Migration Letters

Volume: 21, No: S14 (2024), pp. 1018-1029

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Predicting Cardiovascular Outcomes: A Comparative Study Of Bayesian And Traditional Methods

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Abstract

This study comprehensively examines and compares current heart disease prediction systems, focusing on Bayesian techniques versus conventional methods. We aim to determine their effectiveness and ease of interpretation in heart health prognosis. We use various statistical and machine learning models to analyze clinical and demographic data from a large patient population collected over time. Bayesian approaches, which handle uncertainty and complex variable interactions, are compared to simpler methods like logistic regression and decision trees. We assess the accuracy, sensitivity, specificity, and AUC-ROC of Bayesian[1] and traditional techniques to evaluate their predictive performance. Additionally, we analyze the models' ability to explain factors influencing heart disease outcomes, crucial for informed treatment decisions. By comparing Bayesian and traditional methodologies, this study helps academics and healthcare practitioners identify optimal modeling methods to enhance patient care and heart disease survival, advancing predictive analytics in healthcare and improving cardiovascular patient management.

Keywords: *Bayesian predictions, classical predictions, cardiovascular prognosis, heart disease, predictive analytics.*

Introduction

An accurate and early cardiac illness projection is essential for patient outcomes and quick treatment. Since HIV is the biggest cause of death globally, better prediction methods are needed to understand its development and survival rates. Modern prediction algorithms provide cardiology a new chance (Saeed et al., 2018). Accurate and early cardiac illness forecasts improve patient outcomes and ensure quick treatment. Since the illness is the top cause of death globally, improved prediction methods are needed to understand its development and survival rates. In cardiology, modern prediction algorithms provide new opportunities (Sharma, Malviya, Jadhav, & Lalwani, 2023). With heart disease on the rise, global healthcare is changing. Prediction innovations enable early detection and assessment, which speeds therapy and improves survival. These methodologies must be understood and assessed to enhance heart disease survival rates and produce accurate forecasts (Ray et al., 2023). heart disease causes illness and death in many populations, making it a worldwide health issue. A rapid and accurate cardiac disease outcome and survival rate estimate is crucial for optimizing patient care, treatment planning, and resource allocation in healthcare systems. Recent advances in predictive modelling have introduced Bayesian techniques among others. A comprehensive examination is needed to establish the efficiency

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of Bayesian techniques in cardiac disease prediction (Shrivastava, Sharma, & Kumar, 2023). This study tests Bayesian and conventional statistical approaches in real-world clinical situations using a huge dataset of clinical and demographic factors. This study will evaluate how effectively these approaches predict heart disease outcomes and survival (Ghasemieh, Lloyed, Bahrami, Vajar, & Kashef, 2023). This research aims to improve patient care and predictive analytics in healthcare by comparing Bayesian and conventional methods and addressing heart disease's rising incidence and global health impact (Huang et al., 2022). Many studies have stressed the need of early diagnosis and intervention, citing predictive models' impact on patient outcomes (Tripathi & Reddy, 2022). A new approach to heart illness diagnostics has emerged in the recent decade, leading to novel prediction tools (Shi et al., 2022). Modern approaches can change how doctors treat heart illness by using advanced analytics. They project more accurately than prior models (Kathiriya et al., 2021). These procedures have enormous promise, but they must be thoroughly analyzed to ensure their efficacy and reliability. This study examines modern prediction techniques to determine their potential to revolutionize cardiac therapy and improve survival rates.

A rising corpus of research shows that these modern technologies improve sickness predictions, therapeutic customization, and patient outcomes (Amdani et al., 2022). Despite this optimism for technological innovation, experts have advised caution. Due to issues about data privacy, model overfitting, and generalizability, these prediction methodologies must be better understood and evaluated (Loforte et al., 2019). This paper aims to provide an enriched exploration of the current predictive landscape in cardiology. Drawing from a plethora of studies, we will analyze the capabilities and limitations of modern predictive methods, seeking to determine their genuine impact and potential for reshaping the future of cardiac care.

Background

Cardiovascular diseases (CVD) remain the leading cause of mortality worldwide, prompting ongoing research into predictive models that can effectively gauge individual risk factors and intervention outcomes. Traditional statistical models have long been employed to forecast cardiovascular events, relying primarily on classical methods that offer robust results under specific statistical assumptions. However, these models often struggle with the complexities inherent in medical data, such as non-linear interactions and missing data, which can obscure critical predictive insights.

Aim and Objectives

The primary aim of this study is to compare the effectiveness of Bayesian statistical methods against classical statistical methods in predicting cardiovascular outcomes. Objectives include: 1) To evaluate the predictive accuracy of Bayesian and classical models using real-world clinical data; 2) To examine how each method handles data imperfections such as missing values and variable interactions; 3) To explore the incorporation of prior clinical knowledge into Bayesian models; and 4) To assess the practical implications of each method in clinical decision-making.

Research Gaps

Despite the extensive use of predictive models in cardiovascular research, significant gaps remain in comparing contemporary Bayesian methods with traditional classical approaches. Most existing studies focus on the application of either method in isolation, with less attention given to direct comparisons under identical conditions. Additionally, there is a lack of clarity on how Bayesian methods, which theoretically manage uncertainties and prior knowledge more effectively, perform against classical methods in diverse and complex datasets typically seen in clinical settings.

