Predictive Healthcare: Balancing Innovation and Ethics in Heart Disease Diagnosis through Machine Learning

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10/25/24

Imagine yourself sitting in a doctor's office, waiting for test results that could change your life. For many facing heart disease, this is the harsh reality. Globally, cardiovascular diseases are the leading cause of death, accounting for 32% of all global deaths in 2019 (World Health Organization, 2020). Yet, for most patients, the diagnosis comes far too late to prevent serious consequences. Instead, what if a simple algorithm could predict heart disease early on, even before the first symptoms? Fortunately with the future of medicine, machine learning models could give doctors the ability to detect and treat heart disease. One particular study, "Heart Disease Prediction Using Weighted K-Nearest Neighbor Algorithm" by Barry et al., introduces a novel approach to predicting heart disease using a weighted variant of the K-Nearest Neighbor (KNN) algorithm. This paper will examine the research methodologies, findings, and ethical implications discussed in this study, highlighting how the weighted KNN model could be more than just an advancement in data but an advancement that can save lives.

In their approach to improving heart disease prediction, the authors propose a machine learning model based on the weighted K-Nearest Neighbor (KNN) algorithm. The study aimed to enhance the predictive accuracy for diagnosing heart disease by leveraging feature selection and clustering techniques. The dataset used for this study was an aggregation of five well-known heart disease datasets: Cleveland, Hungary, Switzerland, VA Long Beach, and Statlog (Heart), totaling 1,190 instances and 11 features such as age, sex, chest pain type, cholesterol levels, and maximum heart rate. The authors used these features to classify whether a patient suffered from heart disease.

The methodology begins with data preprocessing, which includes handling missing values, eliminating outliers using the interquartile range (IQR) method, and clustering features using the K-means algorithm. By clustering similar features together and selecting the most relevant ones from each cluster, the authors reduced the dimensionality of the dataset. The selected features were then scored using the relief technique, which assigns weights to each feature based on its relevance in classification. The scores from this method were subsequently used as weights for the KNN algorithm to improve classification performance by focusing on the most essential features.

Several machine learning algorithms were used in this study to benchmark the performance of the proposed weighted KNN model. First, the traditional K-Nearest Neighbor (KNN) algorithm uses the closest data points (neighbors) to classify new data. In addition, the Support Vector Machine (SVM) approach aims to separate classes with a hyperplane that maximizes the distance between them, which is effective in high-dimensional data spaces. Logistic Regression (LR) provides another classification technique that estimates the probability of a data point belonging to a specific class, often used for binary classifications. Moving beyond simpler structures, the study also included the Multilayer Perceptron (MLP), an artificial neural network that processes data through multiple layers and is suitable for capturing non-linear relationships. Finally, the Naïve Bayes (NB) algorithm classifies data based on the probability of features occurring independently, known for efficiency with smaller datasets.

To assess each algorithm's performance, the study relied on a few metrics: Accuracy, which measures the proportion of correct predictions; Precision, indicating the percentage of positive predictions that are accurate; Recall or Sensitivity, reflecting the model's ability to identify all positive cases; F1-score, balancing precision and recall; and AUC-ROC, which evaluates the model's ability to distinguish between classes across various thresholds. These metrics provide a thorough view of each model's effectiveness and reliability in heart disease prediction.

After applying each classification method, the study results provided a comprehensive baseline for evaluating the proposed weighted KNN model. The Naïve Bayes algorithm achieved an accuracy of 83.61%, a precision of 85.38%, a recall of 84.73%, and an F1-score of 85.06%. Logistic Regression (LR) outperformed Naïve Bayes with an accuracy of 86.13%, a precision of 88.28%, a recall of 86.26%, and an F1-score of 87.26%. Similarly, the Multilayer Perceptron (MLP) produced an accuracy comparable to Logistic Regression at 86.13% but with a higher precision of 90.83% and a lower recall of 83.21%, resulting in an F1-score of 86.85%. The Support Vector Machine (SVM) algorithm achieved an accuracy of 88.66%, a precision of 88.24%, a recall of 91.60%, and an F1-score of 89.89%. Lastly, the traditional K-Nearest Neighbor (KNN) algorithm demonstrated a performance with an accuracy of 88.24%, a precision of 88.72%, a recall of 90.08%, and an F1-score of 89.39%. These results highlight the strength of each model and establish a foundation against which the weighted KNN model can be assessed.

