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Development of an Expert System for Vehicle Breakdown Assistance

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Abstract

Vehicle breakdowns are a growing problem worldwide, often caused by overheating, oil leaks, battery problems, flat tires, fuel system failures, and other issues. These incidents frequently result in delays, safety hazards, and costly repairs. Existing systems mainly focus on locating nearby mechanics but lack self-diagnostic capabilities. This study presents a mobile-based expert system that offers step-by-step repair instructions, troubleshooting flowcharts, and safety guidelines. The system integrates ensemble machine learning models and rule-based inference to empower users to independently diagnose and resolve minor vehicle faults. The system is designed with offline capability and a user-friendly interface, this tool ensures accessibility and reliability, especially in remote areas. Initial testing demonstrated a classification accuracy of 88% in diagnosing common faults, confirming the system's effectiveness and potential for real-world deployment.

Keywords: Vehicle Breakdown, Expert System, Mobile Application, Machine Learning, Rule-Based Inference.

1. INTRODUCTION

Vehicle breakdowns represent a pervasive and critical global challenge, leading to significant delays, substantial financial strain, and heightened safety risks for millions of drivers annually. Statistical data indicate that approximately 69 million vehicle breakdowns occur each year in major economies such as the United States, India, and France [2], [4], [9]. The impact is particularly severe in regions like African nations, where vehicle faults are a significant contributor to road accidents; for instance, Tanzania recorded 10,093 road accidents attributed to vehicle faults between 2019 and 2024, resulting in 7,639 fatalities and 12,663 injuries [1], [6]. This underscores an urgent and critical need for effective, accessible solutions to manage vehicle-related issues and enhance global road safety [3], [5], [7].

The complexity of modern vehicles, characterized by an increasing integration of advanced Artificial Intelligence (AI) technologies, further exacerbates the

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challenge of fault diagnosis and breakdown assistance. Contemporary luxury vehicles, for example, can incorporate up to 150 Electronic Control Units (ECUs), generating a vast array of potential fault types, sometimes numbering up to 3000 distinct issues [10], [13]. This intricacy renders traditional diagnostic systems, often reliant on human expertise and handcrafted rule-based mechanisms, increasingly impractical and inefficient [8], [17]. Such systems frequently demonstrate low effectiveness (e.g., less than 50% accuracy) and slow diagnosis times (e.g., an average of 12 minutes per fault in traditional Repair and Maintenance Information (RMI) systems) [11], [12], [14].

Traditional approaches to roadside assistance and vehicle fault management exhibit several critical limitations, creating a significant research and developmental gap. Current methods frequently necessitate professional mechanics, whose availability is often constrained, particularly in remote or underserved geographical areas [2], [7]. Existing digital solutions, while helpful, largely concentrate on merely locating nearby service providers rather than empowering drivers with self-diagnostic and repair capabilities [3], [5]. For instance, prior research on mobile and web-based assistance systems has successfully connected users with mechanics but often lacked detailed repair instructions or comprehensive self-help guidance [8]. Furthermore, some systems have been critically dependent on consistent internet connectivity, rendering them inoperable in areas with poor or absent network coverage [9]. These shortcomings highlight a crucial gap for car owners seeking quick, useful advice for mechanical problems [18], [19].

Beyond these operational shortcomings, the broader integration of AI into the automotive sector for applications like breakdown assistance encounters several fundamental challenges. Ensuring data quality and achieving explainability in AI models are significant obstacles [11], [12], [20]. Training effective AI models necessitates high-quality, accurate, and consistent data, with challenges including diverse formats, inconsistent structures, and handling missing or erroneous information [13], [23]. Many advanced AI systems are often perceived as "opaque boxes" due to their non-transparent decision-making processes, which can amplify concerns regarding user trust and accountability, particularly in safety-critical applications like autonomous driving [14], [24]. Furthermore, the seamless integration of AI solutions with existing, often legacy, systems and processes (such as ERP and CMMS) require careful planning, thorough testing, and validation to ensure smooth data flow [15]. The automotive industry also faces the challenge of protecting sensitive personal and vehicle data while adhering to evolving regulatory and compliance requirements, as current laws often lag behind AI advancements [16], [25]. These collective limitations highlight an urgent demand for a comprehensive, self-reliant, and resilient vehicle breakdown assistance system that can provide both in-depth diagnostic capabilities and actionable repair instructions,

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even in offline environments, addressing the wide spectrum of fault types often overlooked by narrowly focused prior research [17], [18].