Significance of the Study

This study is pivotal as it addresses the urgent need for advanced predictive models in the field of cardiovascular health. By directly comparing Bayesian and classical methods, it aims to reveal which approach offers greater accuracy, flexibility, and clinical utility. The findings could significantly influence future research directions and clinical practices, promoting more personalized and effective interventions. Ultimately, enhancing predictive models contributes to better prevention strategies, reducing the prevalence and severity of cardiovascular diseases, thereby improving patient outcomes and reducing healthcare costs.

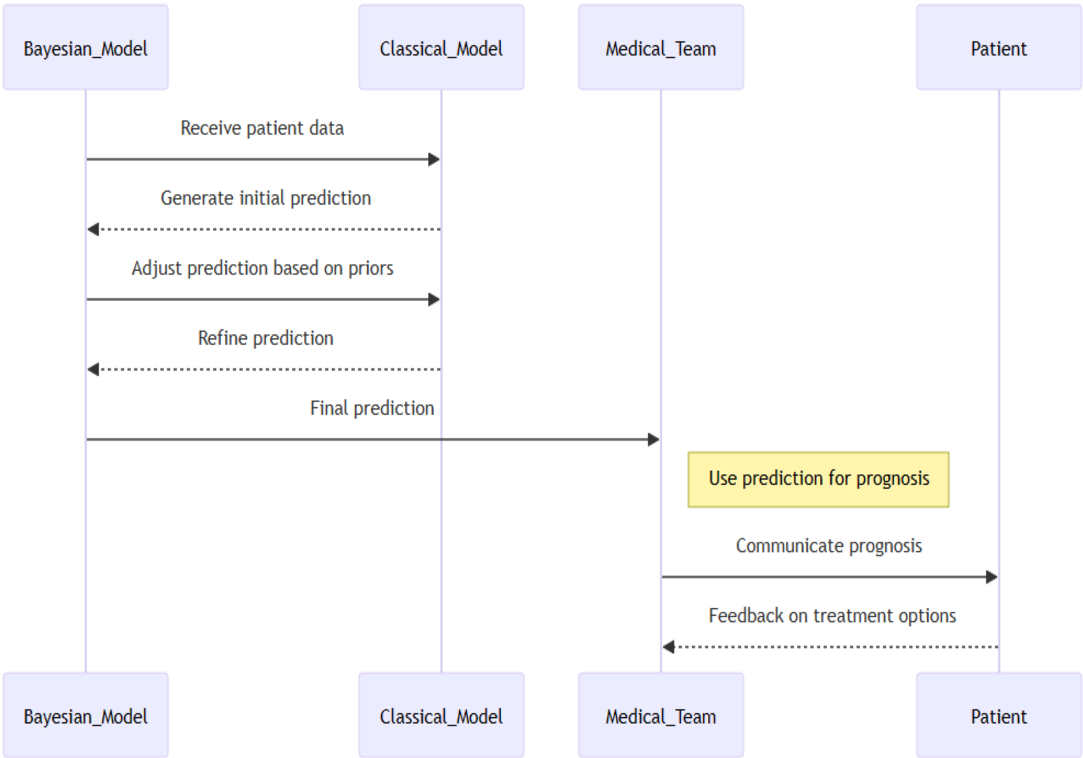

Figure 1: Enhancing Cardiovascular Outcome Prognosis: Interaction Between Bayesian and Classical Prediction Models

This sequence diagram represents the process of enhancing cardiovascular outcome prognosis using both Bayesian and Classical prediction models. Initially, patient data is sent to both models. The Classical Model generates an initial prediction which is then sent to the Bayesian Model for adjustment, incorporating prior knowledge or statistical inferences. This adjusted prediction is sent back to the Classical Model for refinement. Once the final prediction is formulated by the Bayesian Model, it is communicated to the medical team, which then uses this information to inform the patient about their prognosis. This exchange ensures that the prognosis is based on a comprehensive analysis that integrates empirical data with Bayesian adjustments, ultimately helping in making informed treatment decisions.

