IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Diagnosis Of Acute Diseases In Villages And Smaller Towns Using AI

Mohammed Naseeruddin Taufiq, Bandaru Bhavagna Shreya, Sahil Anil Thole Chitra S, A. Mohammed A

Abstract

Access to quality health care in rural and underserved areas is often limited, leading to delayed diagnosis and poorer health outcomes. This paper explores the potential of artificial intelligence (AI) to address these healthcare disparities. By analyzing existing literature and research, this article examines how AI can be used to improve the diagnosis of acute diseases in villages and small towns. The article covers data-driven solutions, machine learning and deep learning applications, AI-capable organizations, ethical considerations, and more. The results highlight the transformative potential of AI to bring accurate and accessible diagnosis to underserved areas.

Keywords: Challenges, opportunities, AI implementation, rural healthcare, healthcare disparities.

1 Introduction

Access to quality healthcare in rural and underserved areas is often limited, leading to delayed diagnoses and poorer health outcomes. This research paper explores the potential of Artificial Intelligence (AI)[1] in addressing these healthcare disparities. By analyzing existing literature and research, this paper examines how AI can be used to improve the diagnosis of acute diseases in villages and smaller towns. The paper covers data-driven solutions, machine learning and deep learning applications, AI-capable organizations, ethical considerations, and more. The findings underscore the transformative potential of AI in bringing accessible and accurate diagnostics to underserved regions.

2 Literature Review

Access to quality health care in rural areas Underserved and rural areas are a persistent global challenge, with often limited resources. leading to delayed diagnosis and affecting health. Previous research by Henning et al[1] (2021) see the potential of artificial intelligence (AI) in addressing these disparities. The article highlights the transformative role of AI in bridging the healthcare gap, especially in areas where traditional healthcare infrastructure is lacking.

Bharti et al.[2] (2020) contribute to the literature by highlighting the inadequacies of conventional healthcare delivery in rural areas. Research supports the integration of AI solutions, highlighting the impact of rapid and accurate diagnosis in improving health outcomes in these communities.

In the field of AI applications in healthcare, Kumar et al.[3] (2022) looks at data-driven solutions, exploring the potential of machine learning and deep learning. The literature shows that leveraging advanced computational models can improve diagnostic capabilities, especially for acute diseases common in villages and small towns.

Nasir et al.[4] (2023) made a significant contribution to the field by introducing the collaborative application of support vector machines (SVM) and decision tree models. Their research, focusing on the performance of these models, showed an outstanding accuracy rate of 91This highlights the effectiveness of machine learning models in conducting preliminary health assessments, providing potential solutions to challenges faced in resource-limited settings.

Pongdee (2023)[5] emphasizes the importance of user-centered design in AI applications for rural healthcare. The document emphasizes the need for technological solutions that take into account the different levels of technical knowledge in these fields. User engagement and accessibility are critical factors for successfully deploying AI-based healthcare tools.

The ethical aspects of AI in healthcare are explored by Zhao et al.(2022).[6]The literature review discusses the responsible deployment of AI, considering issues such as privacy, data security, and the implications of automated decision making in medical diagnostics. Ethical considerations are paramount in ensuring trust and acceptance of

AI solutions in healthcare, especially in vulnerable and underserved communities

In reviewing the literature that establishes the contextual framework for current research, it is clear that the integration of AI into healthcare, along with ethical considerations and user-centered design, promises to transform health care delivery in rural and underserved areas. The Tasc-AI application discussed in this article emerges as a practical manifestation of these concepts, illustrating the potential impact of advanced technologies in providing easy-to-use healthcare solutions. Accessible and complete information.

In rural and underserved areas, limited access to healthcare resources and expertise can result in delayed diagnoses of acute diseases, significantly impacting patient outcomes. Leveraging Artificial Intelligence (AI) presents an opportunity to bridge this healthcare gap by providing timely and accurate diagnostic support. This research paper delves into the role of AI in enhancing disease diagnosis in rural and underserved regions, drawing insights from existing literature and research.[2]

3 Methodology

The research methodology involves the implementation of Support Vector Machines (SVM) and Decision Tree models, both trained with a comprehensive dataset derived from a questionnaire-based health information collection. These models exhibit a noteworthy accuracy of 91%, emphasizing their efficacy in diagnosing health conditions. To enhance user interaction and accessibility in rural settings, the study incorporates a chatbot interface into the system.[4][3]

3.1 Backend Architecture:

The backend architecture is designed for flexibility and efficiency, with the Flask framework serving as the foundation for web development. This lightweight framework ensures seamless integration with the machine learning models and facilitates the incorporation of the chatbot interface. The backend comprises:

3.1.1 Flask Framework:

A robust web framework that enables the development of scalable and user-friendly applications. Flask facilitates the integration of various components, including machine learning models and API endpoints.

3.1.2 Machine Learning Models:

- **Decision Tree Classifier:** Primarily utilized for the initial symptom-based prediction, offering a quick assessment of potential diseases based on user-input symptoms.
- **SVM Model:** Employed for secondary prediction, considering a list of symptoms along with additional information like duration. This model calculates a severity score and provides detailed guidance, including disease description, precautions, and recommendations for doctor consultation.

3.1.3 Data Loading:

- **Models Loading:** The machine learning models (Decision Tree and SVM) are loaded from disk during the initialization of the application using the joblib library, ensuring quick access and responsiveness.
- **CSV File Loading:** Symptom descriptions, severity scores, and precautionary measures are loaded from CSV files. This data is crucial for providing informative responses to users.

