An Intelligent Fuzzy Logic Automobile Fault Diagnostic System

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Abstract:- The advent of intelligent transportation systems and the growing complexity of modern automobiles necessitated innovative approaches to fault detection and diagnostics. This study presents an Intelligent Fuzzy Logic Automobile Fault Diagnostic System. It is designed to enhance the safety and reliability of automotive systems. Fuzzy logic with its ability to handle imprecise and uncertain data is harnessed to develop a robust model capable of identifying and classifying faults in real-time. The system incorporates a hybrid computerized fuzzy system, to aid vehicle owners in identifying issues with their vehicles and providing sound repairs recommendations for any malfunctioning parts. The system was implemented using web technologies; ASP.Net, Bootstrap 3.5, CSS, JavaScript, JQuery and SQL server. The results indicate its potential for widespread adoption, with the ability to reduce accidents and maintenance costs while enhancing the driving experience and provides an accuracy of 73.14% in performance. The Precision 100% and F1 Score 75.72%.

Keywords:- *Fuzzy Logic, Fault Detection, Knowledge-based, Fuzzification and Defuzzification.*

I. INTRODUCTION

Today, automobiles have become an essential part of people's lives. When the engine fails, it can lead to significant troubles for consumers if the issue is not detected early, promptly addressed, and accurately repaired. Such failures can even pose risks to life and property, while also adversely affecting customer satisfaction and the reputation of automobile companies. In some cases, automobile manufacturers need to protect consumers through market actions and recalls, which can result in substantial financial expenditures. It is evident that timely warnings, swift problem-solving, accurate diagnosis, and prompt maintenance of faulty engines serve as crucial foundations for ensuring the smooth operation of vehicles and ensuring people's safety during their travels [1]. Fuzzy logic applications have drawn a lot of interest in recent years as it is used to create intelligent systems for auto defect detection. In order to enhance vehicle performance, safety, and maintenance, the automobile industry must provide effective and dependable defect detection techniques. Fuzzy logic is suitable for auto defect detection as it provides a flexible and understandable way to handle information that is uncertain and imprecise [2]. Researchers want to improve problem detection precision, lower false alarm rates, and facilitate efficient decision-making by introducing fuzzy logic into intelligent systems. The three major components of fuzzy logic-based intelligent systems for auto defect detection are generally fuzzification, fuzzy inference, and defuzzification.

In modern-day automobiles, a multitude of computer systems are integrated to regulate various components such as fuel injections, airbags, and brakes. These systems are overseen by Electronic Control Units (ECUs), which communicate with each other via the car's internal high-speed Controller Area Network (CAN) [3]. Additionally, an On-Board Diagnostics (OBD) computer system is present, capable of detecting and diagnosing issues by analyzing data transmitted by the ECUs [4]. In the event of a problem, the OBD system generates a specific trouble code, enabling service engineers to accurately identify and address the issue. Accessing trouble codes and other diagnostic information can be accomplished by connecting an OBD scan tool to the vehicle's OBD interface [5].

An automobile, commonly referred to as a car, is a motor vehicle designed for transportation purposes. Cars are typically intended for use on roads, accommodating a range of one to eight passengers. The widespread adoption of cars took place during the 20th century, with developed economies heavily reliant on these vehicles for various transportation needs [6]. In recent years, the widespread application of Artificial Intelligence (AI) techniques has revolutionized numerous industries, supplanting traditional methods by incorporating intelligent approaches to tackle complex and demanding problems [7]. AI techniques embody a combination of human expertise, task-specific knowledge, and computational intelligence and processing. These techniques can be classified based on the type of knowledge they employ, distinguishing between structured and unstructured knowledge, as well as the manner in which this knowledge is processed.

II. STATEMENTS OF THE PROBLEM

Due the complex nature of automobile's architecture and improved technology, automobile diagnose has become more challenging. When diagnosing and repairing cars, many mechanics and technicians frequently use the trial-and-error approach. This method of diagnosis is typically unreliable, inefficient, expensive, and time-consuming. In this research work, an intelligent system for fault detection known as a fuzzy logic-based Automobile Fault Detection System is developed.