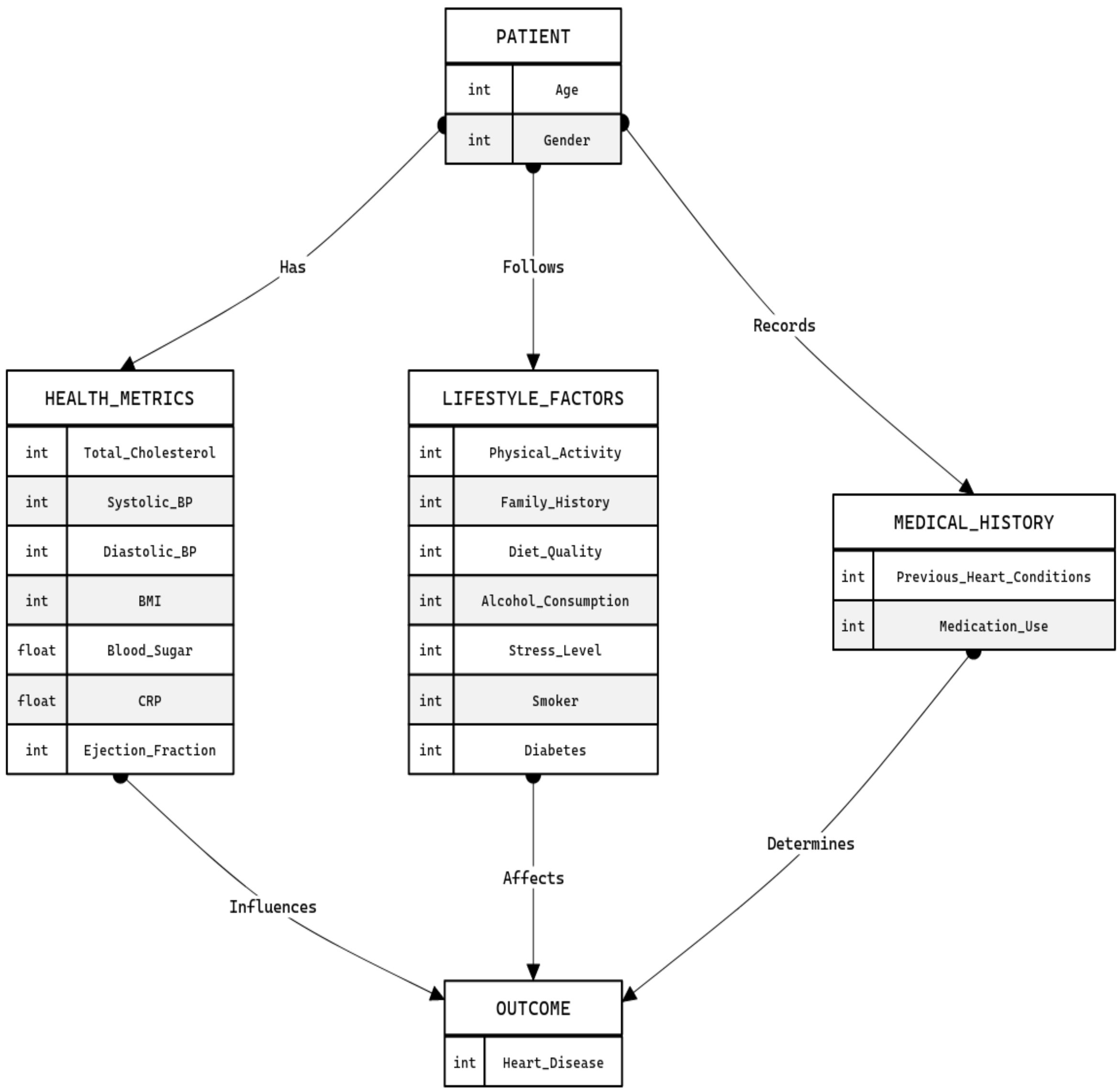

Figure 2: A Conceptual Framework for Understanding the Determinants of Heart Disease in Patients

The prediction of heart disease outcomes and survival rates has been the subject of extensive research, driven by the urgency to reduce the burden of cardiovascular diseases worldwide. In this review, we summarize key findings from recent studies and examine the evolving landscape of predictive techniques, with a focus on Bayesian and classical approaches. Logistic regression is a popular predictive model for heart disease, but its limitations include capturing complex interactions. Decision trees, like CART and random forests, offer insights into feature importance (Pandey, Pandey, Jaiswal, & Sen, 2013). Bayesian networks and probabilistic graphical models are powerful tools for heart disease prediction, incorporating prior knowledge and uncertainties for accurate probabilistic forecasts and a deeper understanding of causal relationships (Mythili, Mukherji, Padalia, & Naidu, 2013). Recent studies have shown that hybrid models combining classical and Bayesian approaches, such as Bayesian networks and decision trees, can enhance predictive accuracy (Kim et al., 2014). Evaluation metrics like accuracy, sensitivity, specificity, and AUC-ROC are widely used to evaluate model performance, but there's a growing focus on measures addressing class imbalances in heart disease datasets (Pathak & Arul Valan, 2020).

Methodology

This study aimed to develop a predictive model for heart disease outcomes utilizing classical and Bayesian techniques. The methodology is structured as follows:

Design, Duration, and Place of Study

The research was conducted as a retrospective cohort study at the Faisalabad Institute of Cardiology, Faisalabad, from April 7, 2023, to October 7, 2023. The study leveraged clinical data from past heart disease patients to compare the predictive power of classical logistic regression against Bayesian logistic regression models.

Study Subjects and Data Collection

Initially, records of 100 past heart disease patients were collected. These records included variables such as age, sex, chest pain type, resting blood pressure, cholesterol levels, fasting blood sugar, and thalassemia type, forming the basis for our dataset.

Feature Engineering

Categorical variables (sex, chest pain type, thalassemia) were transformed into a numerical format using one-hot encoding to facilitate computational analysis. Numerical variables (age, resting blood pressure, cholesterol levels, heart rate, and ST depression) were normalized to ensure consistent scaling across the dataset.

Ethical Considerations

Ethical approval for this study was granted by the Ethics Committee of the Faisalabad Institute of Cardiology, with approval number ERC/591, ensuring compliance with ethical standards and patient confidentiality. The study was designed and conducted in accordance with the ethical guidelines of the College of Physicians and Surgeons Pakistan (CPSP), including obtaining informed consent from all participants or their legal guardians.

