/VP may considerably influence the system's operational conditions. ***Vulnerability Affecting Value*** (A_i) of each VC/VP is the summation of ***Intensifying Factors*** as the product of ***Individual Value*** (I) of each intensifying factor and their ***Intensity of Relative Importance*** (*IRI*). In this case, I is the severity magnitude of every intensifying factor and *IRI* is the important magnitude of each factor among the set of intensifying factors. When ith VC/VP has total jth intensifying factors, then A_i for the ith VC/VP is

$$A_i = \sum_{j=1}^{m} \{I_j \times IRI_j\} \tag{4}$$

where, *j= 1,2,3,4,......* m^{th} are vulnerability intensifying factors for ith individual VC/VP. Finally, from Equation (3),

$$V_i = W_i * \left\{ \sum_{j=1}^{m} I_j \times IRI_j \right\} \tag{5}$$

In Equation (5), both W_i and IRI_j have numerical values, and total weightage of all VC/VP is $(\sum W_i) = 1$ based on Relative Significance (RS_i) of VC/VP and $(\sum IRI_j) = 1$ based on the Relative Importance of the set of intensifying factors. Now considering the sensor reading is S_i for $f(S)$. Then from Equations (1) and (5)

$$SV_i = S_i * W_i * \left\{ \sum_{j=1}^{m} I_j \times IRI_j \right\} \tag{6}$$

However, in Equation (6), whether the installed sensor is working correctly or not at t time interval can be assured by considering the previous reading of the respective sensor. Suppose both the calculated average of previous sensor reading (APS_i) with t time interval of individual reading for the total time-period T and current sensor reading (S_i) crosses the predefined threshold (*Th*) as $\left\{ \begin{array}{c} APS_i > Th \\ S_i > Th \end{array} \right.$, then irregularities would be detected. Where,

$$APS_i = \frac{PS_{1t,i} + PS_{2t,i} + PS_{3t,i} + \cdots + PS_{Nt,i}}{N}$$

So, Equation (6) is perfectly applicable for providing Severity Value of individual VC/VP. But it is only applicable to the ideal condition of vehicles and not valid for older vehicles. In Lim et al. research work, we found that the vehicular performance degraded (based on fuel economy) around 4.1% for nearly 10,000 Km of accumulated driving mileage [17]. It could happen due to the degradation of VC/VP that relates to SV. Now assumed λ is the degradation rate of VC/VP for every 10,000 Km from ***Severity Value*** by neglecting minor variation. Finally, the updated formula from Equation (6) at t time

$$SV_i(t) = S_i(t) W_i \{1 - \lambda\}^k \left\{ \sum_{j=1}^{m} I_j \times IRI_j \right\} \tag{7}$$

where, *k=0,1,2,3,4 …….. and l^th^* 10,000 Km. However, Equation (7) is applicable for the individual VC/VP at t time to identify their fault as ***Critical Problem*** or ***Moderate problem*** or ***Minor problem***, or ***Good Condition***, by comparing with the predefined threshold ***Severity Value*** as VC/VP Condition is Critical (if $SV_i(t) \geq TH_C$); Moderate (if $TH_C < SV_i(t) \geq TH_M$); Minor (if $TH_M < SV_i(t) \geq TH_{MN}$); Good (if $SV_i(t) < TH_{MN}$). Again, Equation (7) indicates that there is a possibility of getting four outcomes for every VC/VP at time t. So, $Total\ number\ of\ outcomes\ for\ each\ VC/VP \times Total\ number\ VC/VP\ in\ vehicular\ Engine$ outcomes possible to decide about overall vehicular engine condition. For the engine subsystem of the vehicle, the overall decision model is proposed as the ***Decision-making Matrix Model*** [18] in Table I at t time. In this case, assuming the category of ***Severity Value*** of individual VC/VP is SV_{iC} for ***Critical problem***, SV_{iM} for ***Moderate problem***, SV_{iMN} for ***Minor problem***, and SV_{iG} for ***Good condition*** at t time.