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III. REVIEW OF RELATED LITERATURE

With the complexity and uncertainties that come with auto errors are sometimes too much for conventional rule-based systems and diagnostic methods to handle. As a result, scientists are now looking into how fuzzy logic, a subset of artificial intelligence, may be used to overcome these constraints [8]. Within the field of artificial intelligence, an expert system refers to a computer system that replicates the decision-making capabilities of a human expert. In the work of [9] a system to tackle intricate problems by employing logical reasoning based on sets of rules and knowledge representation, as opposed to traditional procedural code.

In the work of [10], they focused on the industrial diagnostics approach identification, isolation, and detection of faults within industrial plants. A significant area of scientific research pertains to the detection and diagnosis of faults in induction motors, which is challenging due to the absence of accurate fault models [11], in the work of [12] he opined that defuzzification turns fuzzy outputs into precise values for use in decision-making in real-world situations. To calculate the likelihood or severity of a mistake based on the fuzzified input variables, fuzzy inference uses fuzzy rules, which encapsulate expert knowledge or learned patterns [13]. To express uncertainty and ambiguity, fuzzy language phrases are used to alter clear input variables, such as sensor signals [14]. In the work of [15], the study presented fuzzy logic based online fault detection and classification of transmission line using Programmable Automation and Control technology based national instrument compact reconfigurable i/o (CRIO) devices.

The increased prevalence and utilization of automobiles, coupled with the integration of advanced electronic technologies, emphasize the necessity of integrating fault control system into engine design and usage. In modern times, Artificial Intelligence (AI) technology has emerged as a prominent solution for systematically diagnosing faults, particularly in scenarios where extensive diagnostic knowledge exists, and the process of identifying faults entails a lengthy sequence of steps [16]. From what [17] carried out, it detected that complexity arises from the fact that modern vehicles' electronic control components often function as black boxes, making it challenging for mechanics to accurately diagnose faults unless they possess in-depth knowledge of the system's specifications and functions[18]. Fault diagnosis is a longstanding engineering challenge, encompassing a range of techniques for dynamic system fault detection, including expert systems and statistical models [19]. From the research of [20], they conducted Fault classification in double circuit line with conventional techniques which was found to be ineffective due to mutual coupling between the two circuits. It was proposed that neural network approach for fault classification is established as a successful methodology [21] but it requires tedious training effort, hence it is time consuming and adds to the computation complexity [22]. It was proposed by [23] that fuzzy logic methodology to identify the ten types of faults.

In the work of [24] a novel transmission line relaying scheme for fault detection and classification using wavelet transform and linear discriminant analysis was worked on and it yielded a position result in fault detection and management. It was allayed by [25] that an accurate fuzzy logic-based fault classification algorithm using voltage and current phase sequence components.

IV. METHODOLOGY ADOPTED

The method used in this study is the fuzzy logic inference system that adopted Mamdani's algorithm. This algorithm plays a pivotal role in crafting an advanced intelligent system for detecting faults in automobiles using fuzzy logic principles [26]. This algorithm functions by interpreting imprecise inputs through linguistic variables and predefined rules, allowing it to make decisions despite uncertainties. It employs fuzzy inference rules and membership functions to model the complex relationships between sensor data and potential faults in the vehicle. Through a sequence of steps involving fuzzification, rule evaluation, aggregation, and defuzzification, this algorithm effectively handles intricate and non-linear connections among input variables, aiding in the accurate identification of diverse faults within the automobile's operational components [27].

