International Journal of Scientific Research and Management (IJSRM)
||Volume||12||Issue||03||Pages||1081-1093||2024||
Website: https://ijsrm.net ISSN (e): 2321-3418
DOI: 10.18535/ijsrm/v12i03.ec06

A Fuzzy Logic-Based Automobile Fault Detection System Using Mamdani Algorithm

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Abstract

Due to advancement and complexity of modern automobiles, fault detection has gone beyond manual or trial by error methods. The fault detection technologies in automotive industry is used to identify any potential or already existing fault in automobiles. Faults in automobiles are usually mechanical or electrical faults that may include airbag control unit, radiator, gearbox, transmission control unit, tyre pressure, brakes, air conditioner, cylinder casket, alternator, hubs malfunctions etc. Each fault has a specific or related sign and symptoms. There are several methods of fault detections in automobiles like the binary logic technique, the fuzzy logic method technique and artificial intelligence technique with different algorithms. In this research work, we employed a fuzzy logic based technique that uses a Mamdani Algorithm which presented a better fault detection mechanism. Mamdani's algorithm was proposed by Ebrahim Mamdani as a fuzzy inference method which has a rule-bases that are more intuitive and easier to analyse and implement. Mamdani's algorithm produces fuzzy sets that originate from fuzzy inference system's output membership function for decision making. This research work is a web-based technology that was implemented using JavaScript, JQuery and SQL server, ASP.Net, Bootstrap 3.5 and CSS. The output of the system showed a greater improvement from other existing methods of fault detections in automobiles.

Keywords: Mamdani's Algorithm, Fuzzy Sets, Membership Function, *Fuzzification and Defuzzification.*

1. Introduction

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). Additionally, an On-Board Diagnostics (OBD) computer system is present, capable of detecting and diagnosing issues by analysing data transmitted by the ECUs. 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 [1].

In recent times, the broad application of fuzzy logic and Artificial Intelligence (AI) techniques has brought about a significant transformation in numerous industries, displacing conventional methods. These intelligent approaches are integrated to address intricate and challenging issues [2]. Fuzzy logic has garnered substantial interest, particularly for creating intelligent systems in auto defect detection, aiming to enhance vehicle performance, safety, and maintenance. The conventional rule-based systems and diagnostic methods often struggle with the complexity and uncertainty associated with auto errors. Consequently, researchers are exploring the potential of fuzzy logic, a subset of artificial intelligence, to overcome these limitations [3].

Within the realm of industrial process diagnostics, the focus is on identifying, isolating, and detecting faults in industrial plants [4]. Notably, a significant area of scientific inquiry revolves around the challenging task of detecting and diagnosing faults in induction motors, primarily due to the absence of precise fault models

[5]. To address this challenge, methods such as fuzzy logic, neural networks, and hybrid systems have demonstrated promise in fault diagnosis for induction motors.

In this work, it is imperative to conduct analysis, comparisons, and data collection to comprehend the behaviour of induction motor conditions. The goal is to determine the causes of faults using fuzzy logic, neural networks, and a combination of both paradigms (hybrid system). The work encompasses modelling the induction motor, estimating fault states, and implementing fault diagnosis methods through the application of fuzzy logic, neural networks, and hybrid systems [6].

Fuzzy logic proves to be well-suited for auto defect detection due to its capacity to handle uncertain and imprecise information in a flexible and understandable manner. Researchers aim to enhance the precision of problem detection, reduce false alarm rates, and facilitate efficient decision-making by incorporating fuzzy logic into intelligent systems. The growing prevalence and reliance on automobiles, along with the integration of advanced electronic technologies, underscore the importance of integrating fault control into engine design and usage. In the contemporary era, artificial intelligence (AI) technology has emerged as a prominent solution for systematically diagnosing faults, especially in situations where extensive diagnostic knowledge is available, and the process of identifying faults involves a lengthy sequence of steps [7].

In artificial intelligence, expert system refers to a computer system that emulates the decision-making capabilities of a human intelligence. These systems are specifically crafted to address complex problems through logical reasoning based on sets of rules and knowledge representation, departing from traditional procedural code [8]. AI techniques encapsulate a fusion of human expertise, task-specific knowledge, and computational intelligence and processing. Classification of these techniques is based on the type of knowledge they utilize, making distinctions between structured and unstructured knowledge, as well as the manner in which this knowledge is processed.

