AUTOMOTIVE DIAGNOSTIC APPLICATION UTILIZING THE DEMPSTER-SHAFER THEORY FOR ENHANCED ACCURACY AND RELIABILITY

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ABSTRACT

In the rapidly evolving landscape of automotive diagnostics, integrating advanced computational methods presents significant potential for enhancing accuracy and reliability. This paper presents research about a car diagnostic application leveraging the Dempster-Shafer Theory of evidence for vehicle malfunction diagnosis. The Dempster-Shafer Theory, a mathematical framework for modeling uncertainty and combining evidence from various sources, allows for a comprehensive synthesis of information from vehicle sensors, onboard diagnostic (OBD) data, and user input, providing diagnostic results with quantified confidence levels. The main problem addressed is the challenge of improving accuracy and reliability in automotive diagnostics, especially when dealing with incomplete, imprecise, and conflicting data from these diverse sources. The proposed system effectively manages this data, thus improving the robustness of diagnostic outcomes. To solve this problem, the method applied is the Dempster-Shafer Theory, which is used to manage and combine the data inputs within the application's architecture. This architecture includes a user-friendly interface for vehicle owners and mechanics, a data processing module that applies the Dempster-Shafer Theory, and a cloud-based service facilitating continuous learning and updates. Preliminary testing indicates the system's potential to deliver precise diagnostics, reducing vehicle downtime and maintenance costs. The comparison between the expert's opinion and the expert system's results revealed only a negligible difference, with the system replicating human expertise with about 95% accuracy. These results demonstrate that the applied method has successfully addressed the problem, offering a reliable maintenance and repair tool for vehicles applicable in both personal and professional contexts.

Keywords Intelligent System; Expert System; Maintenance; Vehicle; Paper type Research paper

INTRODUCTION

Transportation is an essential part of daily life, whether for business or personal reasons. Traffic congestion, especially common in urban areas during weekends and holidays, causes significant delays and increased costs. The rising demand for transportation and narrow roads contribute to this problem. Many vehicle owners neglect regular maintenance, only addressing issues when performance declines, which can lead to breakdowns and further traffic disruptions [1]. Many vehicle owners do not fully understand proper maintenance, relying on technicians during scheduled services. Traffic jams can reduce engine oil viscosity, affecting vehicle performance. Expert systems can help by integrating human expertise into computer programs, offering maintenance advice and diagnosing issues [2].

Expert systems, used in various industries like healthcare, simplify complex knowledge for general users and handle repetitive tasks efficiently [3]. These systems consist of a User Interface, Knowledge Base, Inference Engine, and Development Engine [4]. Methods such as Forward Chaining, Backward Chaining, and Dempster-Shafer are commonly used in expert systems. Implementing expert systems for vehicle maintenance can assist owners in identifying issues based on symptoms. This research aims to develop an application using the Dempster-Shafer method to help vehicle owners maintain their vehicles more effectively [5].

The goal of this journal is to showcase how the Dempster-Shafer theory can revolutionize the way we diagnose car damages. Imagine having a method that not only considers multiple sources of information but also handles uncertainty with ease. This journal dives into that, showing how this advanced mathematical approach can make car damage assessments more accurate and reliable. Through real-world case studies and practical examples, we aim to demonstrate how mechanics and automotive experts can benefit from this method, ultimately leading to better, quicker repairs and more satisfied car owners. Our hope is to bridge the gap between complex theory and everyday application, making car diagnostics smarter and more efficient [6].

METHOD

The Dempster-Shafer Theory was initially introduced by Arthur P. Dempster and Glenn Shafer, who experimented with uncertainty by using a range of probabilities rather than single probabilities [7]. Later, in 1976, Shafer published the Dempster theory in a book titled "Mathematical Theory of Evidences [8]. Dempster-Shafer theory is a mathematical framework for hypothesis testing based on belief functions and plausible reasoning [9]. It's used to combine separate pieces of information (evidence) to calculate the likelihood of an event. The theory is based on two main ideas: obtaining degrees of belief from various subjective possibilities and the Dempster-Shafer rules for combining degrees of belief based on the evidence collected. Generally, the Dempster-Shafer theory is represented within an interval [9].