Table I: Decision Matrix for the Complete Vehicular Engine

Critical (SV_{iC})	Moderate (SV_{iM})	Minor (SV_{iMN})	Good (SV_{iG})
SV_{1C}	SV_{1M}	SV_{1MN}	SV_{1G}
SV_{2C}	SV_{2M}	SV_{2MN}	SV_{2G}
SV_{3C}	SV_{3M}	SV_{3MN}	SV_{3G}
-	-	-	-
-	-	-	-
SV_{nC}	SV_{nM}	SV_{nMN}	SV_{nG}

After summing up all elements in column wise of this decision matrix, the vehicular risk management system's VEHMS decision model for the complete vehicular engine condition at t time with ***Threshold*** (TH_D) is

$$\begin{aligned} \sum VEHMS_{\mathrm{D}}(t) = \sum SV_{iC} + \sum SV_{iM} \\ + \sum SV_{iMN} + \sum SV_{iG} \end{aligned} \tag{8}$$

where, Engine Condition is Critical (if $\sum VEHMS_D(t) \geq TH_{DC}$); Moderate (if $TH_{DC} < \sum VEHMS_D(t) \geq TH_{DM}$); Minor (if $TH_{DM} < \sum VEHMS_D(t) \geq TH_{DMN}$); Good (if $\sum VEHMS_D(t) < TH_{DMN}$). These thresholds could be considered for overall vehicular engine conditions by measuring the sum of all elements' minimum prevalent value of the respective engine condition.

3) Risk Assessment:

a) Data Generation: The originality of this research is enhanced by the fact that we used sensor data directly from the individual VC/VP, rather than utilising data from the ECU or OBD II. Furthermore, the data generation step is accomplished through two stages: the vulnerability affecting value and vulnerability value calculation, which are detailed in further detail. Many factors might impact the operation of the engine, increase running costs, and indicate the need for immediate maintenance attention. The model also considers risk factors such as cost, engine age, damage, reliability (new, used, and reconditioned), negative impact on the environment, mounted parts condition (new, used, and reconditioned), the possibility of mechanical failure and the associated risk, as well as safety and security breaches, maintenance complexity due to failure, and the origin of spare parts (local or foreign). To calculate A_i from Equation (4), the Individual Value (I) of each Intensifying Factor is the impact severity on engine performance that needs to be measured. Therefore, the Vulnerability Assessment Questionnaire Technique based on the intuitive questionnaire [9] with a rating and indexing scale None (0.0), Low (0.1 - 3.99), Medium (4.0 - 6.99), High (7.0 - 8.99), and Critical (9.0 - 10.0) from CSVS Qualitative Severity Evaluation Scale [19] are used. Also, IRI for each VC/VP has been calculated using the ***Value Focused Thinking (VFT)*** approach [20] on a scale from 0 to 10 where the sum of ***IRI*** for all intensifying factors is 1, i.e. ($\sum IRI_j$) =1. Suppose the crankshaft is selected for sample calculation. We used a computer-based simulation tool to generate 500 data for all intensifying factors individually. From there, to calculate I, the most frequent ratings have been selected among No, Low, Medium, and High impact for all intensifying factors by following the ***Quantitative Analysis of the Qualitative Data*** approach [21] and presented in Table II. Again, for calculating RI for every intensifying factor, the VFT approach has been employed using a scale of 0 to 10 and generated 500 data similarly as mentioned above. However, an average of 500 data of RI is presented in the same table. Finally, based on Equation (4) and Table II, the Vulnerability Affecting Value for the crankshaft is A_1 = 5.766. Similarly, we calculated it for other VC/VPs of the engine subsystem.

Table II: I (Average), RI (Average), and IRI of Crankshaft's Vulnerability Intensifying Factors

IFC	MFR	F	I (Avg.)	RI (Avg.)	IRI=$\frac{(RI/}{\sum RI)}$
CI	High	275	7.9	8.40	0.0972
AgI	High	320	8.18	9.60	0.1111
DI	High	390	8.32	9.27	0.1073
RI	Medium	381	5.73	7.93	0.0918
EI	Low	489	2.99	5.33	0.0617
CCUII	Medium	367	6.46	8.80	0.1018
MPI	Medium	265	6.77	8	0.0926
RI	Low	400	1.9	3.33	0.0385
SI	Medium	253	5.33	4.30	0.0498
SeI	No	469	0	0.73	0.0084
CI	Medium	267	4.81	6.08	0.0704
MCI	Medium	333	5.15	6.57	0.0760
SPAI	Low	493	1.43	8.07	0.0934

IFC = Intensifying Factors for Crankshaft, MFR = Most Frequent Ratings, F = Frequency, I = Individual Value, RI = Relative Importance CI = Cost Impact, AgI = Age Impact (for 50,000 Km or more used), DI = Damage Impact, RI = Reliability Impact (Reconditioned spare parts), EI = Environmental Impact, CCUII = Condition of Currently Using Items Impact (Reconditioned spare parts), MPI = Mechanical properties Impact, RI = Risk Impact, SI = Safety Impact, SeI = Security Impact, CI = Comfortability Impact, MCI = Maintenance Complexity Impact, SPAI = Spare Parts Availability Impact (Local brand).