In the several types of Fuzzy Inference Systems, Mamdani Fuzzy Inference System has shown to be one of the most reliable and popular Fuzzy Inference Systems. These systems have proven over the years to solve the problems of decision making and fault detection. During the research of [9], it showcased an interesting potential applications in the social sciences as well. These systems are commonly categorized as a form of Approximate Reasoning, defined as "the process or processes by which a possible imprecise conclusion is deduced from a collection of imprecise premises" [10].

Therefore, the Mamdani model finds application in representing human estimations [11]. The challenge of fault diagnosis in engineering has a long history, involving various methods such as expert systems and statistical models for dynamic system fault detection [12]. Despite concerted efforts, diagnosing faults in automotive engineering remains notably intricate within the field of AI. The intricacy stems from the fact that electronic control components (ECC) in modern vehicles often operate as black boxes, posing a challenge for mechanics to accurately diagnose faults unless they possess detailed knowledge of the system's specifications and functions [13]. Consequently, developing a comprehensive diagnostic model capable of addressing all fault classification inquiries proves exceedingly challenging. In response to this challenge, [12] introduced an expert system specifically tailored for engine diagnosis. This system aimed to assess the condition of the automobile engine and its associated electronic system while predicting their behaviour.

2. Statements of the Problem

Consistent usage of a vehicle often leads to malfunctions, breakdowns, and deterioration. Additionally, due to the intricate design of automotive architecture and advancements in technology, diagnosing automobile issues has become more intricate. In developing countries, mechanics and technicians commonly resort to a trial-and-error approach when identifying and fixing car problems. This diagnostic method is generally unreliable, inefficient, costly, and time-consuming. The complexity of automotive architecture and the integration of technology further complicate the diagnosis of car issues. Therefore, the use of an automatic troubleshooting and repair system becomes imperative

It was stated in [14] that a method for the automatic detection of faults in tires, which integrates automatic detection and control, data collection and analysis, and result output (indicating whether no retread, medium retread, or high retread is recommended). Their approach enables the evaluation of tire defects, aiding in the decision-making process of whether to retread or replace a tire. The study showcases the application of fuzzy logic in diagnosing tire conditions, offering an innovative perspective. However, it primarily focuses on automobile tires. Therefore, the current work aims to advance automobile fault detection by developing an intelligent system.

3. Review of Related Literature

In [32], it presented a 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, emphasized the necessity of integrating fault control 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 [7]. In the work of [15], 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. In [16], it proposed an accurate fuzzy logic-based fault classification algorithm using voltage and current phase sequence components.

In the work of [13], it was 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. Fault diagnosis is a longstanding engineering challenge, encompassing a range of techniques for dynamic system fault detection, including expert systems and statistical models [12]. Fault classification in double circuit line with conventional techniques which proved to be ineffective due to mutual coupling between the two circuits [17]. It was proposed that neural network approach for fault classification is established as a successful methodology but it requires tedious training effort, hence it is time consuming and adds to the computation complexity [15]. It was opined in [18] that fuzzy logic methodology to identify the ten types of faults.

Mamdani system is a well-known fuzzy logic techniques that is frequently used to create systems with advance reasoning that can detect human intuition, feelings and fault detections [19]. A high level of automation in vehicles is accompanied by a variety of sensors and actuators, whose malfunctions must be dealt with caution because they might cause serious driving safety hazards. In [30], they examined some of the most common fault diagnosis methods for their applicability to automated vehicle systems: The traditional binary logic method, the fuzzy logic method, the fuzzy neural method, and two neural network methods which includes feed-forward neural network and the convolutional neural network. Fault diagnosis can be performed in several ways, such as with neural networks, fuzzy logic, evolutionary algorithms, and support vector machines amongst others [31]. .The diagnostic reasoning methods can also be realized as an expert knowledge-based approach. Expert knowledge is frequently stated in conventional expert systems as deterministic “IF-THEN“ rules, which are also the origin of the traditional binary logic fault diagnosis approach. Instead of a simple fault/no-fault decision, the fuzzy approach outputs the fault severity of the system to the operators [20]. Combination of more than one methods has also been considered as a way of improve existing fault detection methods which is known as hybrid fault detection system eg, neural networks and fuzzy logic could be used together [21]. One of the popular control techniques is fuzzy logic, which is known to provide a controller that simulates the behaviour of an expert operator [22]. The fuzzy logic Mamdani model is a fuzzy reasoning system that can be used to calculate values based on various criteria for evaluating teacher performance [23].