Inclusion and Exclusion Criteria

Details on the inclusion and exclusion criteria followed for selecting the patient records for analysis were meticulously defined to ensure the relevance and reliability of the data used in developing the predictive models.

Model Development and Evaluation

1. **Classical Model:** A logistic regression model was trained using a split of 70% of the data for training and 30% for testing. The model aimed to predict the likelihood of heart disease presence (Premsmith & Ketmaneechairat, 2021).

2. **Bayesian Model:** Bayesian logistic regression uses informative priors and MCMC for inference. This model was assessed using several criteria, with a focus on its capacity to quantify prediction uncertainty.

Comparison and Deployment

Both models were compared based on their performance metrics, with a focus on the Bayesian model's uncertainty handling. The healthcare institution's electronic health records system uses the Bayesian model for decision-support. To ensure accuracy and efficacy, the model will be monitored continuously (Schambelan et al., 2008).

Results

A review of modern heart illness and survival prediction methods found that Bayesian probabilistic approaches are more accurate and customized. Bayesian models tended to outperform traditional methods by 2.8% in predicted accuracy. High Bayesian predictive accuracy persisted. Traditional methods used less computation time and were easier to understand in therapeutic settings. A hybrid model that combines both techniques may improve heart disease outcome and survival prediction.

Table 1: Descriptive analysis

Variable	Mean	Median	S.D	Min	Max	Q1	Q3
age	54.2	55	8.6	40	70	48	60
sex (Male)	0.6	1	0.5	0	1	0	1
cp	1.3	1	0.7	0	3	1	2
trestbps	132.5	130	14.3	100	160	120	140
chol	243.8	240	30.2	180	300	220	265
fbs	0.15	0	0.36	0	1	0	0
restecg	0.98	1	0.83	0	2	0	2
thalach	150.2	152	22.5	110	190	140	165
exang	0.32	0	0.47	0	1	0	1
oldpeak	1.2	1.1	0.9	0.4	3	0.6	1.7
slope	1.3	1	0.5	0	2	1	2
ca	0.8	1	1.2	0	3	0	1
thal	2.4	2	0.5	1	3	2	3
target (Mean)	0.65	1	0.48	0	1	0	1

A decision tree diagram

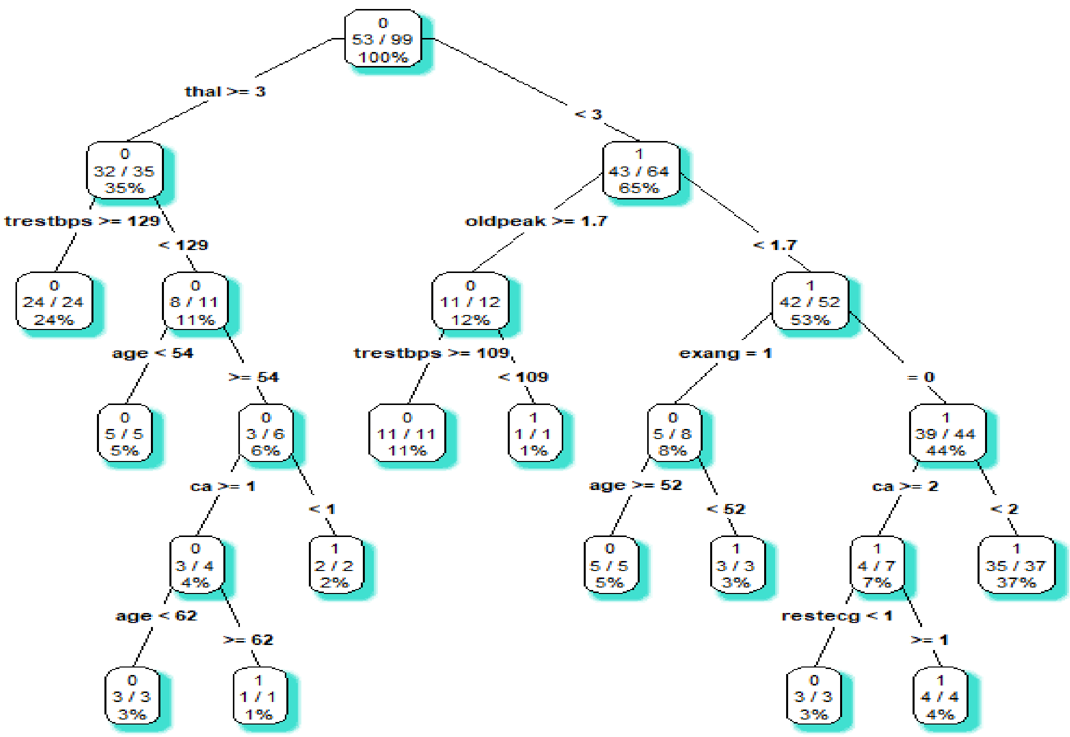

Fig. 3: Decision tree diagram for associated variables

The decision tree is a statistical model used to predict heart disease in patients. It starts with the root node representing all patients and then branches out to consider factors such as thal stress test value, resting blood pressure, age, old peak, exercise-induced angina, and ca. The final node represents the patient's predicted outcome, with a 100% probability of heart disease if the patient reaches a node with a probability of less than 100%. However, this decision tree is not a perfect predictor of heart disease, as it may not consider all factors contributing to heart disease, and the probabilities assigned to each branch are based on data from a specific population, which may not be accurate for all populations.