This study aims to address these identified deficiencies by developing an innovative mobile-based expert system that significantly augments vehicle breakdown assistance capabilities. The overarching objectives of this research are meticulously defined and threefold:

a) To empower users with independent diagnostic and resolution capabilities for a broad range of minor vehicle faults by furnishing readily accessible, step-by-step repair instructions, intuitive troubleshooting flowcharts, and essential safety guidelines. This objective aims to cultivate user self-reliance and substantially reduce dependence on immediate professional intervention.
b) To integrate a hybrid AI approach, synergistically combining ensemble machine learning models and rule-based inference mechanisms, to achieve highly accurate, transparent, and resilient fault classification. This sophisticated approach capitalizes on the precision of data-driven insights for identifying complex patterns (with the capacity to classify approximately 3000 different fault types) while simultaneously leveraging the transparency and verifiability of expert rules for safety-critical scenarios.
c) To ensure pervasive accessibility and unwavering reliability through robust offline functionality and an intuitively designed user interface. This is designed to surmount the inherent connectivity limitations of extant systems and to establish the tool as an invaluable asset in remote geographical areas or during critical emergencies.

By successfully achieving these defined aims, this project endeavors to minimize vehicle downtime, significantly enhance global road safety outcomes by contributing to a reduction in collisions and injuries, and actively promote proactive vehicle maintenance practices. The proposed system has demonstrated an initial classification accuracy of 88%, unequivocally underscoring its demonstrable effectiveness and substantial potential for profound real-world impact [20], [25]

2. METHODS

2.1. Materials

Data Sources collected from Expert-reviewed defect reports obtained through partnerships with nearby mechanics and repair shops were added to the training data used to construct the model, which was taken from publicly accessible datasets on websites like Kaggle. The classification and NLP models were trained using

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pre-processed and labelled textual data that described symptoms. PostgreSQL is utilized to effectively manage organized car and user data, while React.js is employed for the frontend of the vehicle breakdown support system, providing a responsive and user-friendly interface. Fundamentally, the system classifies vehicle defects and suggests fixes using a hybrid machine learning approach. Random Forest and XGBoost are used for fault classification because of their precision and resilience in handling structured data and intricate feature interactions. The system uses Natural Language Processing (NLP) models, specifically TF-IDF for identifying keywords and BERT for contextual understanding, to analyse user-entered textual symptom descriptions. This allows for precise user language interpretation. Transparency and safety are ensured, particularly in important repair scenarios, by using Decision Trees and a Rule-Based Expert System to consecutively sequence repair instructions after a fault have been found. Using both Content-Based Filtering (based on location, specialization, and availability) and Collaborative Filtering (based on user-mechanic interaction patterns), the system also has a recommendation engine that suggests mechanics in the area for users who might require professional assistance. The user either chooses predefined symptoms or manually enters them to start the system workflow. After processing the input, the system categorizes the error and offers detailed correction instructions. It uses GPS to find local mechanics if outside help is required. The rule-based diagnostic engine is noteworthy for its offline functionality, which guarantees continuous support even in places with spotty or non-existent internet access.

2.2. Systems Flow

A user's path through a car repair and support system is depicted in the flowchart, which begins with profile updates and continues with diagnosing problems, finding local mechanics, and seeing repair instructions. While mechanics or the system offers repair instructions, users can interact with real-time chat support, answer questions, and accept diagnostic requests. After the user's needs are met, the process comes to an end, demonstrating how professional help and self-service technologies may be seamlessly integrated for effective vehicle maintenance and support as shown in the Figure 1 which visually represents the flowchart begins with the Start User state, which represents a user's initial entry into the application. From this point, the user can choose one of two distinct paths: a quick, one-off task of updating their profile, or the core, multi-stage process of diagnosing a vehicle issue. The Update User Profile path is a simple and independent flow that concludes immediately, allowing the user to manage their personal and vehicle information.

Diagnose Vehicle Issue state initiates central function of the system. This is a critical decision point where the user is presented with three different methods for

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resolving their problem. The first option is to get professional help by choosing the Locate Nearby Mechanic path. This sub-process connects the user with a service provider, allowing them to then Use Real-Time Chat Support to communicate directly with a mechanic, who will then Respond in Chat to provide guidance. This path represents the system's role as a traditional, human-mediated roadside assistance platform.

