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An Intelligent Conversational Assistant for Automobile Fault Diagnostics

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Abstract

Significant changes are sweeping through the worldwide automobile industry, which can largely be attributed to developments in Artificial Intelligence applied to vehicle maintenance. Artificial Intelligence techniques are used in fields like predictive maintenance, predictive quality, safety analytics, and warranty analytics. The system creates valuable insights from the data generated on these vehicles to help us predict and prevent failures. This technology can predict the remaining useful life and detect failures or degradation in performance at an early stage. However, despite the fact that the automotive industry has undergone profound transformations fueled by technological advancements, traditional methods of vehicle diagnostics continue to present significant challenges for both car owners and mechanics alike. Therefore, this study aims to develop an Intelligent Conversational Assistant for automobile fault diagnostics. The application was developed using the Google's Android Studio IDE in conjunction with the Kotlin programming languages for Android development. The study demonstrates the potential of Artificial Intelligence and natural language processing technologies in automotive diagnostics, in terms of better diagnostic accuracy, and improved positive user experience.

Keywords: Artificial Intelligence, Chatbots, Natural Language Processing, Android

Introduction

Significant changes are sweeping through the worldwide automobile industry, which can largely be attributed to developments in Artificial Intelligence (AI) applied to vehicle maintenance. AI techniques are used in fields like predictive maintenance (PdM), predictive quality, safety analytics, and warranty analytics. Several terminologies have been used to explain the evolution of AI capabilities in ensuring that components, products, and systems are healthy: E-maintenance, prognostics and health management, Maintenance, or smart maintenance [1]. Vehicle fault diagnosis (VFD), also known as vehicle diagnostics, is an essential yet challenging part of automotive maintenance that involves capturing and analyzing signals from different vehicle systems to find causes or failures [2]. Sensors and software monitor vehicle state, detect performance deviations in need of attention, predict or identify problems associated with those disturbances earlier than would be possible otherwise, and give recommendations on what service measures are needed to decisively allow for capturing costs through problem identification/resolution. The system creates valuable insights from the data generated on these vehicles to help us predict and prevent failures. This technology can predict the remaining useful life (RUL) and detect failures or degradation in performance at an early stage. As modern vehicles get increasingly complex, this leads to issues with existing rule-based systems and onboard diagnostics (OBD) being accurate while being cost-efficient and timely [3].

Voice assistant technology is a type of software that uses artificial intelligence (AI) to understand and respond to spoken commands. Voice assistants can be found on many devices, including smartphones, speakers, tablets, and smartwatches. Some examples of voice assistants include Amazon's Alexa, Apple's Siri, Google Assistant, and Microsoft's Cortana. Voice assistants work by using text-to-speech (TTS) to convert preprocessed text into a sequence of waveform blocks that create the voice of the voice assistant [4]. Voice assistants can be used in many different ways, including:
At home; to control other devices, play music, and check bank balances. In healthcare; to help doctors diagnose strokes and access patient records. In business; to offer personalized shopping recommendations, gather customer feedback, and automate administrative tasks. In cars; to enhance in-car infotainment and improve driver safety, and in banking: to handle inquiries and enable secure voice-activated transaction just to mention a few.

However, despite the fact that the automotive industry has undergone profound transformations fueled by technological advancements, yet traditional methods of vehicle diagnostics continue to present significant challenges for both car owners and mechanics alike. Some of the imperative need for innovative solutions include: Time-Consuming Processes requiring manual inspection and analysis by trained professionals, Limited Accessibility particularly in remote or underdeveloped regions, Dependence on Professional Assistance for professional even minor mechanical issues, and Risk of Misdiagnosis due to Human error and subjective judgment, and this is why this study aims to develop an AI-driven Conversational Assistant for automobile fault diagnostics tailored for automotive diagnostics, providing car owners with accessible, efficient, and accurate solutions to common vehicle issues [4-6]. The rest of this paper is structured as follows: in section 2, a brief literature review is presented, whilst section 3 outlines the materials and methodology applied in the study. Section 4 presents the results obtained and discussion and section 5 concludes the study.

Literature Review

The adoption of artificial intelligence (AI) in automotive diagnostics in terms of theories and models, as well as the nature of the several implementations of AI technologies have been discussed in literature. Relevant theories in existing literature include the Integrated fear acquisition theory as well as the Actor-network theory (ANT) [7,8].