Building on the performance of the baseline models, the weighted KNN algorithm further improves classification outcomes by incorporating feature scores as weights. This enhancement led the weighted KNN model to outperform all other algorithms significantly, achieving an accuracy of 93.28%, a precision of 95.28%, a recall of 92.37%, and an F1-score of 93.80%. Additionally, the model's Area Under the Receiver Operating Characteristic Curve (AUC-ROC) reached 97.20%, signaling a high level of classification accuracy and reliability. These results mark an improvement over the traditional KNN, which had an accuracy of 88.24% and an AUC-ROC of 91.90%.

To optimize the model, the authors also used tenfold cross-validation with hyperparameter tuning during the training phase. This step ensured that the model's parameters, such as the number of nearest neighbors (k), were carefully calibrated to achieve the best performance. For the standard KNN algorithm, the optimal value of k was 17, while for the weighted KNN, it was reduced to 9, showing that weighted KNN required fewer neighbors for better predictions.

The weighted KNN model demonstrated superior performance across all evaluation metrics compared to the benchmark machine-learning algorithms. By integrating feature selection and weighting into the traditional KNN model, the authors achieved a model with high predictive accuracy, precision, and recall, making it a valuable tool for early diagnosis of heart disease. Yet, with this advancement comes a critical question of justice: How can we ensure these predictive tools remain accessible, equitable, and beneficial to society? While machine learning models like the one proposed here hold tremendous potential, they also prompt essential discussions around fairness, accessibility, and the risks of misuse.

One key concern is the potential for biased data to influence the outcomes of machine learning models. Medical datasets, especially those related to heart disease, may not fully represent minority populations or individuals with varying socio-economic backgrounds. If the training data used to build the model does not adequately capture many diverse backgrounds, then the predictions generated by the model could disproportionately benefit some groups while leaving others behind. For example, suppose a dataset is skewed towards middle-aged men from the United States. In that case, the model may be less effective in predicting heart disease in women or individuals from other countries. This imbalance can exacerbate existing healthcare inequalities, making it harder for already marginalized groups to access life-saving diagnostics and treatments.

Additionally, integrating machine learning models into healthcare systems raises concerns about transparency and accountability. Medical decisions that impact human lives should be easily understandable by healthcare providers, patients, and policymakers. The “black box” nature of many machine learning models, including KNN, can make it difficult for non-technical users to understand how decisions are made. This lack of transparency can disrupt trust in the healthcare system and make it more challenging to hold stakeholders accountable for a mistake.

Another pressing concern is data privacy. Medical data, particularly data used in predictive models, is highly sensitive. The datasets used to build models like the weighted KNN in this study contain personal information about patients, including their age, cholesterol levels, and history of chest pain. Ensuring the privacy and security of this data is of importance, as breaches could lead to significant harm to patients, both financially and emotionally. In recent years, there has been an alarming increase in cyberattacks targeting healthcare institutions. The potential for misuse of medical data, whether through hacking or corporate exploitation, should not be overlooked.

Lastly, we must consider the moral implications of reliance on predictive models in medical decision-making. While models like the weighted KNN can greatly assist in the diagnostic process, they are not always correct. There is a risk that healthcare providers might overly rely on machine predictions, reducing clinical intuition and individualized patient care. When a patient’s symptoms are ambiguous or do not align with the model’s predictions, doctors may feel pressured to follow the algorithm rather than trust their own judgment. This could result in patients receiving suboptimal care, particularly in complex or edge cases.

Heart disease prediction technology can potentially transform healthcare. The work by Barry et al. on the weighted K-Nearest Neighbor (KNN) algorithm provides crucial advancements in early heart disease diagnosis, achieving impressive accuracy and reliability. With this model, doctors could more readily detect heart disease early, potentially improving outcomes and saving lives. However, with the rise of machine learning in healthcare, it's essential to also address the ethical challenges. Issues of data bias, patient privacy, and transparency in algorithm-driven decisions demand careful consideration to ensure these technologies serve everyone equitably. Balancing novel technological approaches with ethical integrity is critical to ensuring that such tools contribute to an advanced and just healthcare future.

References

World Health Organization. (2020, December 9). Cardiovascular diseases (CVDs) fact sheet. World Health Organization. https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

Barry, K. A., Manzali, Y., Lamrini, M., Rachid, F., & Elfar, M. (2024). Heart Disease Prediction Using Weighted K-Nearest Neighbor Algorithm. Operations Research Forum. https://doi.org/10.1007/s43069-024-00356-2