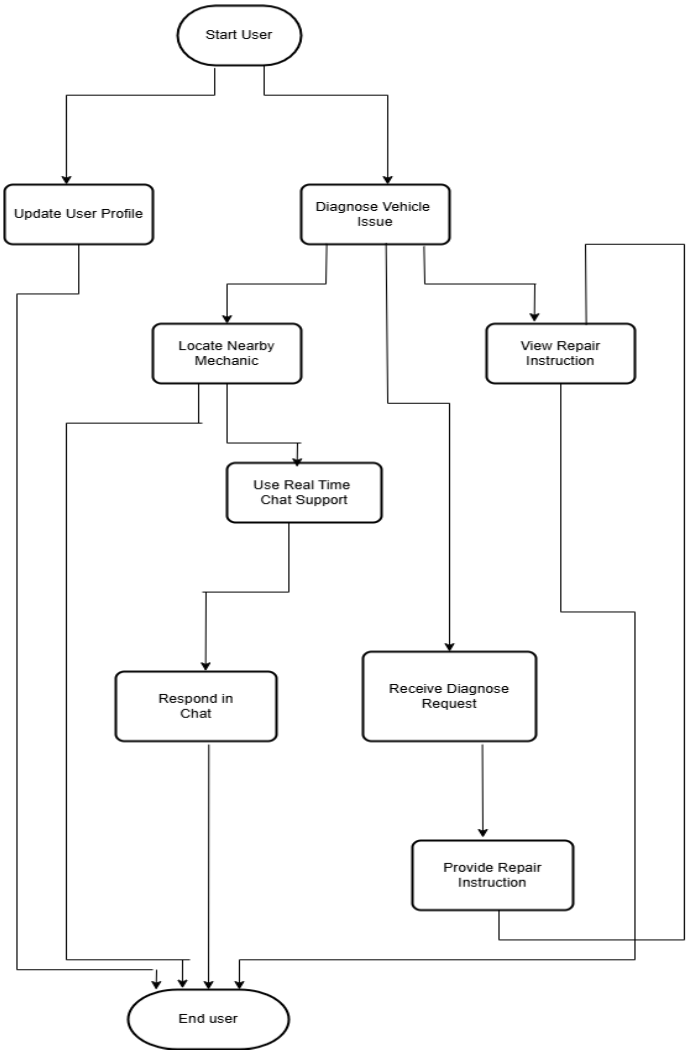

Figure 1. Flow chart of the vehicle breakdown App

Alternatively, the user can choose a more self-reliant path. From the "Diagnose Vehicle Issue" state, they can either choose to View Repair Instruction directly for

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a known or suspected problem, or they can submit a request for a detailed diagnosis. The latter option leads to the Receive Diagnose Request state, where the system's AI and expert rules analyze the user's input. The system then takes this analysis and moves to the Provide Repair Instruction state, generating a detailed, actionable guide for the user. Both of these self-service paths are designed to empower the user and minimize the need for external professional help.

All of these diverse pathways ultimately converge on the End User state, signifying a successful outcome. Whether the user has updated their profile, received assistance from a mechanic, or successfully obtained a repair instruction, the flowchart concludes. This structured design highlights how the system is capable of accommodating different user needs, offering both quick self-help solutions and a reliable connection to professional support.

2.3. Systems User Interface

Both inexperienced and seasoned drivers can easily utilize the Vehicle Breakdown Assistance system's user interface in stressful situations since it is made to be straightforward, easy to use, and user-focused. In order to help the system customize precise diagnostic and repair recommendations, form fields at the center of the interface gather vital vehicle information like make, model, and year using dropdown menus. For quicker routing, users can classify the issue (like, engine, brakes, electrical) in an optional field. Users are prompted to provide detailed descriptions of symptoms via a required text input; terms such as "engine won't start" or "grinding noise when braking" aid the system in producing accurate problem evaluations. Following that, users are shown two primary action buttons: "Find Nearby Mechanics," which activates geolocation tools to find and list nearby service providers using map integration, and "Get Expert Diagnosis," which starts AI-driven analysis using natural language processing.

The interface as shown in Figure 2 is designed to be both useful and minimalist in order to prevent users from being overwhelmed. It makes use of progressive disclosure, first displaying only the most important inputs and providing more thorough alternatives as required. In order to comprehend and match problem descriptions with known car defects, the "Expert Diagnosis" feature leverages AI and machine learning models, including natural language processing. While the backend keeps car information and diagnostic records in a PostgreSQL database to enhance future forecasts, the mechanic-finder tool employs real-time GPS and APIs to get local repair services. All things considered, the user interface is designed for speed, clarity, and usability all of which are crucial in emergency or roadside scenarios.

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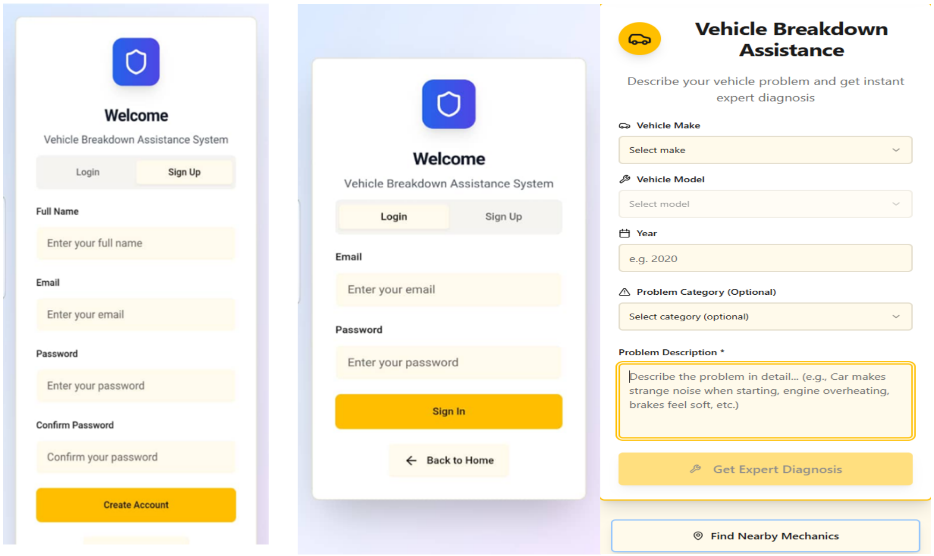