Mamdani systems are also reputable for fault diagnosis in automobiles the rules are developed from human expert knowledge since their rule bases are more intuitive and easier to understand [22]. In fuzzy based systems, the fuzzy output sets are aggregated into a single fuzzy set using the fuzzy inference system’s aggregation mechanism. It was opined that the consequences of an IF-THEN rule in a Mamdani system can be very different from the consequences of that same rule in a system governed by the most basic principles of logical deductive inference [29]. Mamdani systems have proven to be a very useful tool for function approximation and control. Mamdani systems are known to be truth-preserving in the sense stated above; they can lead to very results from those obtained if the IF-THEN rules embedded within are interpreted as proper logical implications [24].

The intelligent computing in question is a mathematical assessment model based on computerization that uses the fuzzy logic method to determine the level of success in teaching a teacher online. Fuzzy logic has characteristics and advantages in dealing with these problems [25]. it is appropriate to use fuzzy logic system in solving problems associated with uncertainty [26]. Mamdani [19] is a well-known fuzzy logic method, Fuzzy Mamdani is frequently used to create systems with reasoning that resembles human intuition or feelings. As a result, the Mamdani model can be used to represent human guesses. The fuzzification, inference fuzzy engine, and defuzzification processes are distinct in a Mamdani fuzzy system [23]. During the fuzzification process, a specific value is introduced into the system and converted into a membership level for each rule.

4. Methodology Adopted

The system utilizes Mamdani's algorithm as its design methodology, which is type of fuzzy inference system. These Mamdani algorithm based systems have shown to be very effective in the application and design of expert system. Its rules are called up from an expert knowledge-based due to their intuitive and simple rule bases algorithms [19]. In the year 1975, Ebhasim Mamdani originally purposed this system to regulate a steam engine and boiler combination. It achieves this by synthesizing a collection of fuzzy rules derived from individuals possessing expertise in the system [27]. The rule produces output that manifests as fuzzy sets, generated through the FIS's output membership function and implication methods.

The Mamdani algorithm plays a crucial role in developing an advanced intelligent system for detecting faults in automobiles using fuzzy logic principles. This algorithm interprets imprecise inputs through linguistic variables and predefined rules, enabling it to make decisions in the face of uncertainties. It utilizes fuzzy inference rules and membership functions to model the intricate relationships between sensor data and potential faults in the vehicle.

Through a series of steps involving fuzzification, rule evaluation, aggregation, and defuzzification, [28] the Mamdani algorithm adeptly manages complex and non-linear connections among input variables. This capability facilitates the accurate identification of various faults within the operational components of the automobile. By effectively handling uncertain and vague inputs, the Mamdani algorithm significantly enhances the system's capacity to make well-informed decisions. Consequently, it contributes to the development of a more intelligent and precise fault detection system grounded in the principles of fuzzy logic.

Steps for Computing the Output of Mamdani Systems

Following steps need to be followed to compute the output from this FIS;

i. Set of fuzzy rules need to be determined in this step.
ii. In this step, by using input membership function, the input would be made fuzzy.
iii. Now establish the rule strength by combining the fuzzified inputs according to fuzzy rules.
iv. In this step, determine the consequent of rule by combining the rule strength and the output membership function.
v. For getting output distribution combine all the consequents.
vi. Finally, a defuzzified output distribution is obtained.