The Dempster-Shafer Theory serves as a mathematical foundation for handling evidence. It provides a method for combining evidence from multiple sources and generating confidence levels (represented through belief functions) drawn from all available evidence [8]. The Dempster-Shafer method includes a formula designed to simplify the process for users, allowing them to generate belief percentages that can determine the likelihood of damage, as discussed in this journal. The relevant formula is as follows [10]:

$$m\mathcal{J}\{\Delta XI\} = \frac{\sum X \cap Y = Zm1(X).m2(Y)}{1 - \sum X \cap Y = \emptyset m1(X).m2(Y)}$$
(1)

where:

m1 = Density for the first symptom

m2 = Density for the second symptom

m3 = Combination of the two symptoms

 Θ (Theta)= Universe of discourse of a set of hypotheses

x and y = Subsets of Z

x' and y' = Subsets of Θ (Theta)

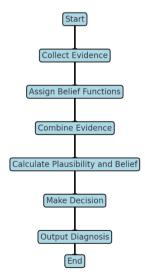


Figure 1. Research Procedure

As depicted above (Figure 1), the procedure undertaken requires evidence that will later be applied to the Dempster-Shafer formula. The data obtained from expert interviews is utilized to determine the weight of each symptom of vehicle damage, thus enhancing the credibility of the application.

To determine the credibility of the application developed, a comparison is needed. In this journal, the classification and clarification methods are used because they can compare expert opinions with the results of the application. Here are the formulas used to determine the credibility of the application [7]:

Classification =
$$\left\{\frac{"Credible"}{"Not Credible"}\right\} \frac{if A \ge T}{if A < T}$$
(2)

$$r = \frac{(A - \bar{A})(E - \bar{E})}{\sqrt{\sum_{i=1}^{n} (A - \bar{A})^2} \times \sqrt{\sum_{i=1}^{n} (E - \bar{E})^2}}$$
(3)

Where:

- r = Correlation Coefficient
- A = Application Performance
- E = Expert Opinion
- \overline{A} = Mean of Application Performance
- \overline{E} = Mean of Expert Opinion

Data collection was undertaken to acquire several pieces of information pertinent to the creation of an expert system application for diagnosing vehicle damages, comprising symptom data and vehicle damage data. These data were gathered through interviews with mechanical experts and professionals, supported by reference materials such as manuals, technical journals, and online research related to vehicle damages. Subsequently, the system processed this data to form both input and output datasets.

Car Damage Data

Vehicle damage, especially in cars, can occur in many forms. However, according to experts, some issues are more common than others. There are five types of damages that frequently happen to cars. These common issues are listed in the Table I:

Number	Car Part Damaged	Damage Conclusion Code
1	Spark Plug	DC1
2	Fuel Pumps	DC2
3	Leaking Radiator	DC3
4	Loose Piston Rings	DC4
5	Clogged Exhaust Pipe	DC5

TABLE I. CAR DAMAGE DATA TABLE [11]

In addition to the types of vehicle damage, each type of damage is associated with certain symptoms. These symptoms can be easily recognized even by non-experts. Table IIa and IIb is a list of common vehicle damages along with their corresponding symptoms:

TABLE IIA. VEHICLE DAMAGE SYMPTOMS TABLE[11]

Number	Car Part Damaged	Symptoms	
		Wasteful Fuel	
		the Car Stalled	
1	Spark Plug	Bad Engine Idling	
		Poor Acceleration	
		Difficult to Start the Engine	
	Fuel Pumps	The Car Stalled	
2		Difficult to Start the Engine	
2		Engine Breaks Down	
		Weak Engine Power	

