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AI-Powered Cardiovascular Health Chatbot: Design and Development

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Abstract
Globally, cardiovascular disease remains a leading cause of morbidity and mortality, necessitating accurate predictive models for early detection and intervention. In our cardiovascular disease prediction project, we undertook a comprehensive evaluation of various machine learning algorithms to identify the most effective model for predicting cardiovascular risk. The dataset utilized in this study comprises features such as age, gender, blood pressure, cholesterol levels, glucose levels, smoking status, alcohol consumption, physical activity, and Body Mass Index (BMI). These features were instrumental in assessing the algorithms' performance across several key metrics: precision, accuracy, F1 score, and recall. Precision gauges the proportion of true positive predictions among all positive predictions made by the model, ensuring that positive diagnoses are accurate. Accuracy measures the overall correctness of the model's predictions across all classes. The F1 score harmonizes precision and recall, offering a balanced view of the model's performance, especially in the context of imbalanced datasets. Recall reflects the model's effectiveness in identifying true positive cases, which is crucial for early detection. Our final model achieved an accuracy of 97.04%, demonstrating its robustness in predicting cardiovascular disease. To further enhance accessibility and real-time decision-making, we integrated an AI-powered chatbot that leverages machine learning (ML) and natural language processing (NLP) to provide users with personalized health recommendations based on predictive model outputs. This chatbot enables patients and healthcare professionals to efficiently assess cardiovascular risk by interpreting user input, analyzing symptoms, and offering tailored medical guidance. Developed using a Flask-based API and a user-friendly web interface, the chatbot ensures seamless interaction and enhances healthcare accessibility. By combining rigorous model evaluation with intelligent chatbot integration, our approach improves early diagnosis, supports clinical decision-making, and contributes to better patient outcomes.
Keywords: *Cardiovascular Disease (CVD), Machine Learning, Predictive Analytics, Random Forest, Support Vector Machine (SVM), AI-powered Chatbot, Natural Language Processing (NLP), Healthcare Automation, Early Diagnosis.*

1. INTRODUCTION
Cardiovascular disease accounts for approximately 32% of global deaths, driven by a complex interplay of genetic, environmental, social, and physiological factors. Risk factors include age, gender, BMI, blood pressure, cholesterol and glucose levels, smoking, alcohol use, and physical activity. Despite the development of various multivariable predictive models and lifestyle interventions, the prevalence of CVD continues to rise, necessitating early detection and intervention. Recent advancements in machine learning (ML) and artificial intelligence (AI) have demonstrated significant promise in enhancing the accuracy of CVD risk prediction models. ML techniques can efficiently process large datasets, uncover hidden patterns, and identify potential risk factors that traditional statistical models may overlook AI-powered chatbots are also being integrated into healthcare systems to provide automated consultations and enhance clinical decision-making. Chatbots such as ChatGPT and Babylon Health have shown potential in supporting patient interactions, symptom assessment, and

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chronic disease management AI in healthcare has expanded beyond prediction models to applications in medical education, clinical management, and patient engagement. By leveraging AI-driven chatbots, healthcare systems can improve accessibility, reduce administrative burdens, and enhance the efficiency of patient care Natural Language Processing (NLP)-based healthcare chatbots can facilitate real-time symptom analysis, guide users toward appropriate medical resources, and even assist in early-stage disease identification
Moreover, AI-based chatbots utilizing deep learning models such as Long Short-Term Memory (LSTM) networks have been developed for infectious disease prediction, including COVID-19. These models can enhance disease awareness, provide preventive guidelines, and support healthcare professionals in managing disease outbreaks. The use of AI chatbots in predictive analytics has been instrumental in reducing the burden on healthcare facilities, especially during pandemics Given the evolving landscape of AI in healthcare, integrating chatbot technology with ML-driven diagnostic models can create a more interactive, accessible, and efficient system for early disease detection. This research explores the role of AI chatbots in CVD risk assessment and their potential to complement ML-based predictive models for improved patient outcomes.