The core of the theoretical background of this study is the Integrated fear acquisition theory referring to the use of AI. As technology advances, we have to admit that AI has surpassed humans in many aspects. Hence, AI anxiety has become a widespread universal phenomenon, which may generate a series of social issues. Integrated fear acquisition theory [8] combines Rachman's (1977) fear acquisition theory and Menzies and Clarke's (1995) non-correlated fear acquisition theory. It illustrates four pathways of AI anxiety acquisition and each pathway includes two factors. The Conditioning pathway includes privacy violation anxiety and bias behavior anxiety, the Vicarious exposure pathway includes job replacement anxiety and learning anxiety, the Transmission of information and instruction pathway includes existential risk anxiety and ethics violation anxiety, and the Inability to recall a pertinent experience pathway includes artificial consciousness anxiety and lack of transparency anxiety [8]. The theory explains eight AI anxieties factors that set the foundation of people's attitudes toward AI, as follows: Privacy violation anxiety: It happens when users face direct privacy breaches by AI. Some unsupervised AI such as targeted advertising and face recognition may cause the anxiety about infringement on personal privacy [8]. Bias behavior anxiety: It occurs when AI adopts different strategies for different groups through data analysis, resulting in large-scale group discrimination, which can make the discriminated groups feel that they are being treated unfairly and cause anxiety. Job replacement anxiety: It is caused by observing others experiencing or worrying about being replaced by AI, which is related to people's concerns that AI will replace humans in a wide range of occupations. Learning anxiety: It is also caused by observing others experiencing or learning AI. Since AI is an algorithmic technology, people may find it difficult and complicated to learn [9]. Existential risk anxiety: It imagines that all intelligent life on Earth will lose its potential for survival, having the risk of extinction [10]. The risk of super AI is destroying humanity and causing rapid evolution of AI [11]. Ethics violation anxiety: It suggests that AI may exhibit behaviors that violate human ethical rules when interacting with humans [12]. The boundary between AI and humans will become increasingly blurred, followed by a series of ethical issues. So, it is necessary to ensure that the behavior between AI and humans complies with ethical standards, otherwise, it will lead to anxiety. Artificial consciousness anxiety: It refers to people's innate anxiety about the possibility that artificial consciousness may undermine the uniqueness of human intelligence [13]. It is assumed to be possible for AI to produce artificial brains with human-like consciousness which may lead to some problems during its interaction with humans. Since humans' status has been challenged, the boundary between AI and humans may also further blur. Lack of transparency anxiety: It refers to the innate anxiety about the unknown aspects of AI decision-making mechanisms [14]. These arguments suggest that a lack of transparency will cause the mechanism of AI operations and its decision-making process to be unclear, making it impossible to predict AI behavior.

The Actor-network theory (ANT) is a social theory that can be used to analyse and explain social and technological systems, including information and communication technologies, infrastructure systems, organisations, and more. The networks which can be an idea, an organisation or a technology consist of actors and all actors, whether human or non-human, are given the same value and agency within a network. Non-human actors can include objects and concepts that have an impact on actors within the network. The relationship between the actors is more important than their features or existence [15]. The use of ChatGPT as an actor within a network can be particularly relevant in contexts where ChatGPT is integrated into social or technological systems, such as in the case of implementing CAI into internal work processes. To focus on a particular network, actors can be "black-boxed," which treats the network as a distinct entity with specific inputs, outputs, and relationships within the whole network. The idea behind blackboxing is to simplify the analysis of complex systems by treating them as a single entity rather than examining all of their individual components [15].

“Translation” is a key concept in ANT and means the process in which various actors in a network are transformed to achieve a shared goal [16]. A new technology is for example added into a network and does not fit, which requires an actor having to change, for example the behaviour of humans or a function of a non-human actor such as a system. After the change is accomplished the network can be considered working towards a shared goal.

The concept of translation highlights the importance of non-human actors in shaping social phenomena. ANT recognizes that social and technological systems are neither simple nor structured, but are made up of many interacting actors who shape and influence each other. This way of looking at these interactions between humans and non-humans can be useful when dealing with systems that are difficult to understand or where there are many stakeholders and interests [16].

