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A SMART FAULT DETECTION SYSTEM USING FUZZY LOGIC TECHNOLOGY

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ABSTRACT

In the present era, automobiles have become an integral aspect of individuals' daily lives. Engine malfunctions can prime to noteworthy issues for regulars if not distinguished early, punctually addressed, and truthfully repaired. Such letdowns may pretense risks to existence and property, negatively impacting customer pleasure and the status of vehicle firms. This novel approach leverages the flexible properties of fuzzy logic, which are strategically applied to strengthen and improve the operational effectiveness, safety, and dependability of automotive systems. To ensure that the prototypical is skillful of handling a wide range of complex and varied automotive data, ML.NET was used to train the dataset that was obtained from the Kaggle Dataset repository. Impressively, this forward-thinking system was developed utilizing an extensive array of state-of-the-art web machineries, including Bootstrap 3.5, JavaScript, ASP.Net, CSS and JQuery, and SQL server, attesting to its commitment to technological advancement and innovation. Rigorous testing and meticulous evaluation have yielded promising outcomes, showcasing the system's potential for widespread adoption while demonstrating its prowess in averting accidents, curbing maintenance costs, and significantly enhancing the overall driving experience. Achieving a commendable performance accuracy of 73.14%, alongside a precision rate of 100% and an F1 Score peaking at 76.62%, this visionary system stands at the forefront of transformative progress in automotive fault detection, promising a paradigm shift in vehicular safety protocols and maintenance standards

1. INTRODUCTION

In the contemporary era, automobiles have become an integral aspect of individuals' daily lives. Engine malfunctions can prime to noteworthy issues for regulars if not distinguished early, punctually addressed, and truthfully repaired. Such letdowns may pretense risks to existence and property, negatively impacting customer pleasure and the status of vehicle firms Yanjun, L. and Niu, C. (2022). In certain instances, automobile industrialists may requisite to safeguard regulars through arcade actions and reminiscences, incurring substantial financial expenditures. This comprehensive study introduces a pioneering intelligent fault

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detection system meticulously engineered for automotive applications Love, K. (2020). Over the past few centuries, the widespread use of Artificial Intelligence (AI) methodologies has modernized various sectors, replacing old-style approaches with intelligent strategies to address intricate and challenging issues Ojugo A. A. Akazue, M. I. Ejeh, P. O. Odiakaose, C. C. Emordi, F. U. (2023). AI methodologies encompass a fusion of human proficiency, domain-specific insights, and computational acumen. Categorizing these methodologies can be done by considering the nature of knowledge utilized, differentiating between organized and unorganized knowledge, and the methodology employed for knowledge processing.

In the work of Shiqing, L, Michael, F and Frank, G. (2023), they evaluated different fault diagnosis methods and their applications in vehicle systems. The intention of the investigation is for assessing which typical failing diagnosis methodologies would work for computerized car systems. As presented by Van-Truong, N., Tien-Xuyen, N., Trong-Minh, H. and Nhu-Lan, V. (2019), research using fuzzy logic for real - time water qualityassessment monitoring system. This study presents the creation and implementation of an actual-time water eminence observing system based on the internet of things (IoT) manner. A fault diagnosis of automobile engine based on improved back propagation neutral network and it presented an improved the efficiency. It was opined by Ojugo, A. A. and Ekurume, E. (2021), that neural network used in detecting and diagnosing automobile fault which shows significant improvement in fault detection but shows some limitation of poor record optimization. Using a number of fault methods for diagnosis, the team modelled the faults in the actuator and variable systems utilized by electric cars. In the work of Achmad, M. and Amin, K. (2021), titled the prototype of an expert car failures diagnosis system with combining forward chaining and bays network. The outcomes of the design and development phase underscore the importance of selecting suitable microcontrollers and water parameter variables for effective water monitoring in aquaculture settings. The primary goal is to enhance precision in determining whether a tire requires retreading or replacement. The objective of this research is to develop a skillful system aimed at diagnosing car malfunctions by employing both the Forward Chaining and Bayes Network approach Akazue M. I. and Ajenaghughrure, I. B. (2015). Amey, S., Nihaal, G., Saumitra, M., Tonu, R. and Gajendra, V. (2018) Utilizing forward chaining based on factual information and expert input yields precise diagnoses for car failures. In contrast, employing Bayes probability offers assurance that the diagnosis chosen corresponds to the most suitable probability. In some cases the light indicator get user confuse on which fault and symbols were typically used. The system provides the cheapest and simplest way for vehicle owners to understand faults. The Feedback Return Pulse System (FRPS) device simplifies decoding complex systems and detects variable faults easily. As presented by Aru, O., Adimora, K. and Mba, C. (2021) in their work, application of artificial intelligence in fault diagnosis of automotive systems, aimed to reduce downtime by introducing an intelligent fault diagnosis system. The system assists design engineers with limited experience by providing knowledge on manufacturing processes, materials, and cost-effective methods for bus production