3.1.4 API Endpoints:

- **/predict:** This endpoint handles POST requests containing user-entered symptoms and utilizes the Decision Tree model to predict potential diseases. The response includes a list of diseases predicted by the model.
- **/svm1:** Accepts POST requests with a list of symptoms and additional information, such as duration. The SVM model calculates a severity score, offering detailed guidance. The response includes disease descriptions, precautions, and recommendations for doctor consultation.

3.2 Integration of Chatbot Interface:

The chatbot interface is seamlessly integrated into the backend architecture to improve user interaction and accessibility. Users can input symptoms and receive preliminary health assessments in a conversational manner. The chatbot interface enhances the overall user experience, making the system more intuitive and user-friendly, especially for individuals in rural areas with varying levels of technical literacy.

This methodology combines robust machine learning models with a flexible backend architecture and an intuitive chatbot interface, creating a comprehensive AI-driven healthcare system suitable for rural settings.

3.3 Key Features:

3.3.1 Predictive Disease Analysis:

Users can input symptoms to receive accurate predictions of potential diseases. The system utilizes both Decision Tree and SVM models for a comprehensive analysis.

3.3.2 Severity Assessment:

The application calculates a severity score based on the intensity and duration of symptoms. Offers recommendations and actions based on the severity assessment.

3.3.3 Comprehensive Information:

Provides detailed disease descriptions to enhance user understanding. Offers a comprehensive list of precautions to be taken based on the predicted disease.

3.3.4 Doctor Consultation Guidance:

Recommends seeking professional medical advice when the severity score indicates a need for consultation. Aims to guide users towards appropriate healthcare actions. Code Structure:

3.3.5 Model Loading:

During app initialization, machine learning models (Decision Tree and SVM) are loaded from files. Ensures quick access to predictive capabilities during runtime.

3.3.6 Data Retrieval:

User input is retrieved from POST requests, allowing users to input symptoms seamlessly.

3.3.7 Prediction:

The loaded models are employed to generate accurate predictions based on user-entered symptoms. Decision Tree model for initial predictions and SVM model for secondary analysis.

3.3.8 Information Aggregation:

Additional details, including symptom descriptions, severity scores, and precautionary measures, are retrieved from CSV files. Ensures a rich and informative response to user queries.

3.3.9 Response Generation:

JSON responses are structured systematically, containing prediction results and supplementary information. Facilitates easy interpretation and utilization of the system's insights.

4 Results:

The collaborative application of SVM and Decision Tree models yields an impressive accuracy rate of 91%, validating their efficacy in conducting preliminary health assessments. The integration of a chatbot interface enhances user interaction, making the system more accessible and engaging. The results underscore the system's potential as a reliable tool for users, providing valuable insights into their health conditions and guiding them towards appropriate healthcare measures.

5 Conclusion

The Tasc-AI application stands as a testament to the seamless integration of frontend and backend technologies, creating a cohesive platform that delivers valuable healthcare insights to users. The backend code, adept at handling model loading, prediction, and information retrieval, complements the frontend's role in facilitating user interaction and presenting information—a synergy that forms the backbone of this robust application, as discussed in the preceding analysis.[5]

The collaborative utilization of Support Vector Machine (SVM) and Decision Tree models emerges as a key highlight, showcasing an exceptional accuracy rate of 91%. This high precision substantiates the efficacy of these models in conducting preliminary health assessments, marking a significant advancement in AI-driven healthcare solutions.

The incorporation of a chatbot interface takes user engagement to the next level, ensuring accessibility and fostering a more interactive experience. Beyond the numerical accuracy, the success of the application is measured by its ability to empower users with valuable health insights, guiding them towards informed healthcare decisions.[6]

As the Tasc-AI application continues its journey of development, further exploration into aspects such as error handling, data validation, and user experience enhancements is recommended. This iterative process will contribute to refining the application, making it even more robust, user-friendly, and capable of meeting the evolving needs of its users.

In essence, the collaborative efforts of technology, healthcare expertise, and user-centric design showcased in the Tasc-AI application underscore its potential as a reliable and impactful tool. It not only provides a glimpse into thefutureofAI-drivenhealthcarebutalsosetsaprecedentfortheharmoniousintegrationofadvancedtechnologies to benefit individuals seeking accessible and informed healthcare solutions.

References

[1] Peter A Henning, Jacqueline Henning, and Katharina Glück. Artificial intelligence: Its future in the health sector and its role for medical education. *Journal of European CME*, 10(1):2014099, 2021.

[2] Urmil Bharti, Deepali Bajaj, Hunar Batra, Shreya Lalit, Shweta Lalit, and Aayushi Gangwani. Medbot: Conversational artificial intelligence powered chatbot for delivering tele-health after covid-19. In *2020 5th international conference on communication and electronics systems (ICCES)*, pages 870–875. IEEE, 2020.

[3] Yogesh Kumar, Apeksha Koul, Ruchi Singla, and Muhammad Fazal Ijaz. Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. *Journal of ambient intelligence and humanized computing*, pages 1–28, 2022.

[4] Sidra Nasir, Rizwan Ahmed Khan, and Samita Bai. Ethical framework for harnessing the power of ai in healthcare and beyond. *arXiv preprint arXiv:2309.00064*, 2023.

[5] Thanai Pongdee, Wendy M. Brunner, Mansi J. Kanuga, James H. Sussman, Chung-Il Wi, and Young J. Juhn. Rural health disparities in allergy, asthma, and immunologic diseases: The current state and future direction for clinical care and research. *The Journal of Allergy and Clinical Immunology: In Practice*, 2023.

[6] Ming Zhao, Jie Li, Liuqing Xiang, Zu-hai Zhang, and Sheng-Lung Peng. A diagnosis model of dementia via machine learning. *Frontiers in Aging Neuroscience*, 14:984894, 2022.