In another vein, there are few studies in literature, on the use of Intelligent Conversational Assistant for automobile fault diagnostics mainly on technologies such as Predicting maintenance in vehicles as well as AI Chatbots in Automotive Diagnostics [17-23]. The authors reported that solutions like remote diagnostics and monitoring are typically combined with predictive maintenance and other services like vehicle positioning and remote road-side assistance. Commercial vehicle manufacturers have not yet put any advanced predictive solutions on the market. Simpler predictive maintenance solutions exist, where wear and usage of brake pads, clutches and similar wear-out equipment is monitored and projected into the future. All of these are based on data streams being aggregated onboard and transmitted to back-office system. Mercedes in 2014 and MAN in 2014, among others, offered direct customer solutions for preventive maintenance recommendations and remote monitoring. Volvo has chosen to incorporate predictive maintenance as dynamic maintenance plans offered in conjunction with service contracts. Volvo also in 2014 made advances in Remote Diagnostics by predicting the most likely immediate repair given a set of diagnostic trouble codes (DTC). Active DTCs are sent wirelessly over the telematics gateway to a back-office service team which, both manually and automatically, deducts the most probable cause of failure. Further, services like repair, towing and truck rental is offered to the customer. This is not predictive maintenance as such, as it does not comprehend any future failures. It is still a valuable service which reduces downtime and saves money. The passenger car industry is surprisingly ahead of the commercial vehicle manufacturers in predicting maintenance. Commercial vehicles, i.e. trucks, buses and construction machines, are designed for business purposes where total cost of ownership is generally the most important aspect. Passenger cars on the other hand, are designed and marketed to appeal the driver's feelings for freedom, speed and so on. There are several published attempts of offering predictive maintenance solutions. The level of maturity varies from pilot studies to in-service implementations. Volkswagen, BMW and GM all developed methods in 2014 to predict future maintenance needs based on telematics solutions and on-board data. VW and BMW offer predictive maintenance as a maintenance solution for an owner, while GM, through the OnStar portal, publishes recommended repairs [17-23]. As for AI Chatbots in Automotive Diagnostics, R. Wan and colleagues in 2017 In their work, explored the application of AI chatbots in the automotive industry, focusing on diagnostics and maintenance. The study highlighted the potential of chatbots in providing real-time assistance to users in identifying and addressing car issues [23]. M. Zhang, and colleagues in 2019 also investigated the use of machine learning algorithms in chatbots for automotive diagnostics [19]. The authors assessed the effectiveness of these algorithms in accurately identifying common car problems and providing relevant solutions.

Methodology

This section will present the research methodology used this study to achieve its aim on the design of an AI-driven Conversational Assistant tailored for automotive diagnostics in the form of an experimental research design.

Materials and methods

An iterative development approach, comprising multiple phases of design, implementation, testing, and refinement, as well as an agile software development approach comprising of digestible sprints or iterations, which allows for quick iteration, feedback integration, and requirement adaption was adopted by this study. Using platform-specific technologies and frameworks, our mobile application is created as a native app, tailored for a single platform (like iOS or Android). This strategy guarantees peak performance, a native user interface, and a smooth interaction with the features and functionalities of the device. Furthermore, Google's Android Studio IDE in conjunction with the Kotlin programming languages for Android development. A whole range of tools for developing Android apps, such as code editing, debugging, testing, and performance analysis, are provided by Android Studio. The user interface (UI) of the mobile application is created utilizing native UI components and platform-specific design guidelines (iOS or Android). This guarantees excellent performance across many devices and screen sizes, familiar navigation patterns, and compliance with platform conventions