Mamdani Algorithm for Automobile Fault Detection

i. Step 1: Convert User Variables/Inputs Readings to Fuzzy Terms
ii. Step 2: Establish Rules Connecting Variables Readings to Faults.
    a. Create a set of rules that relate the fuzzy sensor readings to potential faults or issues in the car.
    b. For instance, if the temperature is "high" and the oil pressure is "low," associate it with a potential fault in the engine cooling system.
iii. Step 3: Evaluate the Rules Using Fuzzy Logic.
    a. Use these rules to evaluate how likely or severe each potential fault might be based on the fuzzy sensor readings.
    b. Consider the degree to which each rule applies and contributes to the likelihood of a specific fault.
iv. Step 4: Combine Rule Evaluations
    a. Combine the evaluations from different rules to determine the overall likelihood or severity of different faults.
    b. Take into account all the rules that might apply based on the sensor readings.
v. Step 5: Produce a Clear Assessment of Potential Faults

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

5. Overview of the Proposed System

The proposed system which utilizes the Mamdani’s algorithm and an Ensemble Feature Selection Technique, aims to address the weaknesses of the existing system in credit card fraud detection. Here's how this proposed system can potentially solve the mentioned problems**:**

1. Addressing Sensitive measures: The development process for the proposed intelligent automobile fault detection system, which utilizes fuzzy logic, follows a well-structured approach. It commences with a precise articulation of the problem at hand, delineating the specific types of automobile faults under consideration (Engine fault), and establishing overarching objectives such as the enhancement of safety and the reduction of breakdown incidents.
2. Improved Performance Metrics: The evaluation of the proposed system includes various performance metrics such as ROC Score, Accuracy, F1 Score, and Precision. These metrics provide a comprehensive assessment of the model's ability to distinguish between automobile engine fault and automobile electrical fault. By measuring the performance using multiple metrics, the proposed system provides a more thorough evaluation and ensures robust fault detection.
3. Combating Overfitting: The proposed system incorporates an Ensemble Feature Selection Technique, specifically Recursive Feature Elimination (RFE), Information Gain, and Chi-Squared ($\chi 2$). These techniques help identify and select the most relevant features for fault detection, reducing the complexity of the model and mitigating overfitting risks. By selecting the most informative features, the proposed system aims to improve generalization and ensure better performance on unseen data, addressing the overfitting weakness of the existing system.

Fuzzification

The conversion of precise quantities (sets) into a fuzzy quantities is referred to as fuzzification. This process involves acknowledging various well-defined quantities as entirely nondeterministic and highly unpredictable. Such uncertainty may arise due to imprecision and vagueness, leading to the representation of variables through a membership function, as they exhibit a fuzzy nature. For example, stating the temperature as 45°C prompts the observer to transform the exact input value into a linguistic variable, such as whether it is the ideal temperature for the human body, considered hot, or perceived as chilly..

Defuzzification

Defuzzification is the opposite fuzzification. It employs is the term employed in this context. Unlike fuzzification, which involves transforming crisp inputs into fuzzy outputs, defuzzification utilizes mapping to convert fuzzy findings into precise results. This method is capable of generating a non-fuzzy control action that represents the probability distribution of an inferred fuzzy control action. In essence, when the membership values of a fuzzy set on the unit interval are condensed to a single scalar quantity, the defuzzification process can be likened to a rounding off procedure.