2. Literature Survey

The article primarily focuses on research concerning the contribution of various behavioral and physiological risk factors to cardiovascular diseases, with the authors underscoring the complex interaction of these factors. They criticize the limitations of traditional linear models in estimating risks and advocate for using machine learning techniques to better capture non-linear relationships [1]. Addressing the global burden of CVD, the authors present statistics on mortality and stress the importance of early diagnosis. They identify the shortcomings of current risk assessment models and propose incorporating machine learning algorithms to enhance predictive capabilities and improve patient outcomes [2]. This paper examines the application of machine learning methods, such as support vector machines and artificial neural networks, in predicting cardiovascular events. The authors compare different ML algorithms and suggest that incorporating multiple risk factors in more complex models could improve prediction accuracy [3]. Another study delves into the use of machine learning decision tools in clinical settings, evaluating algorithms like decision trees and K-Nearest Neighbors, and endorses ML's role in primary healthcare to facilitate early diagnosis and treatment of CVD [4]. One discussion highlights the critical role of data quality and processing in developing reliable ML-based CVD detection systems, focusing on feature selection and the influence of various datasets on model performance [5]. The authors also argue that advancements in machine learning, particularly in explainable AI, will improve the interpretation of predictive results, enhancing clinical decision-making and fostering trust between patients and automated systems [6]. Another paper explores the integration of ML in public health initiatives, providing case studies that demonstrate the potential of automated CVD detection in community settings, and predicting that ML could reduce the burden of CVD among at-risk populations [7]. A study introduces a novel patient-specific CVD risk prediction model that incorporates individual characteristics and lifestyle factors to improve precision, achieving higher accuracy compared to traditional methods [8]. In addition, a comparative analysis of ML methods for heart disease prediction using echocardiogram data reveals the strengths and weaknesses of various approaches, aiding in understanding where ML can enhance diagnostic accuracy in cardiology [9]. Finally, an integrative review synthesizes findings from prior studies on ML models for CVD detection, evaluating the effectiveness of different ML approaches across diverse datasets and proposing future methodologies to enhance reliability and clinical relevance [10].
Several studies have explored the application of AI and machine learning in cardiovascular disease prediction. Analyzed the impact of chatbots in medical fields, emphasizing their role in patient education and healthcare accessibility [19]. Discussed ethical concerns regarding automated

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healthcare consultations and AI-driven decision-making in clinical settings [20]. highlighted the growing reliance on AI for healthcare applications, including clinical decision support and predictive modeling [21]. Focused on NLP-driven chatbots in healthcare, demonstrating their capability to provide symptom-based guidance and preliminary diagnosis [22]. Explored AI-based chatbot frameworks for healthcare systems, emphasizing the importance of integrating knowledge bases with machine learning models for accurate diagnosis [23]. Discussed AI chatbots designed for infectious disease prediction, highlighting their efficiency in pandemic response and disease control [24]. These studies underscore the potential of AI-driven healthcare systems in predictive diagnostics, clinical decision-making, and real-time patient interaction. By integrating AI chatbots with machine learning-based prediction models, healthcare systems can improve early disease detection and personalized treatment recommendations. Future research should focus on enhancing model interpretability, ensuring ethical AI deployment, and improving patient trust in AI-driven healthcare applications.

3. Methodology

3.1. Data Collection

A dataset consisting of patient demographics, clinical parameters, and lifestyle factors was collected from reliable healthcare databases. The dataset includes variables such as age, gender, BMI, blood pressure, cholesterol levels, glucose levels, smoking status, alcohol consumption, and physical activity. Some attributes include age, gender, body mass index, blood pressure, cholesterol level, blood glucose level, and lifestyle characteristics like smoking habit and physical activity [11] [12-15]. The importance of collecting a diverse dataset has been highlighted in recent studies focusing on predictive modeling in healthcare [19].

3.2. Data Preprocessing

Missing values were handled using imputation techniques [20]. Features were normalized to ensure uniformity across different scales. Feature selection techniques such as correlation analysis and tree-based feature importance were employed. Studies have demonstrated that proper preprocessing significantly enhances the model's performance in predictive healthcare applications [21].