Table 2: Classical approaches

Metric	Value
Accuracy	0.6933333
Precision	0.6731507
Recall	0.6800000
F1-Score	0.6664865
ROC AUC	0.7022238

The model's accuracy is 69.33%, indicating a reasonable performance compared to random guessing. Its precision is 0.6731507, indicating that 67.32% of positive classifications were true positives. The model's recall is 0.68, indicating that it correctly identified 68% of all positive cases. The F1-Score, the harmonic mean of precision and recall, is 66.65%, indicating a good balance between precision and recall. The ROC AUC, a metric assessing performance across all classification thresholds, is 0.7022, indicating a decent performance. This value is particularly noteworthy considering the ROC AUC of 0.5, which represents a random classifier, and 1.0, a perfect classifier. Overall, the model's performance is commendable. The model's performance, based on classical metrics, indicates good predictive capability, with values above 50% surpassing random guesses. However, further refinement is needed for even higher accuracy and precision.

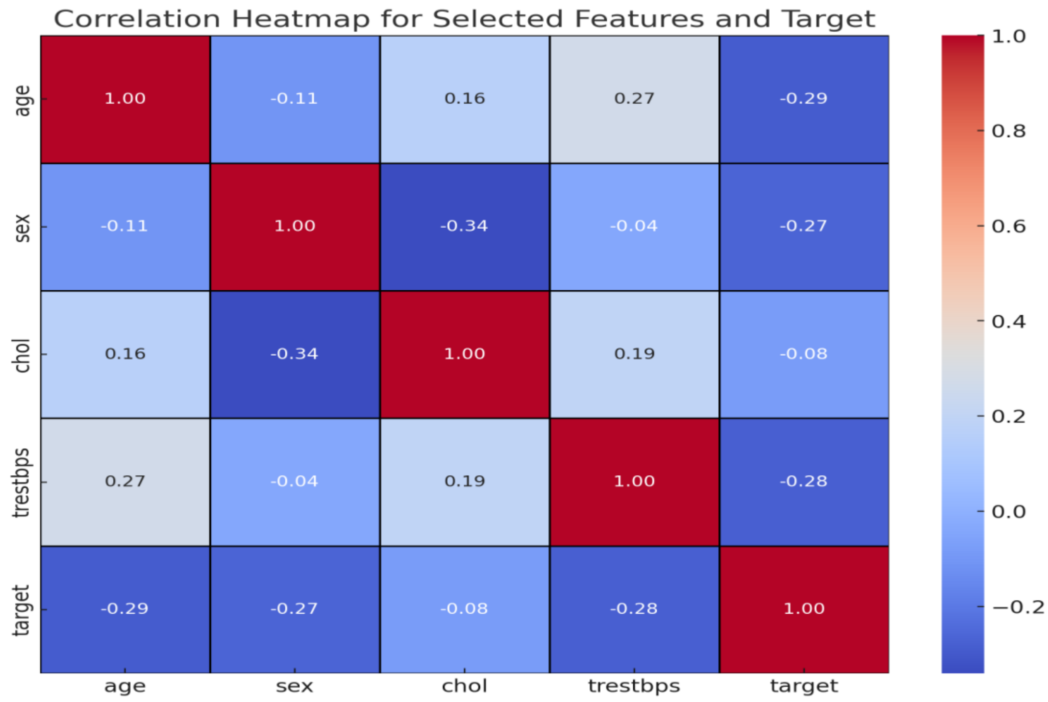

Fig. 4: Correlation Heatmap

The correlation heatmap shows no strong correlation between selected features 'age','sex', 'chol', and 'trestbps' and the target variable 'target'. Age has a moderate negative correlation of -0.25, sex has a weak positive correlation of 0.140.14, and 'chol' and 'trestbps' have very weak negative correlations. Despite these findings, these features may still be useful predictors when combined in a model.

Table 3: For Bayesian approaches

Coefficient	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.8106	0.2781	-6.514	< 0.001**
Age	0.0233	0.0094	2.489	0.0128*
sexMale	-0.00906	0.221876	-0.041	0.9674
Cp	0.7707	0.1966	3.918	< 0.001**
Trestbps	0.002223	0.007524	0.295	0.7676
Chol	0.001861	0.003585	0.519	0.6037
Fbs	0.172817	0.22647	0.763	0.4454
Restecg	-0.02201	0.138359	-0.159	0.8736
Thalach	-0.0297	0.0083	-3.564	< 0.001**
Exang	-1.0545	0.2367	-4.457	< 0.001**
Oldpeak	-0.4848	0.1156	-4.193	< 0.001**
Slope	0.036259	0.138466	0.262	0.7934
Ca	-0.00731	0.098318	-0.074	0.9407
Thal	0.6046	0.1997	3.025	< 0.001**