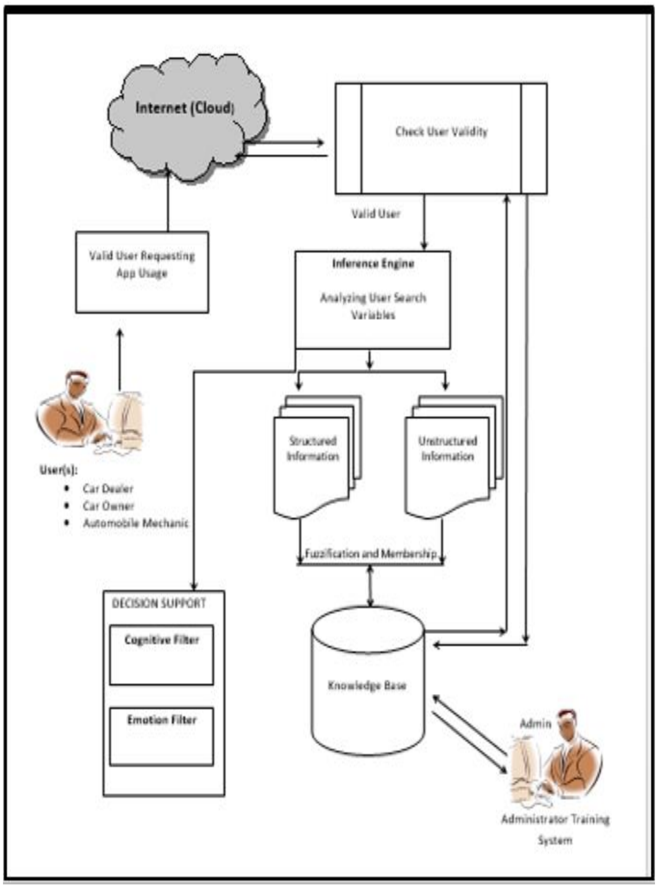

Fig 1: High Level Model Diagram of the Proposed System

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This high-level model of the proposed system has the following components: user, internet (Cloud), decision support system, knowledge base, inference engine, administrator etc. In the sophisticated framework of the knowledge-based Automobile System, the high-level diagram reveals a resilient and interconnected network. Users seamlessly engage through computational or mobile interfaces, a process fluidly facilitated by advanced internet connectivity. This backbone not only serves as the foundation for structured operations like user registration but also acts as a conduit for unstructured processes, allowing users to dynamically explore the system and access real-time vehicle diagnostics with unprecedented ease. Within this dynamic interaction, the integration of cognitive and emotion filters emerges as a pivotal component for decision support. These filters serve as mediums that intelligently assess and incorporate cognitive preferences and emotional states, adding a layer of nuanced understanding to the decision-making process. The online repository, managing both structured and unstructured information, works in tandem with these filters, creating a comprehensive environment where cognitive and emotional aspects influence decision support. Administrators, leveraging the power of internet connectivity, actively participate in the oversight process, integrating cognitive and emotion filters into the decision-making protocols. This collaborative interplay among users, computational devices, the online repository, and administrators establishes a holistic and highly efficient operational paradigm, where decision support is not only structured and unstructured but also infused with cognitive and emotional considerations, all seamlessly orchestrated through the resilient backbone of internet connectivity.

V. DATASET

The dataset used in this study was obtained from Kaggle, a widely recognized online platform that hosts data science competitions, provides datasets for machine learning and data analysis, and offers a collaborative environment for data scientists, machine learning engineers, and researchers.

This dataset comprises three distinct components: the first encapsulates a comprehensive inventory of automobile attributes; the second entails the insurance risk appraisals assigned to each vehicle; and the third segment delineates normalized loss figures, signifying the comparative loss occurrences for each car in the dataset. The second facet, denoting the risk assessment, elucidates the extent to which an automobile's inherent risk deviates from its market value. Initially, vehicles are assigned a risk symbol commensurate with their price point, which can be subsequently adjusted along the risk spectrum, a process commonly referred to as "symboling." Notably, a rating of +3 implies a high-risk classification, while -3 conveys a relatively secure standing. The third dimension pertains to the mean loss payment per insured vehicle per annum, with these values being standardized across cars within specific size classifications (e.g., two-door compacts, station wagons, sports/specialty models), offering insights into the average annual loss rates for each size category.