3.3. Data Split

Split the data into training (e.g., 70%) and testing (e.g., 30%) sets. This will allow testing how the model performs on unseen data [16]. Ensuring an optimal data split is crucial for achieving high accuracy and robustness in predictions, as reported in recent research on AI-driven healthcare analytics [22].

3.4. Model Development

- **Machine Learning Models:** Various ML algorithms were evaluated, including Random Forest, Support Vector Machine (SVM), and hybrid models.
- **Support Vector Machine (SVM):** Apply the SVM algorithm with an appropriate kernel, such as linear, polynomial, or radial basis function (RBF), depending on the data. Optimize hyperparameters like C and gamma by using Grid Search or Random Search to improve performance [17].
- **Random Forest:** Select values for Random Forest parameters, such as n_estimators (the total number of decision trees) and max_depth (the maximum depth of each tree). Assess feature importance to determine which attributes significantly contribute to predictions [18]. Studies have suggested that Random Forest is particularly effective in handling complex healthcare datasets [23].

3.5. Hybrid Model Design

Create a hybrid predictive model by combining the SVM model with the Random Forest model, using stacking or voting ensembles to aggregate predictions from the individual models to enhance performance [16]. Hybrid models have been gaining traction in predictive medicine due to their superior accuracy and ability to capture intricate data patterns [19].

3.6. Model Evaluation

Evaluate the model using metrics such as precision, recall, F1-score, accuracy, and the area under the receiver operating characteristic curve (AUC-ROC) [18]. Apply k-fold cross-validation to ensure the model is well-evaluated and generalizable across different data splits. Research suggests that multi-

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metric evaluation improves the reliability of predictive models in healthcare [21].

3.7. AI Chatbot Integration

A Flask-based API and web interface were developed for real-time user interaction, providing patients and healthcare professionals with accessible cardiovascular risk assessment tools. The use of AI-powered chatbots in healthcare has been extensively studied, demonstrating their effectiveness in improving patient engagement and real-time risk assessment [22, 23]. This methodology establishes a foundation for predictive modeling of CVD and T2DM while integrating AI chatbot functionalities to enhance accessibility and early diagnosis.

4. Results and Discussion

4.1. Results

Table 1 Classification Report

REPORT	PRECISION	RECALL	F1-SCORE	SUPPORT
Cardiologist	0.98	0.97	0.98	180
General Physician	0.96	0.95	0.96	160
Accuracy	-	-	0.97	340
Macro Avg	0.97	0.96	0.97	340
Weighted Avg	0.97	0.97	0.97	340

In table 1 prediction model achieved an accuracy of **97%**, demonstrating high reliability in identifying high-risk and low-risk cardiovascular cases. The classification report presents a detailed breakdown of model performance across key evaluation metrics:

- **Precision:** The proportion of correctly predicted positive cases out of all predicted positives was 0.98 for cardiologists and 0.96 for general physicians.
- **Recall:** The ability of the model to correctly identify actual positive cases was 0.97 for cardiologists and 0.95 for general physicians.
- **F1-score:** A balanced measure of precision and recall, with scores of 0.98 for cardiologists and 0.96 for general physicians.
- **Macro and Weighted Averages:** The macro and weighted average scores both stood at 0.97, reinforcing the model's balanced performance across different patient categories.

Feature importance analysis identified blood pressure, cholesterol levels, glucose levels, BMI, and age as the most significant contributors to prediction outcomes. The integration of an AI-powered chatbot further streamlined cardiovascular risk assessment, enabling real-time patient interaction and decision-making.