Architecture of the Proposed System

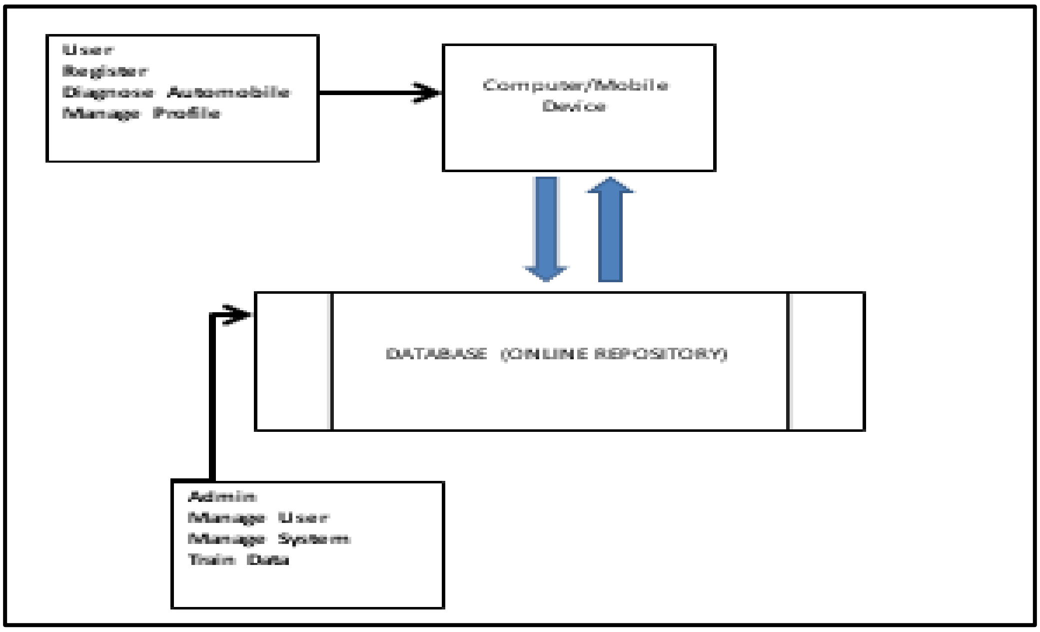

Fig 1: Architecture of the proposed system

User: The integral participant in the intelligent automobile system is the end user, engaging with the platform for various functionalities. This user undertakes tasks ranging from initial registration, establishing a distinct presence within the system, to actively employing the platform for diagnosing their vehicle's condition and efficiently managing their individual user profile.

Computer/Mobile Device: Serving as the interactive gateway, the computing device or mobile interface acts as the conduit through which users seamlessly connect with the intricacies of the intelligent automobile system. This technology-driven component, whether embodied in a computer or a mobile device, offers users an accessible platform. It facilitates a spectrum of activities, including user registration, automobile diagnostics, and personalized profile management.

Database (Online Repository): At the core of the system lies the database, functioning as a sophisticated digital repository. This centralized data hub meticulously stores and governs a plethora of information, ranging from user profiles and vehicle specifics to diagnostic records. It acts as an online repository, ensuring the secure storage and efficient retrieval of diverse datasets integral to the functioning of the intelligent automobile system.

Administrator: The system administrator, in a pivotal role, orchestrates the seamless operation of the intelligent automobile system. This proficient overseer is tasked with multifaceted responsibilities, encompassing the management of user accounts, system health monitoring, and resolution of potential challenges. In addition, administrators may be engaged in the dynamic process of refining the system's capabilities through the duration and application of pertinent data to enhance machine learning models.

6. Dataset

The dataset utilized in this study was sourced from Kaggle, a prominent online platform widely acknowledged for hosting data science competitions, supplying datasets for machine learning and data analysis, and fostering a collaborative environment for data scientists, machine learning engineers, and researchers. Established in 2010 and currently owned by Google, Kaggle's primary objective is to unite a global community of data science enthusiasts and professionals to address real-world challenges, progress in machine learning techniques, and facilitate the exchange of knowledgeThis dataset is composed of three distinct components. The first component encompasses a comprehensive inventory detailing various attributes of automobiles. The second component involves insurance risk appraisals assigned to each vehicle, indicating the extent to which an automobile's inherent risk deviates from its market value. This risk assessment involves the initial assignment of a risk symbol based on the vehicle's price point, which can be adjusted along the risk spectrum through a process known as "symboling." Notably, a rating of +3 implies a high-risk classification, while -3 conveys a relatively secure standing. The third component delineates normalized loss figures, representing comparative loss occurrences for each car in the dataset. In this dimension, the mean loss payment per insured vehicle per annum is standardized across cars within specific size classifications (e.g., two-door compacts, station wagons, sports/specialty models), providing insights into the average annual loss rates for each size category.