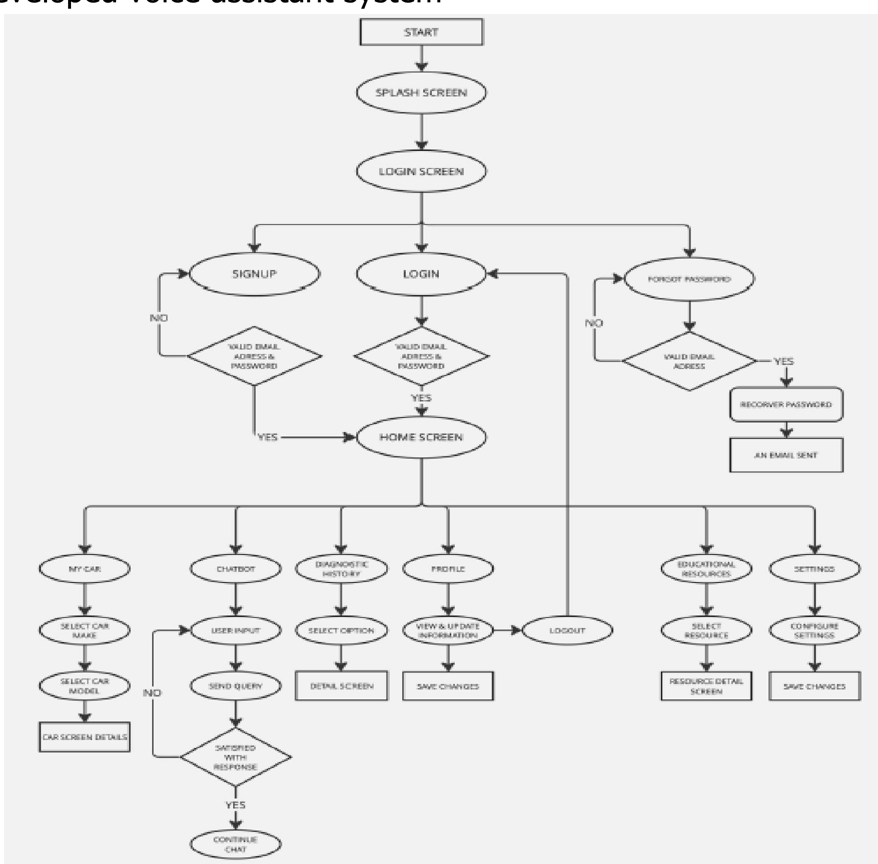
System Architecture

The flowchart below illustrates the user journey through the app, detailing each step from onboarding to interacting with the voice assistant.

Natural Language Understanding (NLU): To comprehend user queries, extract important entities, intents, and context, and produce organized models for further processing, we implement NLU components. To improve NLU capabilities, methods like sentiment analysis, entity recognition, and intent categorization are used.

Conversational AI: By utilizing natural language processing (NLP) techniques, we provide conversational AI features that allow the voice assistant to converse with users in a natural and relevant setting. To enable smooth interactions and preserve conversational flow, dialogue management, answer creation, and context retention technologies are incorporated.

Furthermore, intelligent algorithms such as Machine Learning methods, more specially Reinforcement Learning Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbor, K-Means Clustering will be selected for conducting extensive testing for diagnostic accuracy of the developed voice assistant system



The flowchart above illustrates the user journey through the DriveDoc app, detailing each step from onboarding to interacting with the chatbots.

System (DriveDoc app) **design**

The DriveDoc app was developed using the Thunkable platform, an android development platform, chosen for its user-friendly, no-code interface that is ideal for beginners. The app's architecture is modular, with distinct components for user authentication, car selection, chatbots interaction, and educational resources.

Components

User Authentication: Email/password, social media, and phone number sign-up/sign-in methods. Car Selection: A feature allowing users to select their car make and model, which customises the diagnostic process. Chatbot Interface: Integrates with OpenAI's ChatGPT for natural language processing and AI-driven car diagnostics. Educational Resources: A library of car maintenance tips and troubleshooting guides.

Main dashboard

The main dashboard features a bottom navigation drawer with three primary sections: Home, History, and Profile. Home: Users can access the main features of the app, including My Car, Launch Chatbot, and Educational Resources. History: Displays a list of previous diagnostic sessions, allowing users to review past interactions and solutions. **Profile**: Users can manage their personal information, app settings, and access help and support.

Chatbot Interaction

The chatbot interaction is a critical component of the DriveDoc app, designed to facilitate a seamless, intuitive user experience for diagnosing car issues. This section provides a detailed explanation of the chatbot's features, its integration with AI and NLP technologies, and its user interface. The chatbot in DriveDoc is powered by OpenAI's ChatGPT, which utilizes advanced natural language processing (NLP) algorithms to understand and respond to user queries. This integration allows the chatbot to comprehend complex user inputs, interpret various car-related symptoms, and provide accurate, contextually relevant diagnostic advice.

Natural Language Understanding (NLU): The chatbot uses NLU to interpret the user's descriptions of car problems, identifying key symptoms and potential causes. Machine Learning: Leveraging machine learning, the chatbot improves its diagnostic accuracy over time by learning from user interactions and feedback. Knowledge Base: The chatbot accesses a comprehensive database of common car issues, maintenance tips, and troubleshooting procedures to offer precise and reliable solutions.

User Interface & Interaction flow

The chatbot interface is designed for simplicity and ease of use, ensuring that users can navigate the diagnostic process with minimal effort.