Akazue, M. I. Ahweyevu, K. O. Ogeh, C. O. and Asuai, C. (2024). It provides accurate fault information and offers immediate repair solutions, minimizing downtime to zero. As proposed by Chee, N., and Chee, F. (2018), researches work using an expert system case for salable bus design. They developed a system will must undergo validation with a case study to verify its capability. In the work of Cihun-Siyong, A.,Chih-Hui, S.,Yu-Hua, C. and De-Yu, G. (2022), they designed how to implement automotive fault diagnosis using artificialintelligence scheme. The research work integrated multiple machine learning algorithms to predict and warn about failures in various vehicle components, including transmission, engine operation, and tire condition. An effect of on-board diagnostic system on fault detection in automobile on trainees aimed to assess the compliance of local motor mechanics using traditional diagnosing methods with those utilizing the on-board diagnostic system. Ezeora, B. and Ehimen, E.(2021), Ojugo A. A. Akazue, M. I. Ejeh, P. O. Odiakaose, C. C. Emordi, F. U. (2023). It was state by

Kopbayev, A. (2022) that the primary goal of their research works was to devise a hybrid approach for fault uncovering and diagnosis in chemical industries, integrating machine knowledge components. Emphasizing high diagnosis accuracy is the core aim of this research. Also Krunal, J., Vishal, D., Bharat, B., Bharat, R., Rahul, J. and Nikhil, B. (2019) proposed in their work titled railway track fault detection system using robot car system that will detect obstacles and gradually reduce speed by activating the air brake to prevent the train from colliding. In the work of Wangjie, L., Hu, Y., Gong, C., Zhang, X., Xu, H. and Deng, J (2021), Ojugo, A. A. Ejeh, P. O. Akazue, M. I. Ashioba, N. C. Odiakaose, C. C. Ako, R. E Nwozor, B. and Emordi, F. U. (2023c), their research presented questions of current trends in the use of AI techniques to aid the identification and treatment of motor abnormalities.

As proposed by Wonbin, N., Park, C., Lee, S., Yu, S. and Lee, H. (2018) in their work titled sensitivity-based fault detection and isolation algorithm for road vehicle chassis variables, the paper introduced a novel approach for identifying and isolating faults within a vehicle control system. To diagnose flaws in road structure vehicle conditions, a sensitivity-based identification of mistakes and isolation technique was devised in this article. The proposed algorithm leverages residual sensitivity and is constructed using analytical methods Ojugo, A. A. and Eboka, A. O. (2020). In the work of Adsavakulchai, S. (2018), they proposed a car failure detection using expert system. The car failure detection expert system proves helpful, though it may not offer comprehensive guidance and assistance comparable to that of a human expert, such as a mechanical engineer. Also it was opined by Alexandre, B., Nyobe, Y., Leandre, N. and Laure, M. (2018), they illustrated the use of fuzzy reasoning, neural networks, and combination techniques for recognizing faults of an induction motor. The aforementioned project succeeded in showing a neural network constructed artificially and fuzzy logic-based inducted motor defective diagnostics. It was proposed by Samuel, D. and Francis, K. (2021) the use of artificial intelligence comes towards will be. Such a system's success is dependence upon the caliber of the information used to train laws, and other components Ricardo, F., Roxanne, A.,Jasmin, A.,Felizardo, C. and Reynaldo, E. (2019), 26].

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2. METHOD AND MATERIALS

In creating a smart system for automobile fault discovery using fuzzy logic requires specific materials. They include:

Data Sources: Information from vehicle variables like engine, transmission, and electrical system variables, maintenance records from cars, databases storing diagnostic data and repair histories.

Computing Hardware/Software Tools:Computers or servers with sufficient processing power and memory for analysis and modeling, graphics processing units (GPUs) or specialized hardware for faster computations if needed, Programming languages and libraries for data analysis (e.g., C#, SQL server), fuzzy logic libraries or toolkits for fuzzy inference systems (e.g., MATLAB Fuzzy Logic Toolbox, SciKit-Fuzzy), machine learning frameworks (e.g., TensorFlow, PyTorch), integrated Development Environments (IDEs) for software development.

Data Preprocessing Tools:Tools to clean and preprocess variable data (e.g., filtering, normalization) and algorithms for feature extraction.

Model Development Tools:software for creating fuzzy logic models (e.g., Fuzzy Logic Toolbox in MATLAB, FuzzyToolkitUoN) and tools to tune and optimize models.

Integration Tools:Software for integrating models into a cohesive system and user interface development tools for creating user-friendly interfaces.