VI. FUZZY LOGIC FORMULA

Fuzzy logic works with membership values in a way that mimics Boolean logic. To this end, replacements for basic operators AND, OR, NOT must be available. There are several ways to do this. A common replacement is called the Zadeh operators:

For TRUE/1 and FALSE/0, the fuzzy expressions produce the same result as the Boolean expressions.

Other operators that are more linguistic, called hedges, can be applied. These are generally adverbs such as very, or somewhat, which modify the meaning of a set using a mathematical formula.

However, an arbitrary choice table does not always define a fuzzy logic function. However a criterion was formulated to recognize whether a given choice table defines a fuzzy logic function, and a simple algorithm of fuzzy logic function synthesis has been proposed based on introduced concepts of constituents of minimum and maximum. A fuzzy logic function represents a disjunction of constituents of minimum, where a constituent of minimum is a conjunction of variables of the current area greater than or equal to the function value in this area (to the right of the function value in the inequality, including the function value).

Another set of AND/OR operators is based on multiplication, where

x AND y = x*y
NOT x = 1 – x

Hence,
x OR y = NOT(AND(NOT(x), NOT(y)))
x OR y = NOT(AND(1-x, 1-y))
x OR y = NOT((1-x)*(1-y))
x OR y = 1-(1-x)*(1-y)
x OR y = x+y-xy

Table 1: Boolean/Fuzzy Table

BOOLEAN	FUZZY
AND(x,y)	MIN(x,y)
OR(x,y)	MAX(x,y)
NOT(x)	1 – x

- **Membership Function**: The membership function assigns a degree of membership to an element in a fuzzy set. Let us consider fuzzy set A, A = {(x, μA(x))| x Є X} where μA(x) is called the membership function for the fuzzy set A. X is referred to as the universe of discourse. The membership function associates each element x Є X with a value in the interval [0, 1]. For example, for a triangular fuzzy set A with a defined range [a, b, c], the membership function μ_A(x) is calculated as follows:

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$$\mu_A(x) = \begin{cases} 0 & \text{if } x \leq a \\ \frac{x-a}{b-a} & \text{if } a \leq x \leq b \\ \frac{c-x}{c-b} & \text{if } b \leq x \leq c \\ 0 & \text{if } x \geq c \end{cases}$$

VII. FUZZY SET FORMULA

Fuzzy sets are often defined as triangle or trapezoid-shaped curves, as each value will have a slope where the value is increasing, a peak where the value is equal to 1 (which can have a length of 0 or greater) and a slope where the value is decreasing. They can also be defined using a sigmoid function. One common case is the standard logistic function defined as;

$$\boldsymbol{S} = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{e^x}}$$

Which has the following symmetry property

$$\boldsymbol{S(x) + S(x-1) = 1}$$

From this, it follows that

$$\boldsymbol{S(x) + S(x-1) \cdot \big(S(y) + S(-y)\big) \cdot \big(S(z) + S(-z)\big) = 1}$$

- **Defuzzification**: This is the process of converting fuzzy sets into crisp values. One common method is the Center of Gravity (COG) or centroid method, calculated as the weighted average of the values in the fuzzy set. If μ(x) represents the membership function of a fuzzy set over a universe of discourse U, the defuzzified crisp value can be calculated as:

$$\boldsymbol{Defuzzification} = \frac{\int \boldsymbol{U^x \cdot \mu(x)dx}}{\int_U \boldsymbol{\mu(x)dx}}$$

➢ *Fuzzy Logic Inference Algorithm for Automobile Fault Detection*

- Step 1: Convert User Variables/Inputs Readings to Fuzzy Terms
- Step 2: Establish Rules Connecting Variables Readings to Faults.

✓ Create a set of rules that relate the fuzzy sensor readings to potential faults or issues in the car.
✓ For instance, if the temperature is "high" and the oil pressure is "low," associate it with a potential fault in the engine cooling system.

- Step 3: Evaluate the Rules Using Fuzzy Logic.