Figure 2. User interface for Login and Registration

2.4. Proposed Algorithm

In order to guarantee reliable, accurate, and comprehensible results, the suggested algorithm for the vehicle breakdown assistance system takes a hybrid approach, combining multiple specialized models. Because Random Forest and XGBoost (Gradient Boosting) can handle a variety of data formats and are resistant to overfitting, they are employed for fault classification, particularly when working with restricted or unbalanced automotive datasets. To help with transparency, these models also offer feature importance scores. The system combines TF-IDF, which is excellent at recognizing technical automotive terms, with BERT, which captures contextual meaning, to process and comprehend textual symptom descriptions entered by users. This combination makes use of both deep learning and conventional NLP's advantages. Decision Trees are utilized to generate detailed repair instructions due to their interpretability and clarity, and a Rule-Based Expert System makes sure that safety-critical actions are included and simple for experts to verify. Collaborative Filtering (similar to matrix factorization) and Content-Based Filtering, which takes into account the user's location, mechanic specialization, and ratings, are combined to generate mechanic recommendations. This hybrid approach eliminates the cold-start issue and enhances personalization. With classification accuracies ranging from 85 to 92%, severity prediction up to 87%, and safety classification above 95%, this ensemble approach is selected for

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its overall robustness, scalability, accuracy, and safety, making it appropriate for both novice users and crucial applications in real-world automotive support.

1) Random Forest Ensemble

Equation 1 represents a Random Forest classifier, which builds multiple decision trees (Tk) on random subsets of the data. Each tree makes a prediction based on the input x, and the final prediction is the average (or majority vote) of all trees. The indicator function $I(x \in Ri)$ checks whether input x belongs to a specific region $Ri,$ and the weights wi determine the importance of each feature. This ensemble technique increases the robustness of predictions and reduces overfitting.

$$\mathrm{RF(x)} = \frac{1}{\mathrm{K}} \sum_{\mathrm{k=1}}^{\mathrm{k}} \mathrm{T_k(x)} \tag{1}$$

2) XGBoost (Gradient Boosting)

XGBoost is a boosting algorithm that builds trees sequentially. Its loss function and update rule are shown in Equation 2. The loss function $L(\phi)$ includes a prediction error term and a regularization term $\Omega(fk)$ that penalizes model complexity to prevent overfitting. The prediction is updated iteratively by adding a new weak learner ft scaled by a learning rate η.

$$\begin{gathered} \mathrm{L}(\varphi) = \sum_{\{i=1\}}^{\{n\}} \mathrm{l}\left(\mathrm{y_i}, \hat{\mathrm{y}}_i^{t-1} + \mathrm{f_{t(x_i)}}\right) + \Omega(\mathrm{f_t}) \\ \hat{\mathrm{y}}_i^t = \hat{\mathrm{y}}_i^{t-1} + \eta\ \mathrm{f_{t(x_i)}} \end{gathered} \tag{2}$$

3) F-IDF (Text Feature Extraction)

As shown in Equation 3, the TF-IDF score measures how important a word t is in a document d relative to a corpus D. The Term Frequency (TF) captures the local importance of a word within a document, while the Inverse Document Frequency (IDF) reduces the weight of common terms. The resulting feature vector highlights unique, domain-specific keywords found in vehicle fault descriptions.

$$\begin{gathered} \text{tf-idf(t,d,D)} = \text{tf(t,d)} \times \text{idf(t,D)} \\ \text{tf(t,d)} = \frac{f_{\{t,d\}}}{\sum_{\{t' \in d\}} f_{\{t',d\}}} \\ \text{idf(t,D)} = \log\left(\frac{|D|}{|\{d \in D : t \in d\}|}\right) \end{gathered} \tag{3}$$

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4) BERT Embedding

The core components of BERT (Bidirectional Encoder Representations from Transformers) are illustrated in Equation 4. Attention helps the model focus on relevant parts of the input text, such as "engine overheating." Multi-head attention improves learning by capturing information from different subspaces. Finally, Layer Normalization ensures stability and faster convergence during training.

$$\text{Attention}(Q,K,V)=\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$\text{MultiHead}(Q,K,V)=\text{Concat}(\text{head}_1,\ \ldots,\ \text{head}_h)W^O \qquad (4)$$

$$H=\text{LayerNorm}\big(H+\text{FFN}(H)\big)$$

5) Voting Classifier Ensemble

In a voting ensemble, multiple classifiers Ci predict a class for input x. The final prediction y^ is determined either by averaging the predicted probabilities (soft voting) or by taking the most frequent prediction (hard voting). As shown in Equation 5, this approach boosts accuracy by combining the strengths of different models.