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Number	Car Part Damaged	Symptoms	
		Abnormal Engine Temperature	
3	Leaking Radiator	Radiator Gushes Vapor	
	-	Oil Mixed with Water	
		Decreasing Oil	
		Engine Emits Smoke	
4	Loose Piston Rings	Oil Indicator lights up	
	C C	Engine doesn't Turn	
		Rough Engine Sound	
		Difficult to Start the Engine	
-		Weak Engine Power	
5	Clogged Exhaust Pipe	Abnormal Engine Temperature	
		Oil Mixed with Water	

 TABLE IIB. VEHICLE DAMAGE SYMPTOMS TABLE[11]

Decision Table

In an expert system, the knowledge of specialists is crucial to accurately determine the type of car damage. After conducting interviews with several experts, the weight of each symptom has been established. Table III presents the data along with the weights as consulted with the relevant experts.

Normalian	Damage Type	Damage Conclusion Code						Damage
Number		DC1	DC2	DC3	DC4	DC4	Weight	Type Code
1	Wasteful Fuel	\checkmark					0.5	DT1
2	the Car Stalled	\checkmark	\checkmark				0.6	DT2
3	Bad Engine Idling	\checkmark					0.4	DT3
4	Poor Acceleration	\checkmark					0.4	DT4
5	Difficult to Start the Engine	\checkmark	\checkmark			\checkmark	0.3	DT5
6	Engine Breaks Down		\checkmark				0.7	DT6
7	Weak Engine Power		\checkmark			\checkmark	0.6	DT7
8	Abnormal Engine Temperature			\checkmark		\checkmark	0.6	DT8
9	Radiator Gushes Vapor			\checkmark			0.4	DT9
10	Oil Mixed with Water			\checkmark		\checkmark	0.6	DT10
11	Decreasing Oil				\checkmark		0.5	DT11
12	Engine Emits Smoke				\checkmark		0.5	DT12
13	Oil Indicator lights up				\checkmark		0.6	DT13
14	Engine doesn't Turn				\checkmark		0.5	DT14
15	Rough Engine Sound				\checkmark		0.5	DT15

TABLE III. DECISION TABLE

The following IF-THEN rules were established for easier understanding of the diagnosis based on the table above:

TABLE IV. RULE TABLE

Rule	Car Part Damaged	Damage Conclusion Code
R1	Spark Plug	IF DT1 AND DT2 AND DT3 AND DT4 AND DT5 THEN DC1
R2	Fuel Pumps	IF DT2 AND DT5 AND DT6 AND DT7 THEN DC2
R3	Leaking Radiator	IF DT8 AND DT9 AND DT10 THEN DC3
R4	Loose Piston Rings	IF DT11 AND DT12 AND DT13 AND DT14 AND DT15 THEN DC4
R5	Clogged Exhaust Pipe	IF DT5 DT7 AND DT8 AND DT10 THEN DC5

Analysis of the Dempster-Shafer Method

The Dempster-Shafer Theory, also known as the Dempster-Shafer Theory of Evidence, is a mathematical framework for modelling uncertainty and combining evidence. It was first introduced by Arthur P. Dempster and later extended by Glenn Shafer [7]. The theory provides a way to express and combine degrees of belief based on incomplete or imprecise information, making it particularly useful in expert systems for diagnosing vehicle issues.

Symptoms:

The vehicle being diagnosed is a 2017 Avanza MPV [1]. It has difficulty starting (DT5), and its idling performance is very poor (DT3). Additionally, the fuel consumption is high (DT1), even when driven for just a few kilometers. The emergence of new symptoms necessitates the calculation of new density values for several combinations (m3). To simplify these calculations, the subsets that are formed are first organized into Table 5 as follows:

1110.		
	m2{DC1} 0.4	m2{θ} 0.6
m1{DC1} 0.5	{DC1} 0.20	{DC1} 0.30
$m1\{\theta\} 0.5$	{DC1} 0.20	{θ} 0.30
m3{	$DC1\} = \frac{0,20 + 0.20 + 0.30}{1 - 0} = 0$.70 (4)
	$m3\{\theta\} = \frac{0.30}{1-0} = 0.30$	(5)

