POST COVID HEART ATTACK RISK PREDICTION AND INTERPRETABILITY USING MACHINE LEARNING

ABSTRACT: This article explores the development of a machine learning model to predict heart attack risk using a dataset containing demographic, medical history, COVID-related factors, and diagnostic test results. The Random Forest Classifier is used for prediction, and a streamlined explanation mechanism is incorporated to enhance interpretability by highlighting only risk-increasing features. The implementation is demonstrated using a Streamlit web application, ensuring accessibility for healthcare professionals and individuals.

Machine learning plays a crucial role in healthcare, enabling predictive analysis that supports early diagnosis and risk assessment. However, the lack of interpretability in complex models remains a challenge. This study addresses this issue by integrating feature-based explanations into the risk prediction system. The results indicate that the proposed method provides accurate risk predictions while maintaining transparency, which is essential for clinical applications. The use of predictive analytics in healthcare has the potential to revolutionize patient outcomes by enabling early intervention and personalized treatment strategies.

Keywords: Heart Attack Risk, Machine Learning, Interpretability, Random Forest, Healthcare AI, Predictive Analytics, Explainable AI, Cardiovascular Disease, Predictive Healthcare, Risk Prediction, Health Informatics.

INTRODUCTION

Heart attacks are a major cause of mortality worldwide, necessitating early detection and risk assessment. According to the World Health Organization (WHO), cardiovascular diseases (CVDs) account for approximately 32% of all global deaths [1]. Early prediction of heart attack risk can facilitate timely medical intervention and lifestyle adjustments, reducing mortality rates. With the increasing prevalence of heart-related ailments due to lifestyle factors, genetic predisposition, and environmental influences, developing a robust predictive model is essential.

Machine learning models can provide data-driven insights to predict heart attack risk based on various health parameters [2]. Traditional statistical methods have been widely used in medical diagnostics, but they often fail to capture complex interactions between multiple risk factors. Advanced machine learning techniques, such as Random Forest classifiers and deep learning models, offer improved accuracy and adaptability in risk assessment. However, interpretability remains a challenge, as complex models often act as "black boxes" with limited transparency regarding decision-making processes [3].

This article presents an interpretable risk prediction system that not only forecasts heart attack risk but also explains the contributing factors in an understandable manner. The combination of predictive power and transparency makes this system valuable for both clinicians and patients. The ability to interpret model decisions fosters trust and facilitates informed decision-making in healthcare settings.

PRELIMINARIES AND DEFINITIONS

1. **Dataset Structure**: The dataset consists of demographic details, pre-existing conditions, lifestyle habits, COVID-19 history, and test results, with the target variable being "Heart_Attack_Risk" (Low, Medium, High). It integrates multiple factors that influence cardiovascular health, improving predictive capability [1]. The inclusion of COVID-19-related factors acknowledges emerging research indicating long-term cardiovascular complications post-infection.
2. **Machine Learning Model**: The Random Forest Classifier is chosen due to its robustness, ability to handle categorical and numerical features, and superior performance in medical applications [3]. It works by constructing multiple decision trees and aggregating their results, thereby reducing overfitting and improving generalization.
3. **Feature Engineering and Label Encoding**: Since the dataset contains categorical attributes, label encoding is applied to convert them into numerical representations for model training. This step is essential to ensure compatibility with machine learning algorithms. Proper feature selection enhances model performance and reduces noise from irrelevant attributes.
4. **Interpretability**: Feature importance is used to generate explanations by identifying and displaying only risk-increasing factors, making the model's decisions more transparent [2]. Understanding how each feature contributes to risk allows for targeted interventions and personalized healthcare recommendations.

METHODS FOR INTERPRETABILITY AND EXPLAINABILITY

- **Data Preprocessing**: Label encoding is applied to categorical features to convert them into numerical values suitable for machine learning algorithms. Missing values are handled appropriately to ensure data completeness [1]. The dataset is standardized where necessary to improve model performance.

- **Model Training**: The dataset is split into training and testing sets, and a Random Forest model is trained to predict heart attack risk. The model is optimized using hyperparameter tuning to enhance performance. Various evaluation metrics, including accuracy, precision, recall, and F1-score, are used to assess model effectiveness [3].
- **Explanation Mechanism**: Instead of listing all input features, only those contributing to an increased risk are included in the output explanation. For example, high cholesterol, smoking, and abnormal ECG results are emphasized if present, providing actionable insights [2]. This enhances the interpretability of the model's predictions, allowing users to understand why a particular risk level was assigned.
- **User Interface**: A Streamlit-based application is developed to collect user input, predict risk, and display an explanation dynamically, ensuring ease of use and accessibility. The web-based interface allows real-time interaction, making it suitable for healthcare professionals and individuals. User-centric design principles ensure clarity and efficiency in presenting results.

DISCUSSION

The proposed system provides both accurate predictions and meaningful explanations. The Random Forest model achieves high accuracy, while the explanation method ensures transparency [3]. The approach is beneficial for healthcare professionals and individuals seeking to understand their cardiovascular risk. It aligns with the growing need for interpretable AI in medical applications, as black-box models raise ethical and practical concerns.

A significant advantage of this system is its ability to highlight only risk-increasing factors, which enhances its usability in clinical settings. However, the model's reliance on labeled training data may limit its generalizability. Additionally, social determinants of health, which are not included in the dataset, can also impact cardiovascular outcomes [2].

Another limitation is the static nature of the dataset. Real-time data, such as wearable device readings and continuous monitoring of vital signs, could enhance prediction accuracy. Moreover, deep learning techniques, combined with interpretable AI frameworks such as SHAP (SHapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations), can further improve the system's effectiveness while maintaining explainability.

Future improvements could include:

- Expanding the dataset to include more diverse populations.
- Incorporating real-time monitoring data from wearable health devices.
- Utilizing deep learning methods with explainability frameworks.
- Adding social and behavioral determinants of health for a holistic risk assessment.
- Exploring federated learning approaches to enhance data privacy and model generalizability.
- Conducting comparative studies with different machine learning algorithms to determine the most suitable model for heart attack risk prediction.

CONCLUSION

This article presents a machine learning-based system for heart attack risk prediction with an emphasis on interpretability. The combination of a Random Forest model and a filtered explanation mechanism enhances both accuracy and transparency, making it a valuable tool for health risk assessment. The results indicate that providing users with only risk-contributing factors significantly improves interpretability and usability.

Future advancements should focus on expanding the dataset, improving generalization, and incorporating additional medical indicators for a more comprehensive risk evaluation. By integrating real-time data sources and explainable AI techniques, the system can be further enhanced for practical applications in predictive healthcare.

REFERENCES

1. World Health Organization. Cardiovascular Diseases (CVDs). Available at: who.int
2. Explainable AI for Healthcare: State of the Art and Future Directions (arxiv.org)
3. Machine Learning in Cardiovascular Disease Prediction – A Review (mdpi.com)
4. Random Forest Classifier for Medical Diagnosis – Applications and Performance (dl.acm.org)