Testing and Evaluation Tools:Testing frameworks for evaluating system performance and Tools for performance evaluations and measuring accuracy, reliability, and speed.

Documentation and Reporting Tools:Tools for documenting the development process, including version control systems and reporting tools for summarizing research findings and system evaluations.

Research Design

The research is designed for developing a system for automobile fault detection using fuzzy logic involves a structured style directed at addressing the recognized problems and research questions effectively. Initially, a comprehensive literature review will be conducted to understand existing methods in automobile fault detection, fuzzy logic applications, and related technologies. This review will help identify the strengths and limitations of current fault detection methods and systems, as well as evaluate previous research studies on fuzzy logic applications in automotive diagnostics. Following the literature review, the scope and objectives of the research will be clearly defined, focusing on developing an intelligent system for fault detection beyond tire diagnostics. Methodologically, the research will entail data collection from various sources, including variable data from vehicles, historical maintenance records, and diagnostic databases. The collected data will undergo preprocessing, feature extraction, and fuzzy logic modeling to develop fault detection algorithms. These algorithms will be integrated into a cohesive system, complete with user-friendly interfaces for interaction. Evaluation of the system's performance will involve extensive testing and validation procedures, measuring accuracy, reliability, speed, and usability in detecting various automobile faults. Continuous improvement will be ensured through iterative refinement based on user feedback and performance evaluations, adapting the system to evolving automotive technologies and diagnostic requirements. This structured research design ensures a systematic approach towards developing an effective intelligent system for automobile fault detection using fuzzy logic, contributing to advancements in automotive diagnostics.

These are the elements that make up the architecture;

i. **Knowledge Base**: A computer system uses a knowledge base as a technology to store intricately organized and unstructured data. Expert systems, which were the first knowledge-based systems, were where the phrase was originally used (Luke, 2019).