✓ Use these rules to evaluate how likely or severe each potential fault might be based on the fuzzy sensor readings.
✓ Consider the degree to which each rule applies and contributes to the likelihood of a specific fault.

- Step 4: Combine Rule Evaluations

✓ Combine the evaluations from different rules to determine the overall likelihood or severity of different faults.
✓ Take into account all the rules that might apply based on the sensor readings.

- Step 5: Produce a Clear Assessment of Potential Faults

✓ Translate the combined fuzzy evaluations back into a clear and understandable assessment of potential faults or issues in the car.
✓ Provide a straightforward indication of which faults are more likely or severe based on the sensor data and rule evaluations.

VIII. ACTIVITY DIAGRAM

Activity diagrams are object oriented equivalent of flow charts and data flow diagram from structured development and it describes the work flow of a system. It also illustrates the dynamic nature of a system by modelling the flow of control from one activity to another. An activity diagram represents the operational step-by-step workflows of component in a system.

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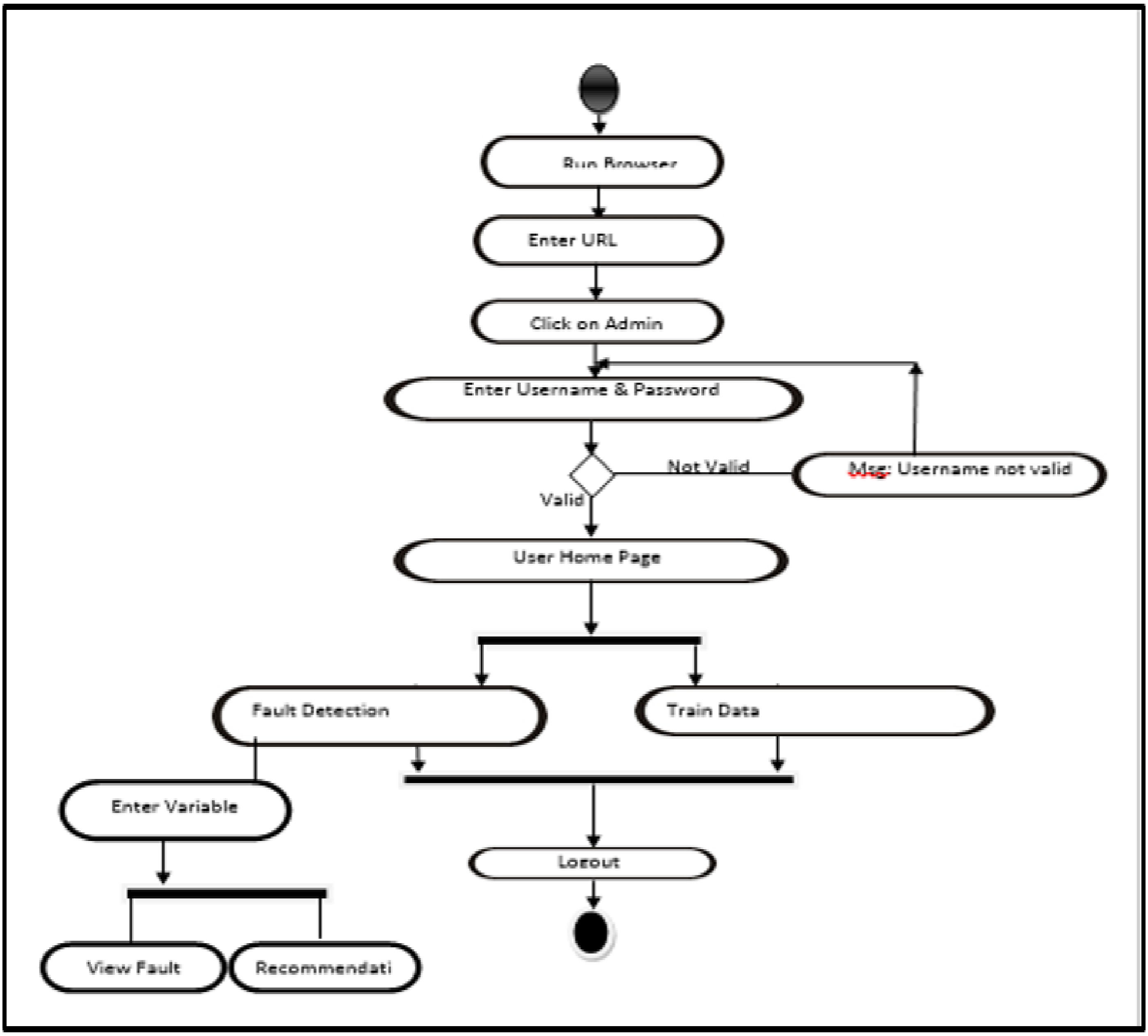