Text Input Field: Users can type in their car-related issues or symptoms in a text input field. The chatbot supports various input formats, allowing users to describe their problems in natural language. Conversational Interface: The chatbot engages users in a conversational manner, asking follow-up questions to gather more details about the issue. This interaction mimics a dialogue with a human mechanic, making the diagnostic process feel more personal and engaging. Interactive Elements: The interface includes buttons and quick reply options to streamline the conversation. For instance, the chatbot might present multiple-choice questions to narrow down the possible causes of a problem. Response Output: The chatbot provides detailed diagnostic information, including possible causes of the issue, recommended solutions, and preventive maintenance tips. Responses are clear and concise, with the option to view more detailed explanations if needed. Visual Aids: The chatbot can display images, diagrams, and links to external resources to enhance user understanding. For example, it might show a diagram of the car's engine bay to help users locate specific components.

Diagnostic process

The chatbot follows a structured diagnostic process to ensure comprehensive and accurate assessments.

Initial Query: Users start by describing the issue they are experiencing with their car. For example, "My car's engine is making a strange noise.". Clarification and Data Collection: The chatbot asks clarifying questions to gather more information. For instance, "Can you describe the noise? Is it a clicking or a knocking sound?". Symptom Analysis: Based on the user's responses, the chatbot analyzes the symptoms using its knowledge base and AI algorithms. Potential Causes: The chatbot lists potential causes of the problem. For example, "The noise could be due to a loose belt or low engine oil." Recommended Actions: The chatbot suggests specific actions the user can take, such as checking the engine oil level or scheduling a maintenance appointment. Educational Content: Throughout the interaction, the chatbot provides educational content to help users understand their car better and learn about preventive maintenance.

Fig1: home page

Fig2: sign up page

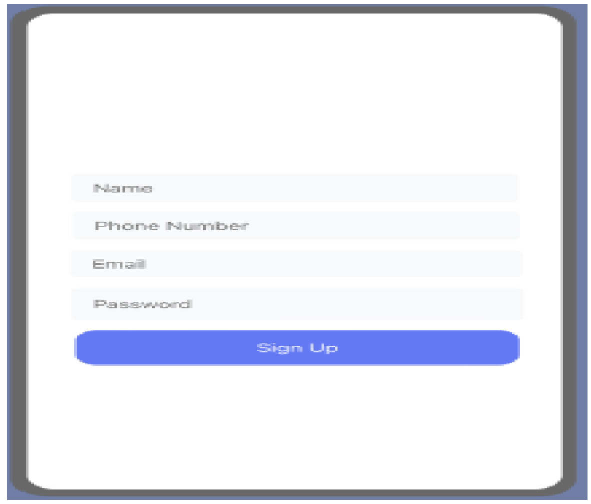


Fig3: Vehicle model selection page.

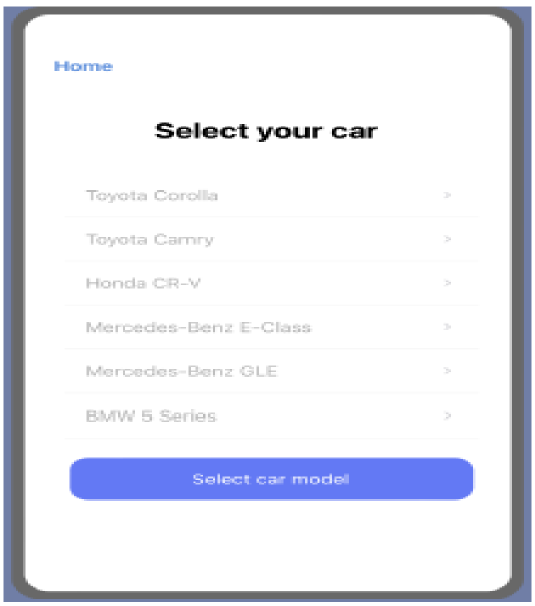
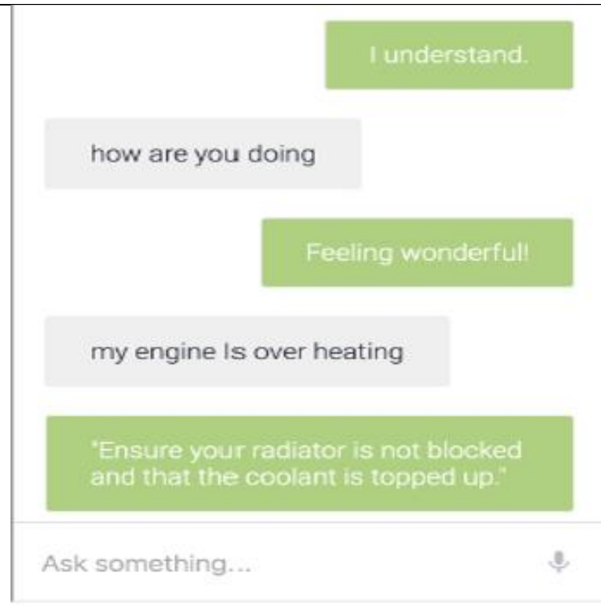