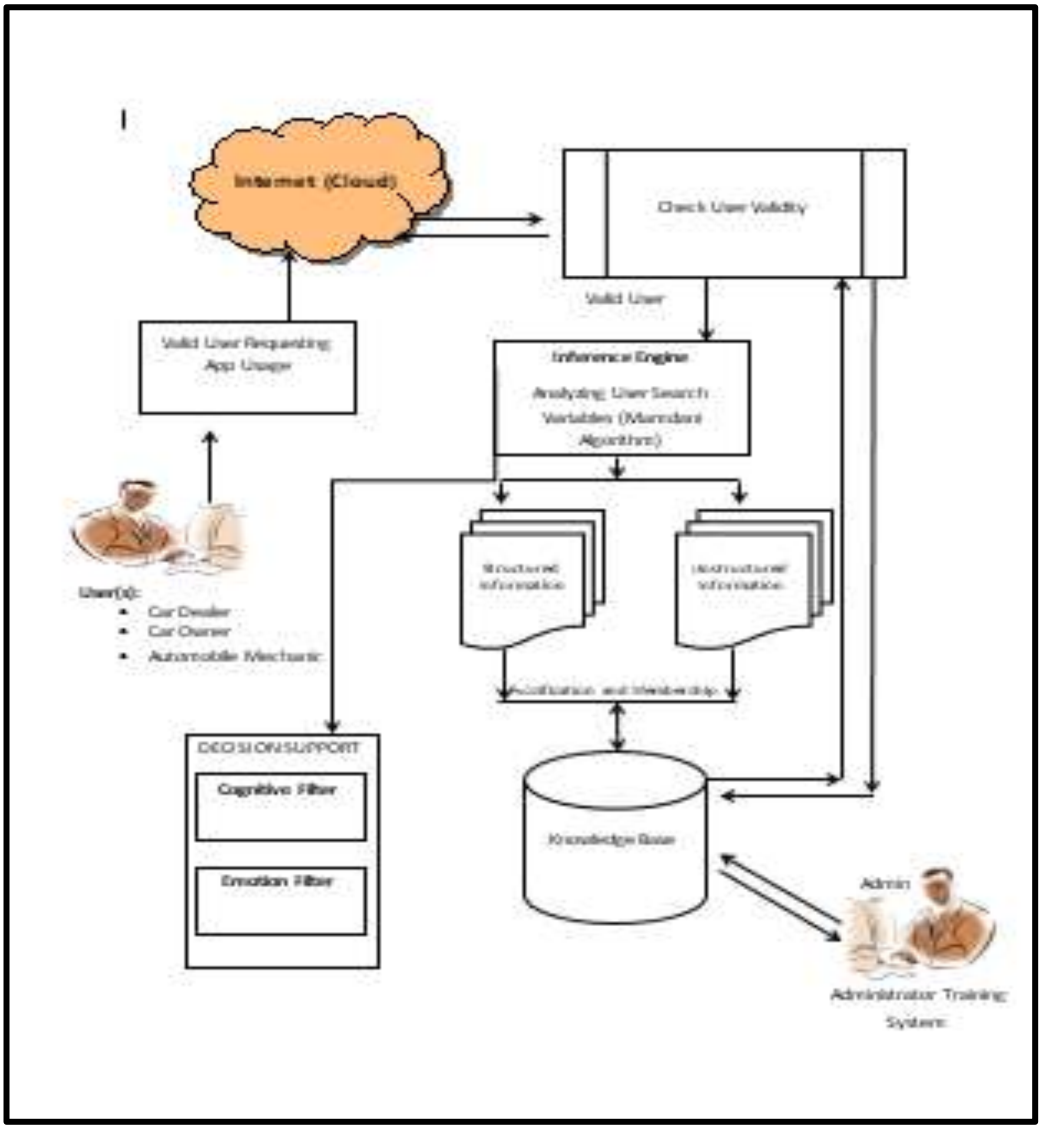

Figure 1: The System Architecture

ii. **Fuzzy Inference**: An inference engine, which is a part of the system that applies logical rules to the knowledge base to derive new information, is a concept in artificial intelligence. Expert systems' initial inference engines were included in them. A knowledge base and an inference engine made up the standard expert system (Luke, 2019).

iii. **Decision Support**: A decision support system is an information platform that aids in organizational or corporate decision-making (James, 2019).

Basic Operation of the System

In the context of developing an intelligent system for automobile fault uncovering using fuzzy logic, the basic operations of fuzzy logic play a crucial role in demonstrating and reasoning with uncertain or imprecise information inherent in automotive diagnostics. Here's how these operations relate to our topic:

Fuzzification: Fuzzification enables the mapping of crisp user variables from automobiles, such as engine temperature or oil pressure, into fuzzy linguistic terms or membership grades. This process accommodates the inherent uncertainty and variability in variable data, allowing for more nuanced representation and analysis of automotive conditions.

Fuzzy Inference: Fuzzy inference forms the core of our fault detection system, where fuzzy rules and logic operators are applied to input variable data to produce fuzzy output sets representing potential automobile faults. By mimicking human reasoning and decision-making processes, fuzzy inference allows the system to interpret variable data in a flexible and adaptive manner.

Rule Evaluation: Rule evaluation involves assessing the relevance of fuzzy rules based on the degree of match between input variable data and the conditions specified in the rules. **Aggregation:** Aggregation combines the outputs of activated fuzzy rules to generate a comprehensive assessment of automobile condition and potential faults. By leveraging fuzzy logic operators such as AND or OR, the system aggregates information from multiple rules to form a holistic view of the automobile's health.

Defuzzification: Defuzzification converts fuzzy output sets representing potential faults into crisp, actionable decisions or recommendations for automobile maintenance or repair. This process translates fuzzy logic outputs into concrete actions, aiding mechanics or vehicle owners in addressing identified faults effectively.

Rule Base: The rule base comprises a collection of fuzzy IF-THEN rules that govern the behavior of the fault detection system. These rules encapsulate expert knowledge and domain-specific insights into the relationship between variable data patterns and potential automobile faults.

Fuzzy Logic Operators: Fuzzy logic operators facilitate the manipulation of fuzzy sets and the execution of operations such as intersection, union, or complementation. These operators allowfor the combination and aggregation of variable data and rules to derive meaningful insights into automobile condition and fault detection.

A dataset, in the realm of information repositories, can be elucidated as a curate assemblage of structured or unstructured data, meticulously gathered, methodically organized, and judiciously maintained for the purpose of academic or practical inquiry. This reservoir of information serves as foundational bedrock for empirical analysis, algorithmic development, and scholarly investigation. The dataset from Kaggle was used in the present research. The widely recognized online platform Kaggle organizes contests for data science, disperses datasets for studying information and predictive modeling, and produces collaboration throughout researchers, data scientists, and machine learning engineers.

Training of Datasets

In our future proposed system for automobile fault detection using fuzzy logic, leveraging Kaggle datasets will be instrumental. Here's how we'll integrate Kaggle data into our system:Data Preparation: In the context of our future proposed system for automobile fault detection using fuzzy logic, leveraging

Kaggle datasets presents a promising avenue for enhancing model training and performance. As we envision the development of an intelligent system capable of accurately diagnosing automobile faults, Kaggle datasets offer a diverse range of automotive data that can be instrumental in training our machine learning models. Curate