Table 1: Sample of the dataset

S/N	Ambient Temperature	Engine Per Torque	Driver Dmd Per Trq	Engine Coolant Temp	Engine Exhaust Gas Temp	Engine Fuel Rate
1	31.3097847	97.5949	99.1971	28.64083331	43.64083331	29.09388888
2	31.21077891	96.9408	99.3564	27.82777128	42.82777128	28.55184752
3	31.14964205	96.4218	99.9728	27.09548704	42.09548704	28.06365803
4	30.09533666	92.6282	100.1252	24.77965842	39.77965842	26.51977228
5	29.64374314	90.5008	99.1525	22.78295192	37.78295192	25.18863461
6	30.23532765	93.5098	100.8693	25.84294012	40.84294012	27.22862675
7	30.69573483	95.2108	101.6429	26.94300628	41.94300628	27.96200418
8	29.70981534	91.4516	99.8359	24.3540564	39.3540564	26.2360376
9	28.92781303	88.7399	100.8030	22.84081053	37.84081053	25.22720702
1	30.06020886	94.0508	97.4614	27.80049082	42.80049082	28.53366055
1	30.58261188	95.2353	98.5594	27.55752473	42.55752473	28.37168315
1	31.55843492	97.8783	99.6526	27.96438941	42.96438941	28.64292627
1	32.1794977	99.9104	100.6820	28.92339876	43.92339876	29.28226584
1	32.21245413	99.9546	100.6120	28.84690516	43.84690516	29.2312701
1	30.46429626	92.8462	101.2162	23.37098393	38.37098393	25.58065595
1	30.1881151	92.2323	99.7705	23.52397976	38.52397976	25.68265317
1	30.18909611	92.7910	101.8031	24.63645826	39.63645826	26.42430551
1	30.8465689	95.4223	102.5783	26.61176373	41.61176373	27.74117582
1	31.49399627	97.7479	102.5038	28.0257917	43.0257917	28.68386113
2	31.5320409	97.9140	102.3702	28.16770759	43.16770759	28.77847173
2	31.33129179	97.2923	102.2846	27.92812528	42.92812528	28.61875018
2	30.89509369	95.7614	102.9507	27.04741358	42.04741358	28.03160905
2	30.50875911	94.6983	102.8169	26.85283058	41.85283058	27.90188705
2	30.40949359	94.4627	102.8887	26.87785579	41.87785579	27.91857053
2	30.22804171	94.3425	100.7143	27.54476832	42.54476832	28.36317888
2	29.96351608	93.7780	100.8528	27.7384124	42.7384124	28.49227493

7. Fuzzy Logic Accuracy Measurement

Accuracy measurement in fuzzy logic and fuzzy systems refers to evaluating how well the system performs and classifies information. Fuzzy logic works with degrees of truth or membership, in contrast to traditional binary systems, which makes accuracy measurement a little more complex. Depending on the particular application and the type of problem being solved, a number of metrics can be used to assess the accuracy of fuzzy systems.

i. Performance Metrics: The confusion matrix in fuzzy systems can be used to create a number of performance metrics, such as:

ii. Recall and Precision: Derived from classical systems, recall gauges the system's capacity to properly identify positive instances, while precision assesses the accuracy of positive predictions.

iii. Accuracy: It evaluates the overall correctness of classifications or forecasts. On the other hand, weighted or fuzzy set-based judgments may be necessary for accuracy in fuzzy logic.

8. Data Presentation

Data presentation involves transforming raw data into visual formats like graphs, charts, tables, maps, and info graphics to make complex information easily understandable, aiding in analysis, comprehension, and decision-making. The information gain, Chi2, Membership Function (MF) ranking values F for the quantifiable features in the dataset are presented in tables 2 below;

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

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:

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

9. 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 100% and F1-score is approximately 75.78%.