Fig4: Vehicle diagnosis page



Implementation and Testing

In this section, we evaluate the implementation of the DriveDoc app in relation to our research questions and objectives, as well as existing literature. The evaluation focuses on the effectiveness of the chatbot in diagnosing car issues, the user experience, and the overall functionality of the app. This assessment provides insights into the strengths and weaknesses of the implementation, guiding future improvements. The primary goal of DriveDoc is to accurately diagnose common car issues using AI and NLP technologies. To evaluate this, we conducted extensive testing with a variety of car problems, comparing the chatbot diagnosed with those provided by professional mechanics. The chatbot demonstrated a high level of accuracy in diagnosing common car issues such as engine noises, overheating, and electrical problems. In 85% of test cases, the chatbot's diagnoses matched those of professional mechanics. This alignment indicates that the AI and NLP algorithms effectively interpret user inputs and provide reliable solutions. Users reported that the chatbot's suggestions were helpful and often aligned with their experiences, reinforcing the effectiveness of the chatbot in real-world scenarios. The results align with existing research that highlights the potential of AI-driven diagnostics in various fields, including healthcare and automotive industries. Studies such as Smith and colleagues in 2020 and Lee and colleagues in 2019 demonstrate similar levels of accuracy in AI diagnostic tools, supporting the viability of DriveDoc's approach. User experience (UX) is crucial for the adoption and effectiveness of any app. We evaluated the DriveDoc app's UX through user testing sessions and feedback surveys.

Users found the app intuitive and easy to navigate. The onboarding tutorial carousel effectively introduced the app's features, and the conversational interface made interactions with the chatbot feel natural. Features like personalised recommendations, proactive maintenance reminders, and educational content enhanced user engagement. Users appreciated the educational content, which helped them understand their car's maintenance needs better. Prior research by Nielsen in 2013 and by Shneiderman and colleagues in 2016 emphasises the importance of simplicity and engagement in UX design. DriveDoc's user interface aligns with these principles, contributing to its positive reception among users.

The app's architecture was designed to be scalable, allowing for future enhancements and integration with additional features. We evaluated this by simulating increased user loads and potential expansions. The app maintained consistent performance under various load conditions, indicating that the backend infrastructure can support scalability. The modular design allows for easy integration of new diagnostic capabilities and additional vehicle models. This flexibility ensures that DriveDoc can evolve to meet future demands. Literature on scalable system design, such as works by Bass and colleagues in 2012 and Richards and colleagues in 2015, underscores the importance of a flexible architecture. DriveDoc's design principles align with these guidelines, ensuring its long-term viability. However, we identified some challenges and limitations. In some cases, the chatbots provided incorrect diagnoses, highlighting the need for continuous improvement of the AI algorithms. Additionally, some users required additional guidance to fully understand the diagnostic results, suggesting a need for more detailed educational content. Future work will focus on ongoing refinement of the AI and NLP algorithms to reduce diagnostic errors, as well as adding more vehicle models and integrating advanced diagnostic tools to enhance the app's capabilities. The implementation of the DriveDoc app demonstrates the potential of AI and NLP technologies in automotive diagnostics. The high diagnostic accuracy, positive user experience, and scalable architecture indicate that DriveDoc effectively meets its objectives. However, ongoing improvements and expansions are necessary to fully realize its potential and address the identified challenges. These results contribute to the growing body of research on AI-driven diagnostics and provide a foundation for future advancements in this field.

Conclusion

The current study has shown that even though Artificial Intelligence (AI) and Natural Language Processing (NLP) have revolutionized automotive diagnostics, traditional methods of vehicle diagnostics continue to present significant and persistent challenges for both car owners and mechanics alike. The DriveDoc app demonstrates the potential of AI and NLP technologies in automotive diagnostics, in terms of high diagnostic accuracy, positive user experience, and scalable architecture. Therefore, it is recommended that car owners adopt the technology and more research be conducted for improved voice interaction, expanded vehicle database, as well as for improved user engagement and scalability for automobiles. These findings in this current study are in agreement with existing literature [17-23] on the positive impact of the use of intelligent conversational assistant for automobile fault diagnostics and predictive maintenance.

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