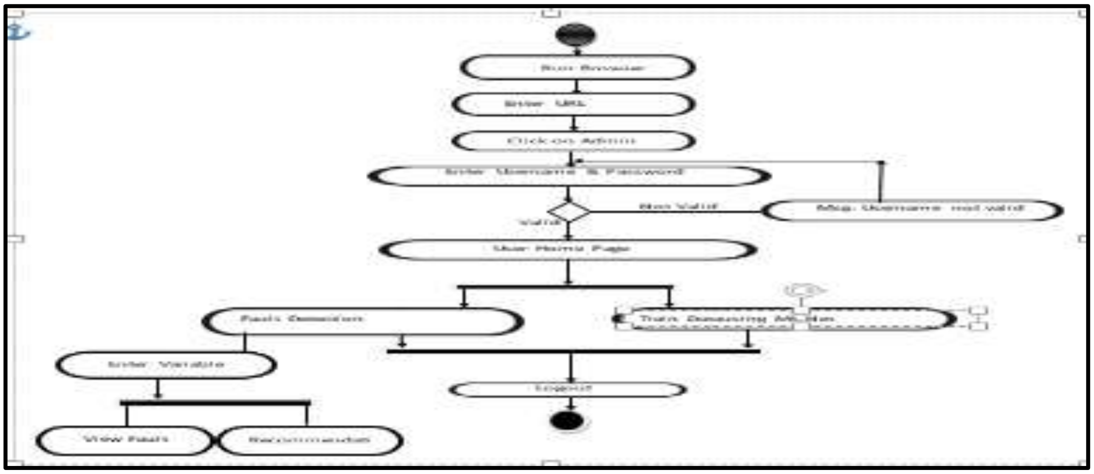

Figure 2: Activity Diagram for Fault Diagnosis Process

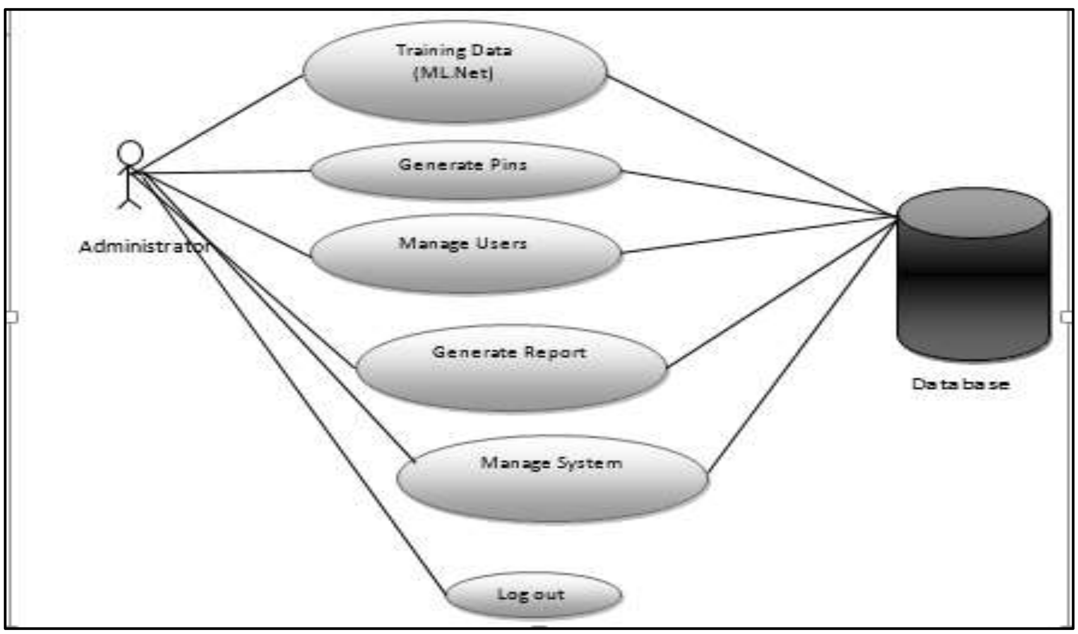

Figure 3: Use Case Diagram of the System Dataset

Table 1: Car Information Datasets

S/N	Ambient Temperature	Engine Per Torque	Driver Dmd Per Trq	Engine Coolant Temp	Engine Exhaust Gas Temp	Engine Fuel Rate
1.	31.35949	98.5404	92.5039	32.78341	47.48341	31.48894
2.	32.34104	101.1458	91.6925	31.5864	46.6864	31.4576
3.	32.04328	101.6539	91.4404	30.89133	46.49133	30.76089
4.	32.43289	101.0132	91.3133	30.86186	46.06186	30.3079
5.	32.16898	100.3759	94.2905	31.20687	46.10687	30.77125
6.	30.47856	94.4736	100.4973	26.55436	42.05436	27.86957
7.	29.94989	91.4986	100.4334	24.4477	39.5477	26.3318
8.	30.03378	91.8557	100.4425	25.04254	40.34254	26.96169
9.	29.53406	93.3931	101.8011	27.4159	42.4159	28.04393
10.	30.53313	97.8048	103.4483	31.24391	46.24391	30.49594
11.	30.66945	97.1321	103.6399	30.61694	46.01694	30.74463
12.	30.65255	97.2943	103.5923	30.5258	45.5258	30.38387
13.	30.5065	96.8004	101.634	29.86839	44.86839	29.57893
14.	30.50497	96.4099	101.4565	29.09486	43.69486	29.46324
15.	30.71358	96.1182	101.6387	29.76848	44.76848	29.91232
16.	30.81154	96.2451	101.7421	28.33243	43.73243	29.22162
17.	30.65253	96.5079	102.4845	28.55313	43.25313	28.60209
18.	30.31851	95.7592	102.726	29.22587	43.82587	29.55058
19.	30.56358	95.3399	102.8435	28.96188	43.56188	29.07458
20.	29.77732	91.9991	100.6301	25.5116	40.9116	27.34107
21.	29.54013	90.8954	100.5598	24.29016	39.29016	26.52677

Kaggle datasets encompassing user variables, maintenance records, and historical fault data. Meticulously preprocess the data, including cleaning, normalization, and feature engineering, to ensure quality and relevance.

Model Training:

i. Integrate the curated Kaggle dataset into the ML.NET framework for model training.

ii. Utilize ML.NET's machine learning algorithms and models, trained on Kaggle data, to discern patterns indicative of potential automobile faults.

Hyperparameter Tuning and Evaluation:

i. Fine-tune model hyper parameters using Kaggle data to optimize performance.

ii. Validate model efficacy through techniques like cross-validation, assessing robustness and generalization ability.

Fault Detection and Diagnosis:

i. Develop robust diagnostic models using fuzzy logic to analyze variable data and identify deviations from expected behavior.

ii. Enable timely fault detection and diagnosis, empowering users with actionable insights for proactive maintenance.

Synergistic Integration:

i. Integrate Kaggle datasets seamlessly into our system architecture, maximizing the utility of available automotive data.

ii. Harness the synergy of Kaggle data and ML.NET's capabilities to create a sophisticated platform for automobile fault detection.