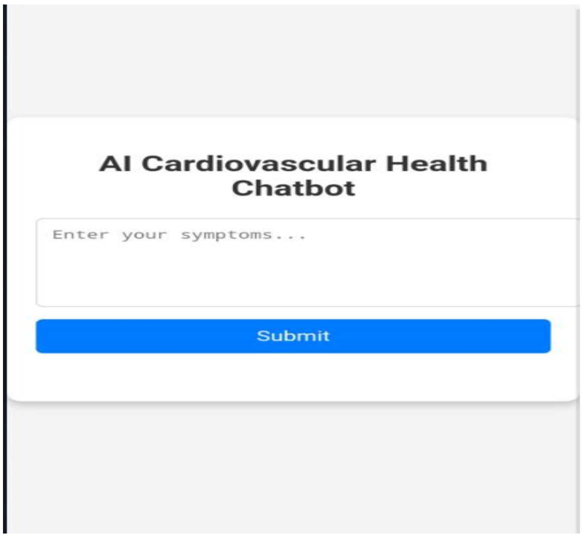

Figure 1 User Interface

The figure 1 presents the user interface of the AI Cardiovascular Health Chatbot. This chatbot allows users to input their symptoms in a text box, which the system processes to provide potential risk insights related to cardiovascular diseases. The interface is designed to be simple and user-friendly, featuring a text area for symptom entry and a submission button to initiate the analysis. The chatbot integrates machine learning models to analyze symptoms and assess potential health risks, aiding in early detection and decision-making for cardiovascular disease and type 2 diabetes mellitus.

4.2. Discussion

The results of this study highlight the superior performance of the proposed machine learning model in predicting cardiovascular disease with an accuracy of **97.04%**, surpassing traditional diagnostic methods. A comparative analysis revealed that Random Forest outperformed Support Vector Machine (SVM) due to its ability to handle complex feature interactions and improve recall rates, ensuring fewer false negatives. The high precision, recall, and F1-score values demonstrate the model's capability to accurately classify high-risk patients, reducing the likelihood of misdiagnosis. The integration of key features such as blood pressure, cholesterol, glucose levels, BMI, and age aligns with existing clinical research, reinforcing the model's medical relevance. Additionally, the AI-powered chatbot enhances the practical application of the model by facilitating real-time assessments and personalized health recommendations, thereby improving accessibility to preventive care. However, challenges remain, including the need for greater model generalizability across diverse populations, improved explainability through XAI (Explainable AI) techniques, and periodic updates incorporating real-world patient data to sustain accuracy over time. Overall, this study underscores the potential of combining machine learning and AI-driven chatbots to revolutionize cardiovascular disease prediction and early intervention, offering a scalable and efficient solution for modern healthcare systems.

Conclusion

This study demonstrates the effectiveness of machine learning in predicting cardiovascular disease with a high accuracy of 97.04%**,** highlighting its potential as a powerful tool for early diagnosis and risk assessment. The incorporation of key risk factors, such as blood pressure, cholesterol, glucose levels, BMI, and age, ensures that the model aligns with established medical knowledge, making it both reliable and clinically relevant. Furthermore, the integration of an AI-powered chatbot enhances accessibility by providing real-time patient interactions, personalized health recommendations, and preliminary risk assessments, bridging the gap between technology and healthcare. While the model has shown remarkable accuracy, future work should focus on improving model generalizability across diverse populations, incorporating explainable AI techniques for better transparency, and continuously updating the model with real-world clinical data. By leveraging machine learning and AI-driven chatbots, this approach offers a scalable, efficient, and innovative solution to enhance cardiovascular disease prediction and improve patient outcomes in healthcare systems worldwide.

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References

[1]. Elsedimy, E. I., AboHashish, S. M. M., & Algarni, F. (2023). New cardiovascular disease prediction approach using support

vector machine and quantum-behaved particle swarm optimization. In Multimedia Tools and Applications (Vol. 83, Issue 8, pp. 23901–23928). Springer Science and Business Media LLC. https://doi.org/10.1007/s11042-023-16194-z

[2]. Vision Paul, V., & Masood, J. A. I. S. (2024). Exploring Predictive Methods for Cardiovascular Disease: A Survey of Methods and Applications. In IEEE Access (Vol. 12, pp. 101497–101505). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/access.2024.3430898