Fig. 2: Activity Diagram of the System

IX. DATA PRESENTATION

Data presentation involves transforming raw data into visual formats like graphs, charts, tables, maps, and infographics to make complex information easily understandable, aiding in analysis, comprehension, and decision-making. This process aims to visually represent patterns, relationships, distributions, and trends within the data, enabling quick identification of insights not readily apparent in raw data. Utilizing techniques such as graphical representations, tables, infographics, dashboards, maps, and various data visualization tools, effective data presentation helps present information in a more accessible and digestible manner, tailored to the audience and intended purpose while ensuring clarity, simplicity, and relevance in conveying the derived insights.

The information gain, Chi2, Membership Function (MF) ranking values F for the quantifiable features in the dataset are presented in tables 2 below;

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Table 2: The F Value or Ranking of Attributes Using Individual Techniques

Attribute Names	Chi-Squared Score	Information Gain	MF Score
F1	0.726	0.543	4.37
F2	1.234	0.812	5.12
F3	0.498	0.632	3.98
F4	0.912	0.745	4.78
F5	0.632	0.498	3.56
F6	1.043	0.923	5.28
F7	0.789	0.654	4.92
F8	0.632	0.542	4.11
F9	0.915	0.789	5.06
F10	0.521	0.634	3.72
F11	0.743	0.592	4.59
F12	0.964	0.748	5.03
F 13	0.667	0.516	3.85
F14	1.124	0.812	5.38
F15	0.732	0.632	4.66
F16	0.819	0.734	4.92
F17	0.632	0.492	3.74
F18	1.012	0.856	5.17
F19	0.742	0.619	4.38
F20	0.579	0.498	3.98
F21	0.988	0.745	5.29
F22	0.687	0.532	4.01
F23	1.067	0.812	5.56
F24	0.754	0.628	4.42
F25	0.632	0.498	3.56

X. RESULT AND DISCUSSION

The random mamdani algorithm is applied for the dataset and the results are obtained as below: The accuracy of testing data is 100%, the recall value is 1.00 for detected fault and 0.78 for undetected fault. Precision for automobile fault detection is 100%, Accuracy is 73.14% and F1-score is approximately 75.72%.

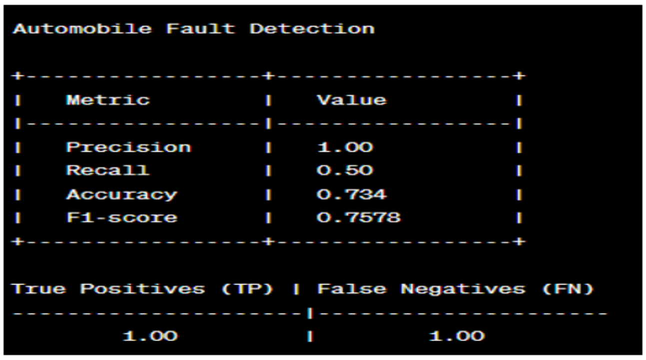

Fig 3: Testing Data Output

Table 3: Output Performance Metric

Model	Accuracy	Precision	Recall	F1-score.	Training time (seconds)
Fuzzy Logic Inference	73.14%	100%	61.07%	77.72%	5 mins

- **Accuracy** – The accuracy of the classification is given as:

$$AC = \frac{TP + TN}{TP + TN + FP + FN} * 100$$

The Accuracy gave 73.14%

- **Precision rate** – The percentage of all correctly classified attack packets, given as:

$$PR = \frac{TP}{TP + FP} * 100$$

The Precision rate is 100%.