TABLE V. COMBINATION RULES FOR M3

The calculation above (4) and (5) applies the Dempster-Shafer theory to determine the percentage of vehicle damage. The additional symptoms identified from the earlier diagnosis necessitate continued calculations using the Dempster-Shafer method, as shown in the following table:

TABLE VI.	COMBINATION	RULES	FOR M	M 5
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	m4{DC1} 0.3	m4{θ} 0.7
m3{DC1} 0.7	{DC1} 0.21	{DC1} 0.49
m3{0} 0.3	{DC1} 0.09	{θ} 0.21

$$1 - 0.21 \quad 0.79$$

$$m3\{\theta\} = \frac{0.21}{1 - 0.21} = \frac{0.021}{0.79} = 0.265823 \tag{7}$$

Based on the symptoms observed in the example above, the highest confidence value is found in DC1 with a value of $0.734177 \times 100\% = 73.4177\%$. Clarification and comparison will be applied to obtain the credibility results from the application:

After interviewing the expert multiple times, it can be concluded that the value of E is 72%, where as E is 71.5%, while T is 70%. With this data, clarification and classification operations can be directly performed as indicated in the following formulas:.

Classification = $\left\{\frac{"Credible"}{"Not Credible"}\right\} \frac{if 73.4177\% \ge 70\%}{if 73.4177\% < 70\%}$	(8)
$r = \frac{(73.4177\% - \overline{73\%})(72\% - \overline{71.5\%})}{\sqrt{(73.4177\% - \overline{73\%})^2} \times \sqrt{(72\% - \overline{71.5\%})^2}}$	(9)
$r = \frac{0.0020885\%}{0.00417475\%}$	(10)
r = 0.4999	(11)

As the credibility formula applied, it can be concluded that according to formula (8) and calculation (9) to (11), this application is deemed credible. Meanwhile, the correlation coefficient r, which represents the correlation and coefficient, is above 0, indicating a correlation between the application's results and expert opinions.

DISCUSSION

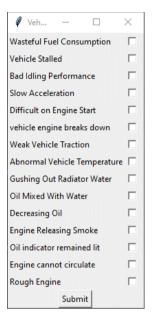


Figure 2. Car Diagnose App

The car diagnostic app as shown on Figure 2 is a game-changer for vehicle maintenance, making it easy to identify and address up to 15 common car symptoms. From engine misfires to battery issues, this app uses advanced computational methods to analyse data from your car's sensors. It then provides clear, actionable insights and recommendations. This means you can quickly and accurately pinpoint problems, whether you're a seasoned mechanic or just someone trying to keep your car in top shape. The intuitive design ensures that anyone can use it, reducing the guesswork and hassle associated with car maintenance and keeping your vehicle running smoothly.

🖉 Result	×
Encountered sparkp Belief Value: (0.7341) plausibility Value: (0.	
	ОК

Figure 3. Sparkplugs Belief and Plausibility Value

The car damage diagnostic program has yielded a result indicating a high likelihood of sparkplug damage. The system reports a 73.41% belief in the diagnosis of sparkplug damage as shown on figure 3, suggesting a very high confidence level that the sparkplugs are indeed malfunctioning. Conversely, there is a 26.58% plausibility, indicating a low probability of alternative issues being responsible for the observed symptoms. This high belief score means that it is almost certain that the sparkplugs require immediate attention and replacement to ensure the vehicle's optimal performance and to avoid potential engine misfires or reduced fuel efficiency.

CONCLUSION

The use of the Dempster-Shafer Theory in automotive diagnostics marks a significant step forward, addressing key challenges like incomplete, imprecise, and conflicting data. The diagnostic tool developed in this research improves the accuracy and reliability of vehicle malfunction detection by offering results with clear confidence levels. Its intuitive interface, along with cloud-based updates, ensures that the system keeps evolving and remains effective over time.

Initial testing has shown that this approach can meaningfully reduce vehicle downtime and cut maintenance costs, providing a smart and practical solution for both everyday car owners and professionals. This application has the potential to reshape the way vehicle diagnostics are done, highlighting the power of advanced computational methods in delivering more accurate and dependable outcomes.

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