Fuzzy Logic Formula

Fuzzy logic operates with membership ethics that resemble Boolean reason but allow for a more nuanced interpretation. This involves replacing basic Boolean operators like AND, OR, and NOT with equivalents suitable for fuzzy logic. One common replacement is the Zadeh Dyadic operators, which produce results akin to Boolean expressions but account for degrees of truth represented by membership values (ranging between 0 and 1).

In addition to these operators, linguistic modifiers known as "hedges" can be applied in fuzzy logic. These hedges, typically adverbs like "very" or "somewhat," adjust the meaning of a set using specific mathematical formulas, enhancing the flexibility and expressiveness of fuzzy logic.

Threshold Values

Threshold values are predefined limits or ranges set for each monitored parameter or feature in the vehicle. These limits are used to define normal operating conditions and deviations that may indicate a potential fault or issue. In the feature selection table provided earlier, characteristics such as mean, standard deviation, minimum, and maximum values are crucial in determining these thresholds. Firstly, the Feature Name column lists the different features selected for analysis. These features include ambient malaise, engine performance twisting, driver demand per torque, engine coolant temperature, engine exhaust fume temperature, and engine petroleum rate. Each feature represents a specific aspect of the vehicle's operation and contributes to the overall assessment of its performance.

The Mean column displays the average value of each feature across all instances in the dataset. For example, the mean ambient temperature is 30.3742 degrees, which indicates the typical operating temperature recorded during the dataset's collection period. Similarly, the mean engine performance torque is 95.7532, providing a baseline for the engine's power output.

The Standard Deviation column measures the variation or dispersion of the feature values from the mean. A higher standard deviation suggests that the values are more spread out. For instance, the standard deviation of the engine performance torque is 3.957, indicating a moderate level of variability in the torque measurements. This information is essential for understanding how consistent the vehicle's performance is under different conditions.

The Minimum value column indicates the lowest recorded value for each feature. This helps in identifying the lower bounds of the vehicle's operational parameters. For example, the minimum engine coolant temperature is 24.290 degrees, marking the lowest temperature the engine coolant reached. This can be important for diagnosing issues related to cooling efficiency.