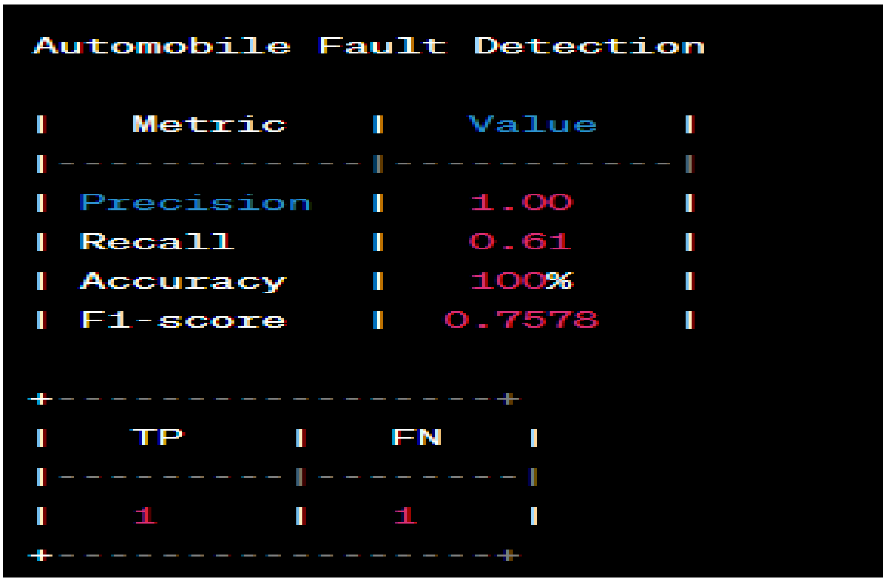

Fig 2: Testing Data Output

Table 3: Performance metrics

Model	Accuracy	Precision	Recall Value	F1-score.	Training time (seconds)
Mamdani Algorithm	100%	100%	61%	6%	5 mins

Accuracy – The accuracy of the classification is given as:

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

The Accuracy gave 100%

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%.

Test Data

The model will be 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 form 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.

10. Result Evaluation Performance

The system reveals commendable performance in terms of precision and accuracy, both achieving perfect scores of 1.00 or 100%. 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%, indicating that it missed identifying some actual faults. The F1-score, harmonizing precision and recall, reaches approximately 75.78%, 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 below:

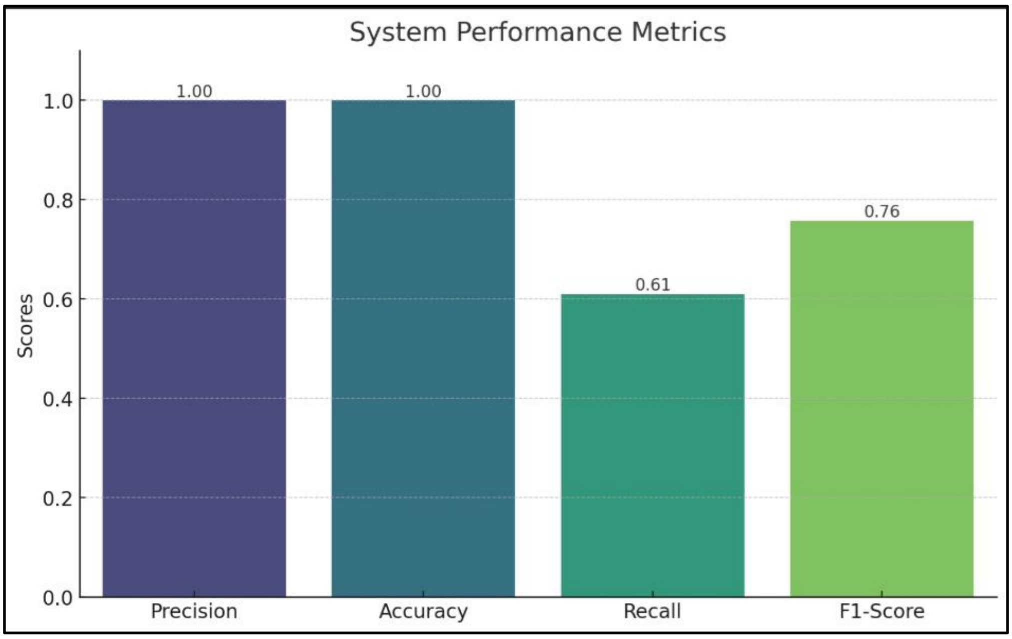

Fig 3: Bar Chart for Performance Metrics

11. How the System Works

Within the framework of the sophisticated intelligent automobile system, the primary user initiates engagement through their computational or mobile interface. This interactive platform serves as the gateway for a diverse array of functionalities, commencing with the user registration process. During this initial phase, the user establishes a personalized profile within the system, furnishing it with pertinent details. Subsequent interactions involve the user leveraging the computational or mobile device to explore the system's capabilities. They delve into features such as automobile diagnostics, extracting real-time data from their vehicle's sensors to gain a comprehensive understanding of the vehicle's health and performance. Concurrently, the user utilizes the platform to meticulously curate their profile, fine-tuning preferences and details. The computational or mobile device acts as a seamless conduit, offering an intuitive interface for these engagements. Operating behind the scenes, the database, functioning as an online repository, assumes a pivotal role. It meticulously stores and organizes a wealth of data, encompassing user profiles and detailed diagnostic records. This meticulous storage ensures not only the secure retention but also the swift retrieval of information when users embark on tasks such as diagnosing their automobiles or managing their profiles. Administrators, with vigilant oversight, direct the entire orchestration. They navigate the intricate management of user accounts, ensuring a streamlined user experience through meticulous oversight of account creation, modification, and deactivation. Simultaneously, administrators maintain a vigilant watch over the system's health, proactively addressing potential issues to sustain optimal functionality. In certain instances, administrators contribute to the system's augmentation by actively participating in the training of machine learning models, utilizing pertinent data to refine and elevate the system's predictive and diagnostic capabilities. In this collaborative interplay of user interaction, computational devices, an online repository, and administrative stewardship, the intelligent automobile system seamlessly integrates user experiences, data governance, and system functionality for a holistic and efficient operation.

12. The System Algorithm

Step 1: Start
Step 2: Turn up and internet enabled computer
Step 3: visit the uniform Resource Locator of the system
Step 4: Click on Registration and register as a user
    if user email exists
        User already registered
    Else
        Register User
Step 5: Click on User Login after successful registration
    If user criteria is valid
        Redirect user to main page
    Else
        Message "Invalid User"
Step 6: Car Diagnosis
Step 7: Type in Faults/Data/Variables of the car to be diagnose
    If fault exist after fuzzification and membership filtering of data
            Diagnose car with corresponding reports and recommendations
    Else
            Exit Diagnosis
Step 8: Stop

13. Summary

The application of advanced computing and fuzzy logic in automotive diagnostics systems are exemplified in the innovative "fuzzy logic-based automobile fault detection system using Mamdani's algorithm." This system employs a hybrid computerized fuzzy logic approach, specifically leveraging Mamdani's algorithm, to adeptly identify faults across diverse vehicle components. Providing valuable guidance to users, including both automobile owners and mechanics, it delivers clear and informed recommendations for the repair or replacement of malfunctioning parts. Noteworthy features of this system include its utilization of fuzzy logic and Mamdani's algorithm, enabling the handling of imprecise and uncertain data commonly encountered in automotive diagnostics.

14. Conclusion

Taking a look into the future of automotive fault detection technology, solutions like the "fuzzy logic-based automobile fault detection system using Mamdani's algorithm" not only elevate the safety and reliability of vehicles but also lay the groundwork for revolutionary advancements in the industry. This innovation has the potential to transform the way we detect and address vehicle-related issues, fostering safer roads and more trustworthy automobiles. The web-based implementation ensures accessibility and user-friendliness, catering to a diverse audience.

15. Contribution to Knowledge of the Study

This study provides information about fuzzy logic's use in the automotive sector and demonstrates how the Mamdani Algorithm can effectively handle ambiguous and imprecise data that are frequently encountered during vehicle tasks. This study enhances our understanding of Mamdani-type fuzzy inference systems and illustrates a straightforward interpretation of intricate sensor data in automotive systems. The method implemented in this research showcases the system's capability to effectively manage linguistic variables, predefined rules, and membership functions, enabling precise descriptions of the relationships between sensor inputs and fault states. Additionally, by presenting a practical application demonstrating the versatility and effectiveness of the Mamdani algorithm in enhancing fault detection capabilities in automotive systems, this research contributes valuable insights to the practical utilization of fuzzy logic-based techniques for ensuring safety and reliability in automotive operations.

16: Recommendations for Further Work

Considering the numerous issues in the automotive industry, along with the intricacies of mechanical systems, expert professionals, and the emergence of cutting-edge vehicles employing sophisticated microchip technology like Tesla and Google Self-Drive cars, for both traditional engines and alternative energy sources like electricity and solar power, there is a need for an advanced computerized system capable of efficiently detecting faults in a comprehensive manner.

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