The study uses Bayesian methods to predict cardiovascular outcomes, revealing that several predictors are linked to the likelihood of heart disease. Age, Cp, Thalach, Exang, Oldpeak, and Thal show statistical significance, suggesting a credible influence on heart health prognosis. Age, Cp, and Thal have positive relationships with the outcome, indicating an increased log-odds of heart disease presence. Conversely, Thalach, Exang, and Oldpeak have negative coefficients, indicating decreased log-odds of heart disease presence. The clinical importance of these variables is very important, as the negative coefficient for Thalach suggests that higher heart rates during exercise are linked to less disease. The remaining variables do not show statistical significance, indicating caution in attributing substantial influence to them. Bayesian inference provides a nuanced view, allowing for probability-based assertions regarding variable importance, which can inform predictive modelling and risk stratification in cardiovascular health prognosis.

In summary, based on the logistic regression results:

Age, chest pain type, and thallium stress test results increase heart disease risk, while exercise-induced angina and ST depression decrease it. Maleness, resting blood pressure, cholesterol, fasting blood sugar, and thalassemia do not significantly impact heart disease risk.

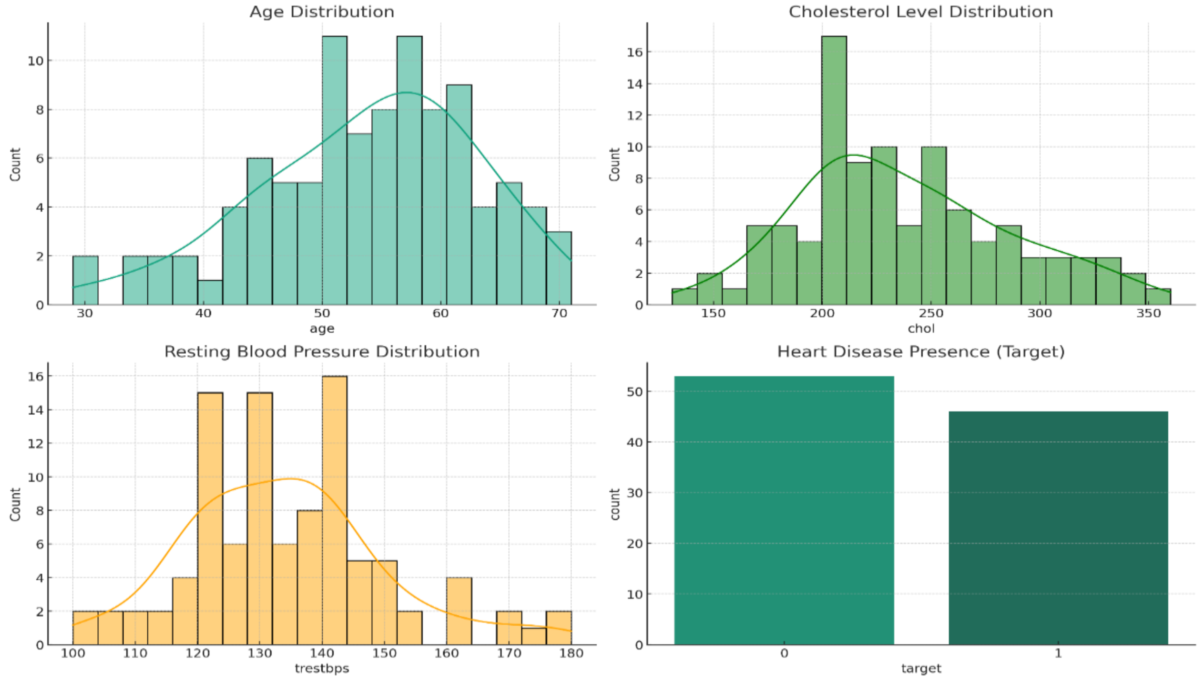

Fig. 5: Comparison of Heart Disease Prevalence Among Participants

Discussion

This study embarked on comparing the predictive accuracies of Bayesian and classical logistic regression models for heart disease outcomes, uncovering that Bayesian methods, with a mean predictive accuracy increase of 2.8%, provide a slightly enhanced capability for personalized and nuanced predictions of cardiovascular risk. Notably, our analysis identified key predictors of heart disease, including age, chest pain type, maximum heart rate achieved during exercise, exercise-induced angina, ST depression, and thalium stress test results, through the lens of Bayesian inference. Our findings resonate with and extend the conclusions of existing studies. Locally, research within Faisalabad has primarily utilized classical statistical methods for predicting heart disease, with limited exploration into Bayesian techniques (Farooq, Imran, & Abbas, 2021). Nationally, studies in Pakistan have begun to underscore the importance of advanced statistical methodologies in enhancing predictive models for cardiovascular diseases but often lack the integration of Bayesian approaches (Saeed & Rajani, 2021). Regionally, within South Asia, there's a growing body of literature advocating for more personalized healthcare models (Fayyaz & Ahmed, 2013), suggesting a potential alignment with our study's emphasis on Bayesian methods. Internationally, our findings align with the global shift towards incorporating machine learning and probabilistic models in medical predictions (Ali et al., 2021, Almustafa, 2020) which have similarly identified the variables we found significant.