- **Recall** – The percentage of all rightly classified attacks in the dataset. This is given as:

$$RC = \frac{TP}{TP + FN} * 100$$

- The Recall is 61.07%.

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XI. RESULT EVALUATION PERFORMANCE

The system reveals commendable performance in terms of precision and accuracy, both achieving perfect scores of 100% or 73.14%. This signifies that when the system flags a fault in an automobile, it is consistently accurate, and overall predictions are error-free. However, the system's recall rate, measuring the ability to detect actual faults among all present, stands at 61.07%, indicating that it missed identifying some actual faults. The F1-score, harmonizing precision and recall, reaches approximately 75.72%, showcasing a balanced performance between accurate fault identification and the ability to detect actual faults. The display of True Positives (TP = 1) and False Negatives (FN = 1) further illustrates a correct identification of one fault but missing the detection of another. Overall, while the system demonstrates exceptional accuracy and precision, there's room for improvement in enhancing its ability to detect a higher percentage of actual faults, as evidenced by the recall rate and the occurrence of undetected faults. This is illustrated in figure 4.6 and 4.7.

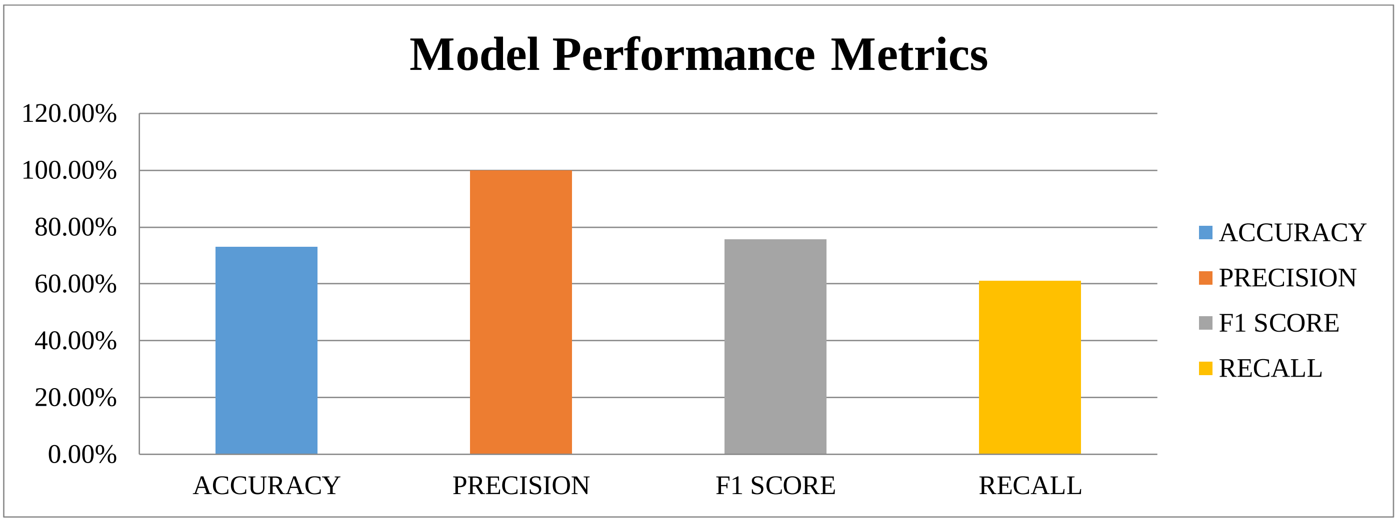


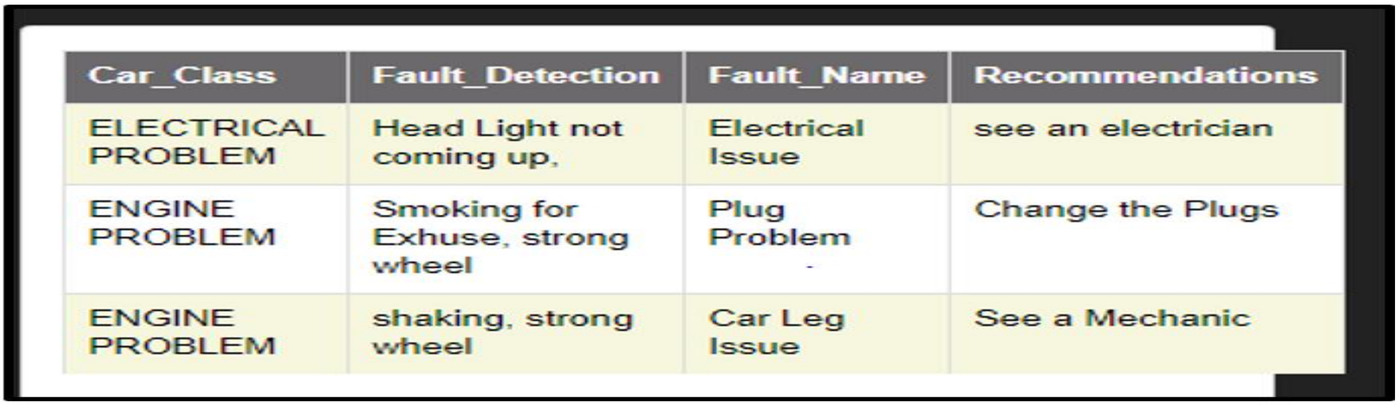
Fig. 4: Bar Chart for Performance Metrics

XII. TEST DATA

The data is fed into the testing set after it has been trained to observe how it performs. Depending on the threshold (0.5), performance might be rated as poor or good. A poor performance (< 0.5) metric after training simply implies that the model probably suffers from overfitting. A good performance (>0.5) during testing simply means that the model is ready for further testing against real-world data. The data tested was based on programmer’s developed data and real life data.

Table 4: Actual Test Result Versus Expected Test Result

Actual Test Done	Expected Result