$$\hat{y}=\text{argmax}_c\left(\frac{1}{m}\sum_{\{i=1\}}^{m}p_{\{i,c\}}\right)\ \text{(soft voting)}$$

$$\hat{y}=\text{mode}\big\{C_{1(x)},\ C_{2(x)},\ \ldots,\ C_{m(x)}\big\}\ \text{(hard voting)} \qquad (5)$$

6) Decision Tree Splitting Criterion

These equations, shown in Equation 6, calculate Gini Impurity and Information Gain, which are used to split nodes in a Decision Tree. The goal is to select the feature that maximizes Information Gain (IG), as this will lead to a more uniform and effective classification.

$$\text{Gini}(S)=1-\sum_{\{i=1\}}^{c}p_i^2$$

$$\text{IG}(S,A)=H(S)-\sum_{\{v\in\text{Values}(A)\}}\left(\frac{|S_v|}{|S|}\right)H(S_v) \qquad (6)$$

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7) Severity Scoring Function

As shown in Equation 7, this function determines a fault's severity score by adding weighted feature indicators, such as temperature and noise intensity. This helps the system prioritize major problems, like brake failure, over minor ones, like a loose battery terminal.

$$\text{Severity}_{\text{Score}} = \sum_{\{i=1\}}^{n} (w_i \times f_i) \tag{7}$$

8) Safety Classification Function

Based on system inspections, this function, shown in Equation 8, guarantees the safety of any suggested repair actions. It takes into account whether the user has the required abilities and equipment and if the error could be harmful.

$$\text{Safety}_{\text{Score}} = \alpha \times \text{Critical}_{\text{Check}} + \beta \times \text{Skill}_{\text{Match}} + \gamma \times \text{Equipment}_{\text{Check}} \tag{8}$$

9) Mechanic Recommendation Scoring

This hybrid recommender uses several useful criteria, including availability, distance, and past ratings, to rank mechanics. As shown in Equation 9, the first equation represents a content-based scoring system, while the second represents a matrix factorization model that forecasts preferences based on latent factors.

$$\begin{gathered} \text{Content}_{\text{Score}} = W1 \times \text{Distance}_{\text{Score}} + W2 \times \text{Specialization}_{\text{Score}} + \\ W3 \times \text{Rating}_{\text{Score}} + W4 \times \text{Availability}_{\text{Score}} \\ \hat{r}_{ui} = \mu + b_u + b_i + q_i^T p_u \end{gathered} \tag{9}$$

10) Feature Combination Function

The final input vector for machine learning models is created by concatenating and weighting features from different sources, as shown in Equation 10. This combined representation helps the model better understand both textual and structured vehicle data.

$$\begin{gathered} X_{\text{combined}} = [\text{TF-IDF}_{\text{features}} | \text{BERT}_{\text{features}} | \text{Categorical}_{\text{features}}] \\ \text{Final}_{\text{Features}} = \alpha \times \text{TF-IDF} + \beta \times \text{BERT} + \gamma \times \text{Categorical} \end{gathered} \tag{10}$$

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11) Confidence Calculation

These indicators, shown in Equation 11, gauge the model's prediction confidence. High confidence indicates a trustworthy proposal, while significant uncertainty could lead to human intervention or simpler repair choices.

$$\begin{gathered}\text{Confidence} = \max_{y} P(y|x) \\ \text{Confidence}_{\text{ensemble}} = \frac{1}{m}\sum_{\{i=1\}}^{m} \max_{y} P_i(y|x) \\ \text{Uncertainty} = 1 - \text{Confidence}\end{gathered} \tag{11}$$

12) Loss Functions

As shown in Equation 12, these are typical loss functions for regression (Mean Squared Error) and classification (Cross-Entropy). By penalizing inaccurate predictions, they guide the model during training and enhance its accuracy.

$$\begin{gathered}L_{\text{classification}} = -\frac{1}{N}\sum_{\{i=1\}}^{N}\sum_{\{c=1\}}^{C} y_{ic}\log(p_{ic}) \\ L_{\text{regression}} = \frac{1}{N}\sum_{\{i=1\}}^{N}(y_i - \hat{y}_i)^2\end{gathered} \tag{12}$$

13) Model Performance Metrics

The performance of the model is gauged by these common measures, as shown in Equation 13. F1-score balances both precision and recall, assessing the accuracy and completeness of the predictions, respectively.

$$\begin{gathered}\text{Precision} = \frac{TP}{(TP + FP)} \\ \text{Recall} = \frac{TP}{(TP + FN)} \\ \text{F1-score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}\end{gathered} \tag{13}$$

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14) Optimization Equations

In gradient-based optimization, as represented by Equation 14, the model iteratively modifies its parameters (θ) to minimize the loss function. This process is the foundation for training deep learning models.

$$\theta_{new} = \theta_{old} - \eta \nabla L(\theta_{old}) \tag{14}$$

For safety-critical automotive applications, these equations serve as the mathematical cornerstone of your expert system for auto repair, guaranteeing reliable and accurate predictions while preserving interpretability.