To prioritise vehicular engine components during real-time health monitoring and make the right judgments, the **Vulnerability Value** (V_i) calculation has been implemented. The VFT technique was employed using a scale from 0 to 10, and created 500 data for RS of each VC/VP using a computer-based simulation tool, considering their functionality and relevance in the engine subsystem. Table III shows the average Relative Significance of these components, as well as the Weightage (W_i) derived after normalising the results of these calculations., where $(\sum W_i)$ =1.

Table III: Calculation of Relative Significance and W_i

Vehicular Engine's VC/VP	Relative Significance (RS_i) (Avg.)	Weightage (W_i)
Crankshaft	7.63	0.1789
Engine Overheating	9.44	0.2213
Cylinder & Piston	6.82	0.1599
Engine Starter	4.60	0.1078
Engine Misfires	4.79	0.1123
Engine Lubricant	9.38	0.2199
Total=	42.66	1

To summarise, the crankshaft Vulnerability Value is V_1= 0.1789*5.766 = 1.0315 when applying Equation (3) for the period t. Since we anticipated that the vehicle travelled 50,000 Km or more and, the performance deterioration rate was 4.1 per cent for every 10,000 Km travelled according to [17]. SV for the crankshaft at t time is calculated based on Equation (7).

$$\mathrm{SV_1(t) = S_1(t) * (1 - 4.1\%)^5 * 1.0315 = 0.8367 * S_1(t)} \quad (9)$$

Similarly, other VC/VP's Severity Value SV_2 = $0.9824 * S_2(t)$ for overheating issue, SV_3 = $0.7230 * S_3(t)$ for cylinder-piston issue, SV_4 = $0.3704 * S_4(t)$ for starter issue, SV_5 = $0.4212 * S_5(t)$ for misfires issue, and SV_6 = $1.0485 * S_6(t)$ for engine lubricant issue. Afterwards, we evaluated the defect diagnostic report of each VC/VPs by basing sensor decisions on the severity values of the corresponding VC/VPs.

b) Sensor: Data Acquisition

The sensor reading must be restructured by following the procedure discussed in Section III-A and labelled as 10 for the respective VC/VP's smooth operational condition and 1000 for the respective VC/VP's irregularity due to different dimensions of these data.

c) Data Pre-processing : Given that the sensor has identified an irregularity in the crankshaft, then S_1 is 1000, and the Severity Value at t time is $SV_1(t) = 836.7$, as determined by Equation (9). In this instance, the Severity Value is fractionally more than 99, which might be further classified depending on the condition from Equation (7). Similarly, for no irregularities of other respective VC/VP, the severity value at t time is $SV_2(t) = 9.8240$, $SV_3(t) = 7.230$, $SV_4(t) = 3.704$, $SV_5(t) = 4.212$, and $SV_6(t) = 10.485$. However, for our research, in Equation (7), the numerical value for the conditional limit at t time is $SV_i(t) \geq 745.3$, $745.3 < SV_i(t) \geq 407.79$, $407.79 < SV_i(t) \geq 99.0$ and $SV_i(t) < 99.0$ indicate VC/VP has Critical, Moderate, Minor problem and Good condition, respectively. These are considered as the minimum value of the most prevalent VC/VP, and we found that the crankshaft has a Critical problem, while other VC/VP's are in good condition.