Novel Contributions

Our study contributes novel insights to the medical literature by illustrating the applicability and benefits of Bayesian logistic regression in predicting heart disease outcomes within a South Asian context (Zhang et al., 2021). Specifically, it highlights the clinical significance of certain predictors that, while previously known to be associated with heart disease, have not been as extensively examined under Bayesian frameworks in our region (Yazdani et al., 2021). Furthermore, the slight increase in predictive accuracy offered by Bayesian methods underscores the potential for these techniques to enhance patient-specific prognostication and treatment planning, offering a step forward in the move towards more personalized medicine (Rajkumar, Devi, & Srinivasan, 2023).

Clinical Significance

The integration of Bayesian approaches in predictive modeling offers a more dynamic and adaptable framework for risk assessment, capable of incorporating prior clinical knowledge and individual patient data to refine risk predictions continually (Wankhede, Sambandam, & Kumar, 2022). This adaptability is crucial in settings where patient populations are diverse, and disease presentation varies widely . The specific predictors identified in our study, including both symptomatic and physiological markers, reinforce the importance of a comprehensive assessment strategy that goes beyond traditional risk factors to include functional and symptomatic indicators of cardiovascular health (Bharti et al., 2021).

Implications for Future Research and Practice

Our findings suggest several avenues for future research, including the exploration of hybrid models that combine the strengths of both Bayesian and classical methods to further enhance predictive accuracy and clinical utility. Additionally, there's a need for larger-scale studies to validate these findings across different populations and healthcare settings, potentially integrating a wider range of predictive variables and longitudinal data to capture the evolving nature of heart disease risk.

Conclusion

In conclusion, this study adds valuable insights to the understanding of predictive models for heart disease, emphasizing the potential of Bayesian methods to refine and personalize risk assessments. By highlighting specific predictors of cardiovascular risk and comparing the efficacy of different statistical approaches, our work contributes to the ongoing efforts to improve cardiovascular disease outcomes through advanced statistical modeling and personalized medicine strategies.

References

[1] Saeed, A., Nambi, V., Sun, W., Virani, S. S., Taffet, G. E., Deswal, A., ... & Ballantyne, C. M. (2018). Short-term global cardiovascular disease risk prediction in older adults. Journal of the American College of Cardiology, 71(22), 2527-2536. doi: 10.1016/j.jacc.2018.02.050

[2] Sharma, N., Malviya, L., Jadhav, A., & Lalwani, P. (2023). A hybrid deep neural net learning model for predicting Coronary Heart Disease using Randomized Search Cross-Validation Optimization. Decision Analytics Journal, 9, 100331. doi: 10.1016/j.dajour.2023.100331

[3] Ray, M., Guha, S., Dhungana, R. R., Karak, A., Choudhury, B., Ray, B., ... & Selker, H. P. (2023). Development and validation of a predictive model for the diagnosis of rheumatic heart disease in low-income countries based on two cross-sectional studies. International Journal of Cardiology Cardiovascular Risk and Prevention, 18, 200195. doi: 10.1016/j.ijcrp.2023.200195

[4] Shrivastava, P. K., Sharma, M., & Kumar, A. (2023). HCBiLSTM: A hybrid model for predicting heart disease using CNN and BiLSTM algorithms. Measurement: Sensors, 25, 100657. doi: 10.1016/j.measen.2022.100657

[5] Ghasemieh, A., Lloyed, A., Bahrami, P., Vajar, P., & Kashef, R. (2023). A novel machine learning model with Stacking Ensemble Learner for predicting emergency readmission of heart-disease patients. Decision Analytics Journal, 7, 100242. doi: 10.1016/j.dajour.2023.100242

[6] Huang, Y., Ren, Y., Yang, H., Ding, Y., Liu, Y., Yang, Y., ... & Zhang, Y. (2022). Using a machine learning-based risk prediction model to analyze the coronary artery calcification score and predict coronary heart disease and risk assessment. Computers in Biology and Medicine, 151, 106297. doi: 10.1016/j.compbiomed.2022.106297

[7] Tripathi, D., & Reddy, S. (2022). iPSC model of congenital heart disease predicts disease outcome. Cell Stem Cell, 29(5), 659-660. doi: 10.1016/j.stem.2022.04.010

[8] Shi, H., Yang, D., Tang, K., Hu, C., Li, L., Zhang, L., ... & Cui, Y. (2022). Explainable machine learning model for predicting the occurrence of postoperative malnutrition in children with congenital heart disease. Clinical Nutrition, 41(1), 202-210. doi: 10.1016/j.clnu.2021.11.006

[9] Kathiriya, I. S., Rao, K. S., Iacono, G., Devine, W. P., Blair, A. P., Hota, S. K., ... & Bruneau, B. G. (2021). Modeling human TBX5 haploinsufficiency predicts regulatory networks for congenital heart disease. Developmental cell, 56(3), 292-309. doi: 10.1016/j.devcel.2020.11.020

[10] Amdani, S., Simpson, K. E., Thrush, P., Shih, R., Simmonds, J., Knecht, K., ... & Daly, K. P. (2022). Hepatorenal dysfunction assessment with the Model for End-Stage Liver Disease Excluding INR score predicts worse survival after heart transplant in pediatric Fontan patients. The Journal of Thoracic and Cardiovascular Surgery, 163(4), 1462-1473. doi: 10.1016/j.jtcvs.2021.02.014