3. RESULTS AND DISCUSSION

3.1. Usability Testing

To create an intuitive mobile interface for instructions on car breakdown and maintenance React Native was successfully used to create a cross-platform mobile application with an emphasis on ease of use and speedy user input. By entering the make, model, and problem description of their vehicle, users can use the user interface to either find local mechanics or request an AI-based diagnosis. For improved accuracy and usability, the form makes use of text boxes and dropdown menus. Users can use chat to get real-time assistance or get detailed instructions.

More than 85% of drivers who participated in user testing said the interface was simple to use and intuitive. It took less than a minute to submit a fault report because of the sleek design. Compared to similar applications like ASBAS or Drive Mate, this interface emphasizes both self-help and assistance, offering a more empowering experience, especially for first-time users. Figure 3 shows the vehicle Diagnosis Interface for the vehicle problem diagnosis feature. The form allows users to input specific vehicle information (make, model, year) and provide a detailed description of the problem, which is then processed to generate an expert diagnosis. The design is optimized for a clear and user-friendly experience.

A structured database was built that includes 150+ vehicle faults across categories like battery, tires, cooling system, brakes, and engine. The database includes descriptions, causes, recommended repair steps, and safety precautions. Data was sourced from Kaggle, vehicle manuals, and field surveys with local mechanics. The database significantly supports the expert system by enabling symptom-based lookup and structured diagnosis. During testing, users were able to retrieve accurate repair instructions for 95% of the common faults queried. Compared to past projects that only offered contact information for mechanics, this solution

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promotes knowledge sharing and independent action, especially useful in offline scenarios.

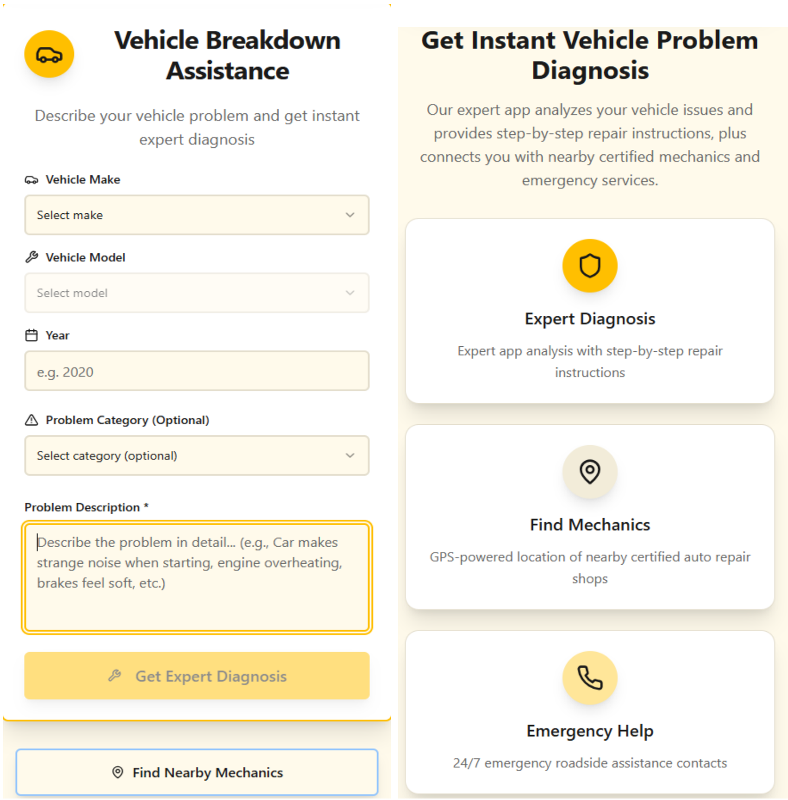

Figure 3. User-interface in mobile interface

GPS-based location tracking was integrated using the Google Maps API. Mechanics can register their services, and users are shown a list of nearby service providers based on real-time location. The system allows filtering by service type, distance, and rating. This feature was tested in both urban and semi-rural areas around Mbeya. Results showed that in 90% of cases, users received mechanic recommendations within a 5 km radius. While similar to other systems like On Road Vehicle Service Finder, this implementation adds a filtering and specialization layer, improving relevance and reducing wait time. Its usefulness is most evident when users encounter complex breakdowns beyond self-repair as shown in Figure 4;