d) Data Labeling: The 6×4 decision matrix is developed using Equation (7) based on six VC/VP's current conditions to decide about overall vehicular engine condition. Such as the severity value distribution in developed matrix is $(836.7, 0, 0, 0,$ for 1×1,1×2,1×3,1×4); $(0, 0, 0, 9.8240$ for 2×1,2×2,2×3,2×4); $(0, 0, 0, 7.230$ for 3×1,3×2,3×3,3×4); $(0, 0, 0, 3.704$ for 4×1,4×2,4×3,4×4); $(0, 0, 0, 4.212$ for 5×1,5×2,5×3,5×4) and $(0, 0, 0, 10.485$ for 6×1,6×2,6×3,6×4). According to Equation (8), the sum of all elements could be anything among four conditions as a final decision, and these are labeled as Critical, Moderate, Minor, and Good condition of the vehicular engine, respectively. Again, our extensive research found the minimum prevalent numerical values as boundary conditions to decide overall vehicular engine conditions: $TH_{DC} = 925.29$, $TH_{DM} = 478.79$, $TH_{DMN} = 99.0$, $TH_{DG} < 99.0$. Finally, the sum of the formed matrix's all elements is $\sum VEHMS_{\mathrm{D}}(t) = 872.155$, and that meet the $TH_{\mathrm{DC}} < \sum VEHMS_{\mathrm{D}}(t) \geq TH_{\mathrm{DM}}$ condition and indicates that the vehicular engine has a Moderate problem as the overall decision though individual VC/VP has a critical problem because the vehicular engine is older enough and operated 50,000 Km or more than it.

e) Feature Engineering: A dataset is further analysed once it has been prepared in a tabular format to reveal key insights and patterns of behaviour. There are seven features in the dataset, including the target feature and 3003 observations. However, based on the data distribution and the correlation factors between independent variables, essential features are selected for use in deep learning and machine learning algorithms. Figure 4 shows a distribution graph used to determine whether the data is evenly distributed. All independent variables have numerical values, but a distribution plot (see Figure 4a) indicates the categorical opposite. Several transformation techniques have been applied to overcome this issue. Box-cox transformation outperforms all other transformations for all independent features except Starter. Therefore, the reciprocal transformation has been implemented in the case of Starter. Following box-cox transformation formula is utilised since all of the independent features have positive values.

$$a(\gamma) = \begin{cases} \frac{a^{\gamma}-1}{\gamma}, & \gamma \neq 0 \\ \log a & \gamma = 0 \end{cases} \tag{10}$$

where γ operates as an exponent and has values ranging from -5 to 5. Furthermore, the optimal values of γ for the crankshaft, overheat, lubricant, misfire, and cylinder-piston are -2.234, -2.129, -1.498, -1.291, and -1.990, respectively. Once the skewness is reduced and the distribution of the data is normal enough (as depicted in Figure 4b), a correlation heatmap Figure 4c is generated to select crucial features to use the data to train DL algorithms. It shows that none of the features is strongly correlated with each other and important for making predictions through DL algorithms alone.

4) Performance Evaluation: In this research study, a DL strategy based on MLPs is developed and is used as the base model. To enhance the effectiveness of the underlying model, a number of techniques such as model averaging, weighted model averaging and stacked ensemble learning are used. Additionally, four ML techniques are used, including Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbor (KNN), to enhance our argument when selecting the most appropriate artificial intelligence strategy for analytics. Finally, a comparative analysis has been performed between ML and DL algorithms.

IV. Results and Discussion

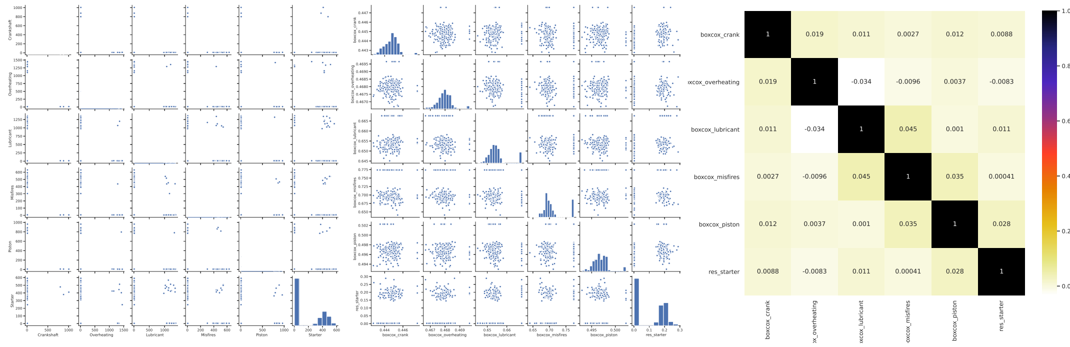
On the basis of acquired data, we conduct a complete evaluation of numerous strategies for applying an MLP model. Using prominent ML methods as a benchmark, we further confirm the most effective DL method. With an input layer of six nodes and three hidden layers, we use an MLP model to predict the probability for each of our four classes. The activation function ReLU has been utilised for the hidden layers, while the activation function softmax has been used for the output layer. Because of the multi-class nature of the problem, we choose to utilise the categorical entropy loss function and Adam to effectively optimise the model. Using half of the dataset, we fit our model for 300 training epochs, while the remaining datasets are utilised as the validation set.