Application in Automobile Fault Detection

In the context of automobile fault detection using fuzzy logic:

Thresholds for Anomaly Detection: Fuzzy logic systems utilize thresholds to detect anomalies or deviations from expected behavior. For instance, if the engine coolant temperature exceeds the maximum threshold (e.g., 32.783 degrees Celsius), it could indicate overheating, triggering a fault alert. Fuzzy Membership Functions: Thresholds are often defined within fuzzy membership functions, which describe how each parameter's value relates to various degrees of membership (e.g., normal, warning, critical). Parameters falling outside the normal membership function are flagged as potentially faulty.Fault Classification: By comparing current sensor readings against established thresholds, fuzzy logic systems classify faults into categories based on severity and type. This helps prioritize maintenance actions and prevents potential breakdowns.Real-time Monitoring and Response: Establishing effective thresholds allows for real-time monitoring of vehicle parameters. When thresholds are exceeded, immediate actions can be initiated, such as triggering warning lights, adjusting engine settings, or notifying the driver or maintenance personnel.

In conclusion, threshold values derived from features such as mean, standard deviation, minimum, and maximum play a pivotal role in fuzzy logic-based automobile fault detection systems. They enable proactive maintenance by identifying deviations indicative of potential faults, thereby enhancing vehicle reliability, safety, and performance.

Module Specification

The specification of an individual module is enriched with intricate particulars. Alongside the pedagogical, educational, and evaluative approaches, it incorporates insights into the module's objectives and learning outcomes. It furnishes an overview of both the substance and the modalities and regularity of instructional delivery.

The following are some of the modules present in the system;

The Automobile Detection and Diagnosis Page: This module or page is used by registered users for the detection and diagnosis of an automobile to identify automobile fault when the problems variable are being presented to it. Using the mamdani's algorithm, the inference engine will have to classify each variable into a membership function.

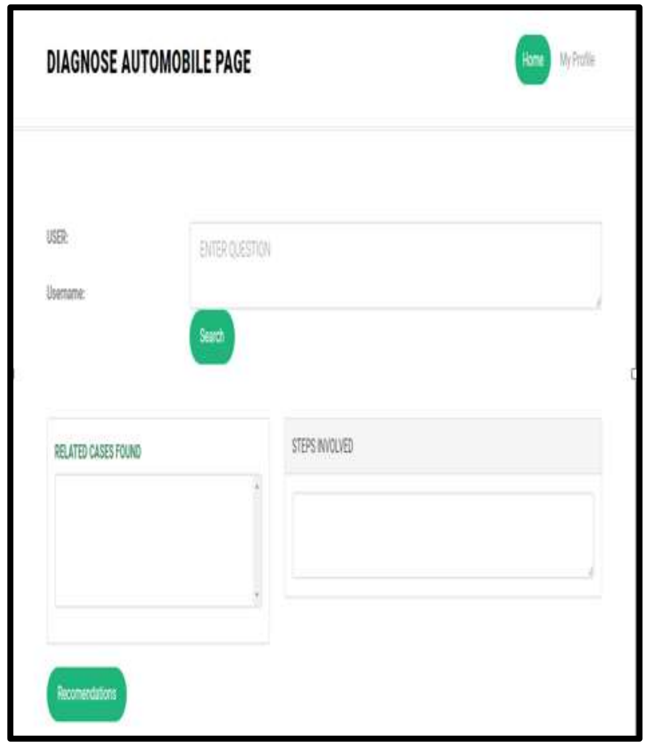

Figure 4: Fault Self-Detection and Diagnosis Module

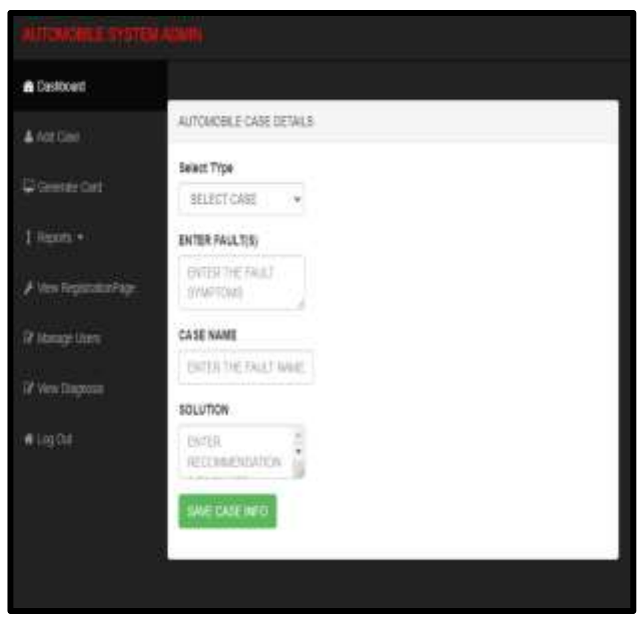

Figure 5: Module training

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

Figure 5: Database Specification

Evaluation of the Proposed System

With both precision and accuracy reaching flawless ratings of 1.00 or 100%, the system exhibits impressive performance. This means that the general forecasts are error-free and the system is consistently correct when it flags a car defect. Though it was able to identify some genuine defects, the recall rate of the system, which gauges its capacity to recognize true faults among all those present, is just 61.07%. Finding a balance between precise fault identification and the capacity to detect real defects is demonstrated by the F1-score, which equates accuracy with recall, reaching around 75.72%. Furthermore illustrative of accurately identifying one issue but failing to detect another is the display of True Positives (TP = 1) and False Negatives (FN = 1). As the recall rate and the frequency of undiscovered faults show, there is still opportunity for development in the system's capacity to detect a greater percentage of true errors, even though it now operates with remarkable accuracy and precision. Here are some examples of this in figures below;