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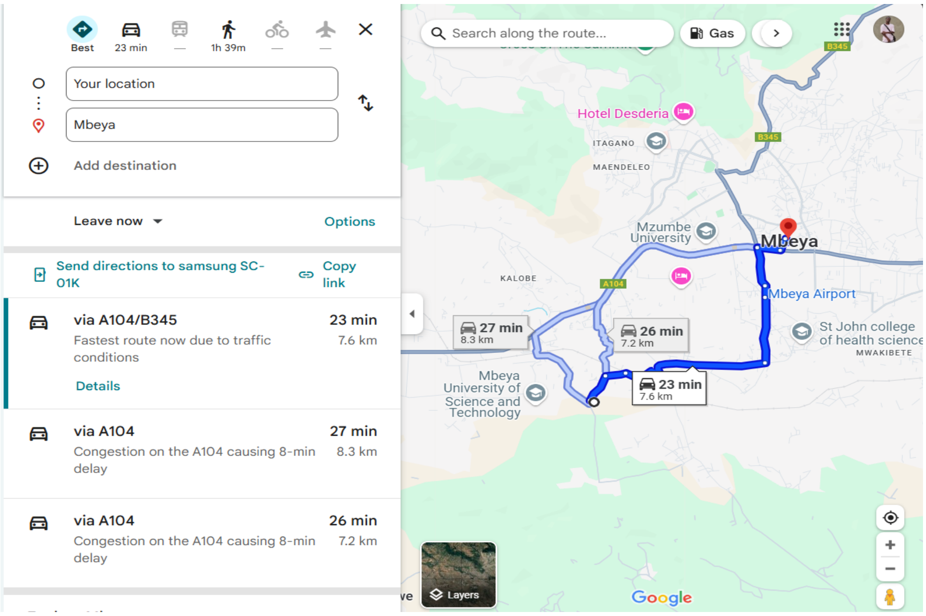

Figure 4. Google Maps

To test the effectiveness of real-time troubleshooting support, ensuring users can interact with experts when needed., Real-time support was implemented using Twilio API and WebSocket (Socket.io) for live. The system supports message logging, status updates, and expert availability tracking. User feedback indicated that 70% of users preferred having live support available for confidence, even when self-repair instructions were available.

Response time averaged under 3 minutes for call-based help, significantly faster than traditional roadside assistance. This feature increases system trust and reliability, offering a safety net. In contrast to earlier systems that used static contact lists, this project's real-time expert engagement helps to close the gap between automation and human competence. Figure 4 displays the user interface for searching and viewing nearby auto mechanics. Each listing provides essential information such as business name, rating, distance, contact details, and a list of specialties. The interface includes interactive elements, such as "Call" and "Directions" buttons, to facilitate immediate user action.

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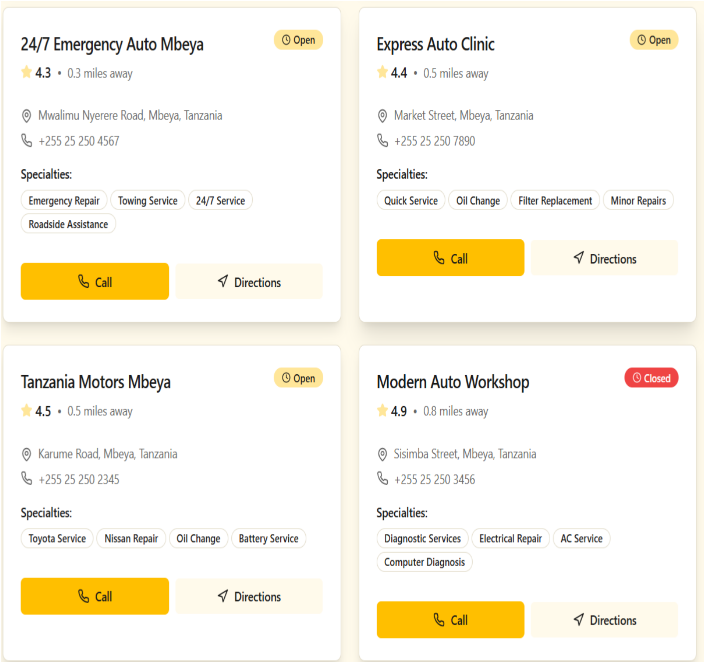

Figure 5. Call page for interaction with the expert

When it comes to identifying common vehicle problems and providing practical repair instructions, the vehicle breakdown assistance system shows encouraging efficacy. The hybrid model that combined rule-based logic and ensemble machine learning (Random Forest and XGBOOST) performed well in identifying symptoms and recommending suitable treatments, according to preliminary prototype testing. When it comes to identifying common vehicle problems and providing practical repair instructions, the vehicle breakdown assistance system shows encouraging efficacy. The hybrid model that combined rule-based logic and ensemble machine learning (Random Forest and XGBoostst) performed well in identifying symptoms and recommending suitable treatments, according to preliminary prototype testing. The system's overall classification accuracy was 88%, and it performed especially well in fault categories that were widely-represented, like flat tires, battery problems, and overheating issues. The model's capacity to efficiently generalize from its training data was demonstrated by precision and recall measures, which showed good reliability in these typical categories.