A. Experimental Results

1) Multi-layer Perceptron Model: The performance of the basic MLP model for the validation set is quite low. From Figure 5a, we see that gradually the training accuracy increases to 82% after 300 epochs, whereas the validation accuracy remains almost at the point of around 75% after approximately 50 epochs. This creates a high variance problem.

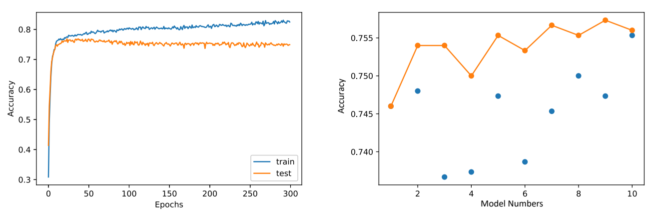
2) Model Averaging Ensemble: To develop an ensemble, we create and fit a single model and repeatedly call to increase the number of members for the ensemble. As the optimal number of members is unknown, we create an ensemble of different sizes from one to 10 members. Next, we ensemble the predictions from multiple models by summing the probabilities. From this experiment, after plotting obtained data in Figure 5b, it is evident that model averaging ensemble depicted as orange line performs better than a random single model which is denoted as blue dots. Because the average performance of solo models is reported as around 74.5%, whereas an ensemble with at least three members performs better than all other single models with 75.7% accuracy. However, after profound scrutinisation of graphical presentation, the overall performance of this approach is not satisfactory.

3) Weighted Model Averaging Ensemble: In the previous experiment, all the models contributed equally. However, in this experiment, we emphasised the models' weights for a better outcome. Each ensemble member is weighted by a coefficient value between 0 to 1. After that, we calculate



(a) Original data (b) Transformed data (c) Independent features

Figure 4: Pairplot data distribution and correlation.



(a) (b)

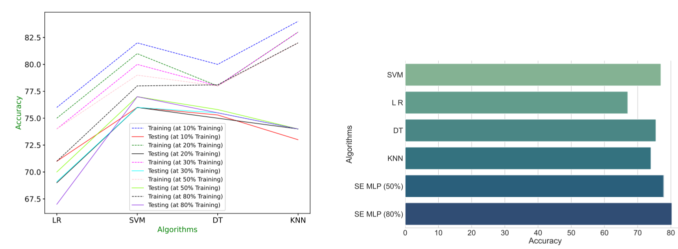
Figure 5: (a) Training vs testing accuracy of MLP. and (b) Model averaging ensemble accuracy against model numbers.

the weighted sum and update the weights while making predictions for the ensemble. A fair-sized ensemble of five members is used in this experiment. We initialise the weight value as 0.2 for each ensemble member, often called an equal-weight ensemble. Next, we normalised the weights and used a directed optimisation approach for the weighted model averaging ensemble. This search optimisation technique does not sample the space of possible solutions rather finds a set of weights that has a lower error rate. We use different available libraries to construct the overall optimisation search. We set the max iteration to 100 and a small default tolerance for detecting any convergence during the search process.

Table IV: Weighted Average Accuracy

Number of Model	Weighted Accuracy	Optimized Weights
1	0.761	0.31796291
2	0.737	0.10808001
3	0.753	0.19825068
4	0.740	0.02027721
5	0.762	0.35542919
Equal Weighted Average = 0.759		Optimized Weighted Average = 0.774

Moreover, the obtained equal weighted average accuracy, weighted accuracy and optimised weighted accuracy for 50% trained data are presented in Table IV. It shows that model 1 and model 5 perform better than other models with more than 76% decision accuracy. Though, the equal weight average score is better than few models but not all the single ones. The optimisation process finds a set of weights that emphasises model 1 and model 5, which aids in improving the accuracy of 77.4%, outperforming all the single models and the equal-weighted average model.