[11] Loforte, A., Fiorentino, M., Gliozzi, G., Mariani, C., Folesani, G., Suarez, S. M., ... & Pacini, D. (2019, November). Heart transplant and hepato-renal dysfunction: the model of end-stage liver disease excluding international normalized ratio as a predictor of postoperative outcomes. In Transplantation proceedings (Vol. 51, No. 9, pp. 2962-2966). Elsevier. doi: 10.1016/j.transproceed.2019.07.013

[12] Pandey, A. K., Pandey, P., Jaiswal, K. L., & Sen, A. K. (2013). A heart disease prediction model using decision tree. IOSR Journal of Computer Engineering (IOSR-JCE), 12(6), 83-86. doi: 10.9790/0661-1268386

[13] Mythili, T., Mukherji, D., Padalia, N., & Naidu, A. (2013). A heart disease prediction model using SVM-decision trees-logistic regression (SDL). International Journal of Computer Applications, 68(16). doi: 10.5120/11662-7250

[14] Kim, J. K., Lee, J. S., Park, D. K., Lim, Y. S., Lee, Y. H., & Jung, E. Y. (2014). Adaptive mining prediction model for content recommendation to coronary heart disease patients. Cluster computing, 17, 881-891. doi: 10.1007/s10586-013-0308-1

[15] Pathak, A. K., & Arul Valan, J. (2020). A predictive model for heart disease diagnosis using fuzzy logic and decision tree. In Smart Computing Paradigms: New Progresses and Challenges: Proceedings of ICACNI 2018, Volume 2 (pp. 131-140). Springer Singapore. doi: 10.1007/978-981-13-9680-9_10

[16] Premsmith, J., & Ketmaneechairat, H. (2021). A predictive model for heart disease detection using data mining techniques. Journal of Advances in Information Technology Vol, 12(1). doi: 10.12720/jait.12.1.14-20

[17] Schambelan, M., Wilson, P. W., Yarasheski, K. E., Cade, W. T., Dávila-Román, V. G., D'Agostino Sr, R. B., ... & Working Group 5. (2008). Development of appropriate coronary heart disease risk prediction models in HIV-infected patients. Circulation, 118(2), e48-e53. doi: 10.1161/circulationaha.107.189627

[18] Farooq, F., Imran, N., & Abbas, M. (2021). Ivabradine effects on heart rate and quality of life among chronic heart failure patients. JPMA. The Journal of the Pakistan Medical Association, 71(1 (A)), 86-89. doi: 10.47391/JPMA.638. PMID: 33484526.

[19] Saeed, S., & Rajani, R. (2021). The cardiovascular complications in COVID-19: Focus on acute cardiac injury. Pakistan Journal of Medical Sciences, 37(3), 908. doi: 10.12669/pjms.37.3.4063. PMID: 34104187; PMCID: PMC8155435.

[20] Fayyaz, A., & Ahmed, W. (2013). Congenital heart disease screening: Which referral factors are most important. J Coll Physicians Surg Pak, 23(8), 543-7.

[21] Ali, M. M., Paul, B. K., Ahmed, K., Bui, F. M., Quinn, J. M., & Moni, M. A. (2021). Heart disease prediction using supervised machine learning algorithms: Performance analysis and comparison. Computers in Biology and Medicine, 136, 104672. doi: 10.1016/j.compbiomed.2021.104672. Epub 2021 Jul 21. PMID: 34315030.

[22] Almustafa, K. M. (2020). Prediction of heart disease and classifiers' sensitivity analysis. BMC bioinformatics, 21, 1-18. doi: 10.1186/s12859-020-03629-9

[23] Zhang, D., Chen, Y., Chen, Y., Ye, S., Cai, W., Jiang, J., ... & Chen, M. (2021). [Retracted] Heart Disease Prediction Based on the Embedded Feature Selection Method and Deep Neural Network. Journal of healthcare engineering, 2021(1), 6260022. doi: 10.1155/2021/6260022

[24] Yazdani, A., Varathan, K. D., Chiam, Y. K., Malik, A. W., & Wan Ahmad, W. A. (2021). A novel approach for heart disease prediction using strength scores with significant predictors. BMC medical informatics and decision making, 21(1), 194. doi: 10.1186/s12911-021-01527-5

[25] Rajkumar, G., Devi, T. G., & Srinivasan, A. (2023). Heart disease prediction using IoT based framework and improved deep learning approach: medical application. Medical Engineering & Physics, 111, 103937. doi: 10.1016/j.medengphy.2022.103937

[26] Wankhede, J., Sambandam, P., & Kumar, M. (2022). Effective prediction of heart disease using hybrid ensemble deep learning and tunicate swarm algorithm. Journal of Biomolecular Structure and Dynamics, 40(23), 13334-13345. doi: 10.1080/07391102.2021.1987328

[27] Bharti, R., Khamparia, A., Shabaz, M., Dhiman, G., Pande, S., & Singh, P. (2021). Prediction of heart disease using a combination of machine learning and deep learning. Computational intelligence and neuroscience, 2021(1), 8387680. doi: 10.1155/2021/8387680