• **Training Module:** the training module was tested using programmer’s developed data and also real data generated via information from the case study	**The** training phase was a success as every tiny detail of automobile fault was well filtered through the inference engine and outputs where given accordingly.
• **User Registration Module:** this stage was tested with several data generated by the programmer and as well real data from the hospital as well. These data are basic data that identifies a valid user.	The registration module worked as expected but some mobile devices did not display the UI/UE as expected but tracing the Cascading Style Sheet involves in that module, the issue was solved.



Car_Class	Fault_Detection	Fault_Name	Recommendations
ELECTRICAL PROBLEM	Head Light not coming up,	Electrical Issue	see an electrician
ENGINE PROBLEM	Smoking for Exhuse, strong wheel	Plug Problem	Change the Plugs
ENGINE PROBLEM	shaking, strong wheel	Car Leg Issue	See a Mechanic

Fig 5: Fault Display Output Page

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XIII. SUMMARY/CONCLUSION

The "Development of an intelligent fuzzy logic automobile fault diagnostic system" is an innovative application of advanced computing and artificial intelligence in the field of automotive diagnostics. This system incorporates a hybrid computerized fuzzy logic approach, utilizing fuzzy logic inference system, to efficiently detect faults within various vehicle components. It offers users, including automobiles owners and mechanics, clear and informed recommendations for repairing or replacing malfunctioning parts.

As a peer into the future of automotive technology, solutions of this nature not only enhance the safety and reliability of vehicles but also pave the way for ground breaking advancements within the industry. The "an intelligent fuzzy logic automobile fault diagnostic system" carries the potential to revolutionize how we identify and resolve vehicle-related issues, thus promoting safer roads and more dependable automobiles. Its web-based implementation ensures accessibility and user-friendliness for a wide audience.

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