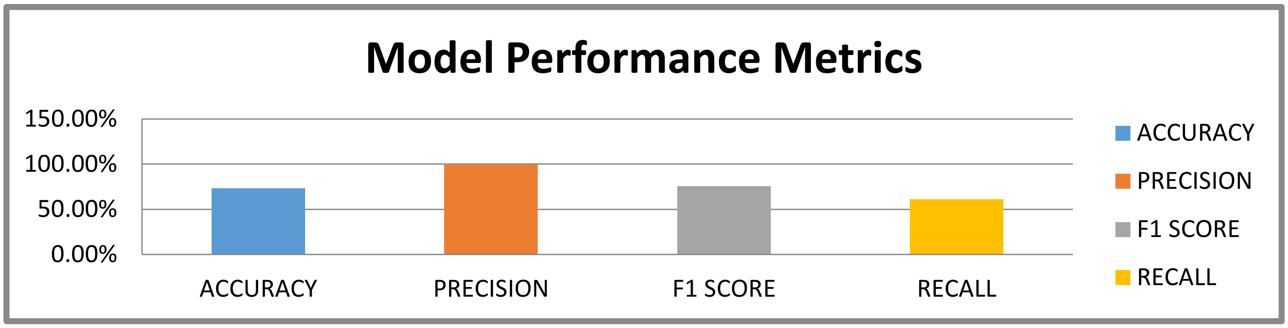

Figure 6: Bar Chart for Performance Metrics

Confusion matrices, also called error matrices, are certain table layouts used in machine learning that enable the visualization of algorithm performance, particularly in the context of statistical classification problems. Assuming a simplified scenario where an automated fault detection system categorizes faults into two classes: "Fault Present" and "No Fault Present," here's an example of a confusion matrix:

True Positive (TP): Cases where the fault detection system correctly predicts the presence of a fault when a fault is actually present.

i. False Negative (FN): Instances where the system fails to detect a fault when a fault is actually present.

ii. False Positive (FP): Occurrences where the system indicates a fault is present when there is no actual fault.

iii. True Negative (TN): Cases where the system correctly identifies the absence of a fault when there is no fault present.

Discussion

The table below show the data analysis and performance of the individual base learners, the fault classifier, and conduct an analysis of the results achieved using a fuzzy logic model using Mamdani algorithm. More specifically, our emphasis is on the application of fuzzy logic. The table displayed below offers a comprehensive summary of the Fuzzy Logic classifier's performance, including assessments of accuracy, precision, recall, F1 score, and training time.

3. RESULT AND DISCUSSION

The following outcomes are achieved after applying the random mamdani algorithm to the dataset:

Testing Data Output

The testing data accuracy is 73.14%, and the recall values for identified and undiscovered faults are 1.00 and 0.73, respectively. The car defect detection precision is 100%, accuracy is 73.14%, and the F1-score is around 75.72%.

```
Automobile Fault Detection

+----------------+----------------+
|   Metric       |   Value        |
|----------------|----------------|
|   Precision    |   1.00         |
|   Recall       |   0.50         |
|   Accuracy     |   0.734        |
|   F1-score     |   0.7578       |
+----------------+----------------+

True Positives (TP) | False Negatives (FN)
--------------------|--------------------
      1.00          |        1.00
```

Figure 7: Testing Data Output

Summary

The intelligent fault detection system using fuzzy logic emphasizes a creative use of intelligence and sophisticated technology in the automotive test kits industry. To correctly detect flaws in different car component parts, this mechanism combines a hybrid a computer-generated fuzzy logic algorithm with Mamdani's algorithm. It provides audiences with competent advice for replacement or repair of broken parts, including skilled workers and owners of motor vehicles.

4. CONCLUSION

These kinds of solutions, presenting a glimpse into the foreseeable future of automotive technology, not only strengthen the quality and security of cars but also open the door for groundbreaking improvements in the sector. The system has got the potential to completely change how we identify and address flaws with vehicles, resulting in safer roads and more competent cars. A large audience may access and utilize it easily because to its web-based architecture.

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