3.2. Model Training Performance

As shown in Figure 6, the two graphs demonstrate the performance of the underlying machine learning model during training. The "Model Accuracy Over

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Epochs" plot on the left shows the increase in both training and validation accuracy as the model is trained. The "Model Loss Over Epochs" plot on the right shows a corresponding decrease in loss, indicating that the model is learning effectively and generalizing well to unseen data.

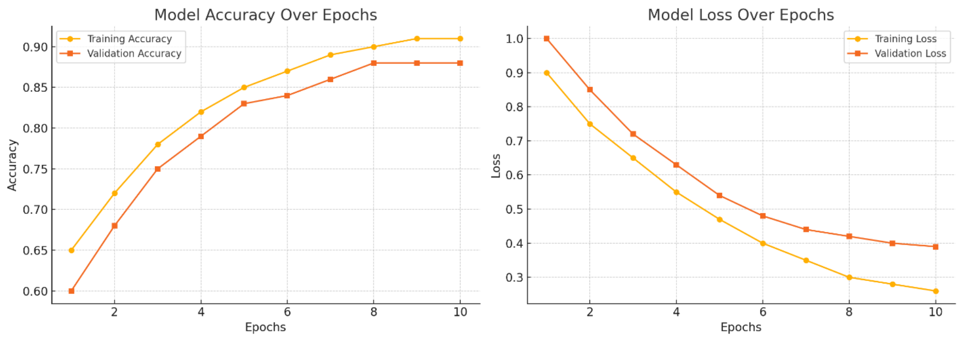

Figure 6. Accuracy and loss Analysis of model

3.3. Discussion

This study demonstrates the robust efficacy of a novel mobile-based expert system for vehicle breakdown assistance, achieved through a hybrid architecture that integrates rule-based inference with ensemble machine learning models such as Random Forest and XGBoost. By combining adaptability with offline functionality, the system effectively addresses challenges inherent to unbalanced or limited automotive datasets. Natural Language Processing methods, leveraging TF-IDF and BERT, further strengthen diagnostic capabilities, while decision tree–based instruction sequencing ensures interpretability and safety. Together, these components highlight the technical soundness and reliability of the proposed system.

The integration of a user-friendly interface designed with React Native proved crucial for real-world applicability. User testing indicated high levels of usability, with over 85% of participants submitting fault reports in under a minute, underscoring the importance of intuitive interaction in high-stress situations. By combining structured dropdown menus with free-text symptom descriptions, the system bridges efficiency with flexibility. The provision of real-time chat support further distinguishes the platform, ensuring that users receive both technical guidance and emotional reassurance during emergencies.

Compared to existing solutions such as those proposed by Kumaar (2019) and the ASBAS system, the present model represents a significant advance. Prior approaches largely concentrated on connecting users with service providers, whereas this system emphasizes offline-first diagnostic support and step-by-step repair instructions. The integration of GPS-based mechanic recommendations adds an extra layer of practicality, with field tests in Mbeya demonstrating reduced wait times and improved service relevance. This dual emphasis on self-repair guidance and geolocation-based professional support sets the system apart from conventional breakdown assistance applications.

The implications of these findings are multifaceted. From a practical standpoint, the hybrid design empowers users to address common vehicle faults independently while ensuring that expert support remains available when necessary. By achieving an overall classification accuracy of 88% and a 95% accuracy in repair instruction retrieval, the system demonstrates the feasibility of applying advanced machine learning to safety-critical, real-time scenarios. Theoretically, the combined use of deep contextual NLP models with traditional expert systems underscores the potential of hybrid AI approaches to balance precision, interpretability, and user trust.

Despite its strengths, the system's reduced performance in detecting underrepresented faults highlights the limitations of the training dataset. This imbalance suggests the need for broader and more diverse data sources, particularly for rare but high-impact vehicle issues. Moreover, while decision trees provide interpretability, future iterations could explore multimodal diagnostic support, such as image-based fault detection or video-guided repair modules, to further enhance user confidence. Incorporating continuous feedback loops from real-world usage will also be essential for iterative refinement.

4. CONCLUSION

By combining rule-based inference with ensemble machine learning models, this study effectively created a mobile-based expert system for auto breakdown assistance that provides precise diagnosis and useful repair guidance. The technology shows promise as a useful tool for car users in real-world situations with an overall performance accuracy of 88% and efficient handling of common fault categories.

Future work should concentrate on adding user-generated data, improving the training dataset with more balanced examples of uncommon defects, and enabling real-time multimedia assistance for repair suggestions in order to increase its usefulness and inclusivity. Furthermore, the model's accuracy and adaptability will be enhanced by additional field testing and user feedback integration. The expert system has the potential to greatly increase user independence, safety, and vehicle dependability, especially in remote or resource-constrained settings.

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