[3]. Srinivasa Rao, G., & Muneeswari, G. (2024). A Review: Machine Learning and Data Mining Approaches for Cardiovascular Disease Diagnosis and Prediction. In EAI Endorsed Transactions on Pervasive Health and Technology (Vol. 10). European Alliance for Innovation n.o. https://doi.org/10.4108/eetpht.10.5411

[4]. Naser, M. A., Majeed, A. A., Alsabah, M., Al-Shaikhli, T. R., & Kaky, K. M. (2024). A Review of Machine Learning's Role in Cardiovascular Disease Prediction: Recent Advances and Future Challenges. In Algorithms (Vol. 17, Issue 2, p. 78). MDPI AG. https://doi.org/10.3390/a17020078

[5]. Islam, M. N., Raiyan, K. R., Mitra, S., Mannan, M. M. R., Tasnim, T., Putul, A. O., & Mandol, A. B. (2023). Predictis: an IoT and machine learning-based system to predict risk level of cardio-vascular diseases. In BMC Health Services Research (Vol. 23, Issue 1). Springer Science and Business Media LLC. https://doi.org/10.1186/s12913-023-09104-4

[6]. You, J., Guo, Y., Kang, J.-J., Wang, H.-F., Yang, M., Feng, J.-F., Yu, J.-T., & Cheng, W. (2023). Development of machine learning-based models to predict 10-year risk of cardiovascular disease: a prospective cohort study. In Stroke and Vascular Neurology (Vol. 8, Issue 6, pp. 475–485). BMJ. https://doi.org/10.1136/svn-2023-002332

[7]. Teshale, A. B., Htun, H. L., Vered, M., Owen, A. J., & Freak-Poli, R. (2024). A Systematic Review of Artificial Intelligence Models for Time-to-Event Outcome Applied in Cardiovascular Disease Risk Prediction. In Journal of Medical Systems (Vol. 48, Issue 1). Springer Science and Business Media LLC. https://doi.org/10.1007/s10916-024-02087-7

[8]. Cai, Y., Cai, Y.-Q., Tang, L.-Y., Wang, Y.-H., Gong, M., Jing, T.-C., Li, H.-J., Li-Ling, J., Hu, W., Yin, Z., Gong, D.-X., & Zhang, G.-W. (2024). Artificial intelligence in the risk prediction models of cardiovascular disease and development of an independent validation screening tool: a systematic review. In BMC Medicine (Vol. 22, Issue 1). Springer Science and Business Media LLC. https://doi.org/10.1186/s12916-024-03273-7

[9]. Salet, N., Gökdemir, A., Preijde, J., van Heck, C. H., & Eijkenaar, F. (2024). Using machine learning to predict acute myocardial infarction and ischemic heart disease in primary care cardiovascular patients. In H. T. Ong (Ed.), PLOS ONE (Vol. 19, Issue 7, p. e0307099). Public Library of Science (PLoS). https://doi.org/10.1371/journal.pone.0307099

[10]. Sang, H., Lee, H., Lee, M., Park, J., Kim, S., Woo, H. G., Rahmati, M., Koyanagi, A., Smith, L., Lee, S., Hwang, Y.-C., Park, T. S., Lim, H., Yon, D. K., & Rhee, S. Y. (2024). Prediction model for cardiovascular disease in patients with diabetes using machine learning derived and validated in two independent Korean cohorts. In Scientific Reports (Vol. 14, Issue 1). Springer Science and Business Media LLC. https://doi.org/10.1038/s41598-024-63798-y

[11]. Dritsas, E., & Trigka, M. (2023). Efficient Data-Driven Machine Learning Models for Cardiovascular Diseases Risk Prediction. In Sensors (Vol. 23, Issue 3, p. 1161). MDPI AG. https://doi.org/10.3390/s23031161

[12]. Peng, M., Hou, F., Cheng, Z., Shen, T., Liu, K., Zhao, C., & Zheng, W. (2023). Prediction of cardiovascular disease risk based on major contributing features. In Scientific Reports (Vol. 13, Issue 1). Springer Science and