(a) (b)

Figure 6: (a) Accuracy of ML at different training data, and (b) Accuracy comparison of DL and ML at 80% training data.

4) Stacked Ensemble: The stacked ensemble is a further generalisation of the weighted ensemble by replacing the linear weighted sum model with any learning algorithm. Here, an algorithm receives the output of the sub-model as input and pursuit to learn a combination of input predictions. As the metalearner learns from the combination of input predictions, it reduces the over-fitting problem and achieves an overall better performance. We used a single hidden layer-based neural network as our meta-learner. The input layers of five sub-models are used as a separate input head to the stacked ensemble model. The output of each model is merged, and we define a hidden layer to interpret to the meta-learner. Finally, an output layer performs its probabilistic prediction. This stacked ensemble model provides an accuracy of nearly 78% for 50% of the training examples, which is better than any other approach mentioned above.

B. Performance Validation

Only half of the total dataset has been processed when training the MLP model in the prior trials. A reasonable level of performance is achieved using the stacked ensemble MLP model. However, to assess the performance of that model, we compare it with common ML methods, such as LR, SVM, DT and KNN algorithms on different percentages of training samples; the accuracy obtained is shown in Figure 6a. This figure depicts ML algorithms' training and validation accuracy as dotted and solid lines with different colours. The most notable finding is that the accuracy of all ML algorithms decreased as the number of training samples increased. However, the accuracy of the DT approach at the training phase has remained nearly the same for different percentages of training data, except for 10 per cent of total datasets, which has increased. On the other hand, we revealed that the prediction accuracy of SVM approach outperformed other ML algorithms approaches for every increment of the training dataset. Maximum is 77 per cent due to using 80 per cent for training and 20 per cent of the entire dataset for validation purposes. The effectiveness of the stacked ensemble MLP (SE MLP) technique over other DL and ML approaches demonstrated in Figure 6b. In addition, we decided to investigate further how increasing the number of training instances affected the effectiveness of the stacked ensemble MLP algorithms. It appears that increasing the number of training examples leads to an increase in total accuracy (which is 80.3 per cent). In contrast, the achieved maximum prediction accuracy by an ML technique is 77 per cent.

C. Discussion

We extracted some significant insights from the experimental investigation section. We have emphasised a model-centric approach to improving overall performance by adjusting a basic MLP model for a multi-class classification problem to achieve the best overall performance. The stacked ensemble MLP approach outperforms current ML approaches in terms of performance can be attributed to the data distribution. Because the data is not linearly separable, ML algorithms underperform. We fed the ML algorithms by changing the number of training samples but could not improve their performance. The stacked ensemble MLP model, on the other hand, performed significantly better when given a more significant number of training samples. It has improved overall performance and reduced variance by achieving almost equal accuracy for training and testing. Because it achieves almost comparable accuracy for training and testing, it has improved overall performance and reduced variance. The developed VEHMS decision model of the proposed risk management system may acquire a large amount of data from various sensors over time. We observed in this experiment that increasing the number of training samples helps DL algorithms, particularly stacked ensemble MLP, perform higher decision accuracy by analysing a massive quantity of data and providing actual engine conditions. As a result, it may be given significant priority in the vehicular risk management system.

V. Conclusion

A framework for real-time risk management of vehicle engines was presented in this article. Along with exploiting the vulnerable components of the vehicular engine, an enhanced decision model is developed through infrastructure vulnerability assessment to diagnose and notify the user with the highest priority about the vehicular engine fault in real-time. In addition, we evaluated the related risk factors and degradation rate of the engine's vulnerable components, as well as verified the embedded sensor's real-time actual reading, to achieve satisfactory results from the proposal. Furthermore, we revealed that the DL-based stacked ensemble MLP outperforms other DL and ML algorithms in terms of decision accuracy, achieving 80.3 per cent for the 80 per cent training data, although handling large amounts of data, during the evaluation of decision accuracy. Although we obtained good results during the validation phase of the proposed systems using computer-generated data, this research was not done in the real-world perspective, which is a significant drawback because the practical outcome may vary somewhat from the obtained result. We expect that the proposed risk management framework would benefit the automotive industry and serve as a guide for the development of reliable risk management systems for autonomous vehicles, electric vehicles, and railway systems, which will manage large amounts of data.

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