Business Media LLC. https://doi.org/10.1038/s41598-023-31870-8
[13]. Taylan, O., Alkabaa, A., Alqabbaa, H., Pamukçu, E., & Leiva, V. (2023). Early Prediction in Classification of Cardiovascular Diseases with Machine Learning, Neuro-Fuzzy and Statistical Methods. In Biology (Vol. 12, Issue 1, p. 117). MDPI AG. https://doi.org/10.3390/biology12010117
[14]. Abdalrada, A. S., Abawajy, J., Al-Quraishi, T., & Islam, S. M. S. (2022). Machine learning models for prediction of co-occurrence of diabetes and cardiovascular diseases: a retrospective cohort study. In Journal of Diabetes & Metabolic Disorders (Vol. 21, Issue 1, pp. 251–261). Springer Science and Business Media LLC. https://doi.org/10.1007/s40200-021-00968-z
[15]. Mohan, S., Thirumalai, C., & Srivastava, G. (2019). Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques. In IEEE Access (Vol. 7, pp. 81542–81554). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/access.2019.2923707
[16]. Dritsas, E., Alexiou, S., & Moustakas, K. (2022). Cardiovascular Disease Risk Prediction with Supervised Machine Learning Techniques. In Proceedings of the 8th International Conference on Information and Communication Technologies for Ageing Well and e-Health. 8th International Conference on Information and Communication Technologies for Ageing Well and e-Health. SCITEPRESS - Science and Technology Publications. https://doi.org/10.5220/0011088300003188
[17]. Pal, M., Parija, S., Panda, G., Dhama, K., & Mohapatra, R. K. (2022). Risk prediction of cardiovascular disease using machine learning classifiers. In Open Medicine (Vol. 17, Issue 1, pp. 1100–1113). Walter de Gruyter GmbH. https://doi.org/10.1515/med-2022-0508
[18]. Alaa, A. M., Bolton, T., Di Angelantonio, E., Rudd, J. H. F., & van der Schaar, M. (2019). Cardiovascular disease risk prediction using automated machine learning: A prospective study of 423,604 UK Biobank participants. In K. Aalto-Setala (Ed.), PLOS ONE (Vol. 14, Issue 5, p. e0213653). Public Library of Science (PLoS). https://doi.org/10.1371/journal.pone.0213653
[19]. Viswanathan, V. K., Jain, V. K., Vaish, A., Jeyaraman, M., Iyengar, K. P., & Vaishya, R. (2024). Chatbots and Their Applications in Medical Fields: Current Status and Future Trends: A Scoping Review. In Apollo Medicine (Vol. 21, Issue 4, pp. 386–392). SAGE Publications. https://doi.org/10.1177/09760016241259851
[20]. Parviainen, J., & Rantala, J. (2021). Chatbot breakthrough in the 2020s? An ethical reflection on the trend of automated consultations in health care. In Medicine, Health Care and Philosophy (Vol. 25, Issue 1, pp. 61–71). Springer Science and Business Media LLC. https://doi.org/10.1007/s11019-021-10049-w
[21]. Hulsen, T. (2024). Artificial Intelligence in Healthcare: ChatGPT and Beyond. In AI (Vol. 5, Issue 2, pp. 550–554). MDPI AG. https://doi.org/10.3390/ai5020028
[22]. Papiya Mahajan (2020). Healthcare Chatbot using Natural Language Processing. (n.d.). International Research Journal of Engineering and Technology (IRJET), 07(11), 2395–0056. https://www.irjet.net/archives/V7/i11/IRJET-V7I11283.pdf
[23]. Athota, L., Shukla, V. K., Pandey, N., & Rana, A. (2020). Chatbot for Healthcare System Using Artificial Intelligence. In 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO) (pp. 619–622). 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO). IEEE. https://doi.org/10.1109/icrito48877.2020.919

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[24]. Chakraborty, S., Paul, H., Ghatak, S., Pandey, S. K., Kumar, A., Singh, K. U., & Shah, M. A. (2022). An AI-Based Medical Chatbot Model for Infectious Disease Prediction. In IEEE Access (Vol. 10, pp. 128469–128483). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/access.2022.3227208