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Analysis of Machine Learning Methods for Diseases Prediction

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Abstract

The deployment of data mining techniques has gathered significant its capability to increase diagnostic accuracy. This paper exploration and evaluation of data mining strategies for disease prediction. Our investigation covers an assortment of algorithms. Furthermore, we explore an extensive array of diseases. This paper further investigates the variety of datasets. An analytical comparison of various data mining strategies imparting understanding into their individual strengths, limitations. our paper also identifies gaps in the research and proposes potential avenues for future exploration, which may encompass the integration of advanced machine learning methodologies and utilization of data categories. The purpose of paper provides all encompassing perspective on the present status of data mining in the context of disease prediction, assist scholars in making informed choices. The analysis of various studies revealed significant inconsistencies in the performance certain algorithms, may be attributed to factors such as the choice of dataset, preprocessing steps, and dataset size.

Keywords: Machine Learning, Deep Learning, Predictive Analytics, Disease Prediction, Feature Selection, Medical Data Processing, Classification Algorithms.

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تحليل أساليب التعلم الآلي للتنبؤ بالأمراض

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الملخص:
أدى استخدام تقنيات التنقيب في البيانات إلى زيادة قدرتها بشكل كبير على زيادة دقة التشخيص. تستكشف هذه الورقة البحثية وتُقيّم استراتيجيات التنقيب في البيانات للتنبؤ بالأمراض. يغطي بحثنا مجموعة متنوعة من الخوارزميات. علاوة على ذلك، نستكشف مجموعة واسعة من الأمراض. كما نتعمق في دراسة تنوع مجموعات البيانات. تُجري هذه الورقة مقارنة تحليلية لمختلف استراتيجيات التنقيب في البيانات، مما يُسهم في فهم نقاط القوة والضعف لكل منها. كما تُحدد ورقتنا البحثية الثغرات في البحث، وتقترح سبلًا محتملة للاستكشاف المستقبلي، والتي قد تشمل دمج منهجيات التعلم الآلي المتقدمة والاستفادة من فئات البيانات. تهدف هذه الورقة البحثية إلى تقديم منظور شامل للوضع الحالي للتنقيب في البيانات في سياق التنبؤ بالأمراض، ومساعدة الباحثين على اتخاذ قرارات مدروسة. كشف تحليل دراسات مختلفة عن تناقضات كبيرة في أداء بعض الخوارزميات، والتي قد تُعزى إلى عوامل مثل اختيار مجموعة البيانات، وخطوات المعالجة المسبقة، وحجم مجموعة البيانات.
الكلمات المفتاحية: التعلم الآلي، التعلم العميق، التحليلات التنبؤية، التنبؤ بالأمراض، اختيار الميزات، معالجة البيانات الطبية، خوارزميات التصنيف.

Introduction

Cardiovascular conditions continue to be the world's primary cause of mortality, taking millions of lives annually (Ahsan et al., 2021). The considerable impact of these diseases on global health infrastructures underscores the critical importance of prompt detection and early treatment, which can profoundly influence the course of the disease and the results for patients (Islam & Majumder, 2023). Even with improvements in diagnostic methods and a greater

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depth of medical knowledge, accurately forecasting heart disease remains a complicated task, complicated by its intricate and varied contributing factors [Obenshain, 2024].

The advent of predictive analytics, especially with statistical and machine learning (ML) techniques, has revolutionized the approach to tackling the issue of heart disease prediction. Within healthcare, such cutting-edge methods are celebrated for their proficiency in navigating through extensive and complex data, yielding precise forecasts regarding the likelihood, advancement, and response to treatment of diseases . Specifically, ML has introduced a transformative perspective to cardiology, enabling earlier prediction of heart conditions through the analysis of diverse data types, including clinical profiles, medical imaging, and genetic information.

The emergence of machine learning (ML) in medical diagnostics signifies a pivotal departure from traditional statistical approaches to advanced algorithms designed to handle large and varied datasets. This survey delves into the range of ML methodologies employed in heart disease forecasting, examining the performance of various models and their assimilation into medical routines.

This survey aims to evaluate the present state of machine learning (ML) implementations for predicting heart disease, confront the real-world difficulties clinicians encounter when integrating these tools, and pinpoint directions for further investigation. Additionally, it intends to gauge the impact of ML on medical decision-making processes and explore how it could improve patient care quality.

The approach of this survey included a thorough examination of the literature, choosing research that was pertinent and impactful to the area of ML in forecasting heart conditions. Literature searches spanned databases like PubMed, IEEE Xplore, and Google Scholar, with an emphasis on studies released in the past decade to provide an up-to-date viewpoint.

Upon analyzing various studies, we have observed a striking inconsistency in the results concerning the performance of different algorithms in disease prediction. There appears to be a lack of consensus among the studies. For instance, some research papers have highlighted Decision Tree algorithms as superior compared to others in terms of performance. In contrast, other studies have advocated for the superiority of the Naive Bayes algorithm. The

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contradictions in the results are especially stark when considering the Support Vector Machine (SVM) algorithm. Certain studies hail SVM as the most effective algorithm for disease prediction, while others categorize it as the least effective in terms of accuracy. This apparent discord among the findings necessitates a careful and critical examination of the methodologies and datasets employed in different studies to identify the factors contributing to these discrepancies. The reasons behind the contradictory results are not immediately apparent, but one can speculate that the choice of dataset and the preprocessing steps undertaken prior to applying the algorithms may play significant roles. Moreover, the size of the dataset can also be a crucial factor influencing the results. Many studies have acknowledged dataset size as a potential threat to the validity of their findings. They emphasize that the evaluation of the same algorithms with larger datasets is essential for a more comprehensive understanding of their performance. Thus, it's imperative to consider the nature and size of the dataset, along with the preprocessing techniques used, when analyzing the efficacy of different algorithms.

Literature review

Recently, several studies have been conducted to predict diseases using data mining Algorithms(Neesha et al,2025) the author conduct a comparison of various algorithms to predict cardiac disease. The research presents the outcomes of significant data mining techniques, which can be leveraged to develop a prediction model that is highly efficient and accurate. This model holds the potential to assist doctors in minimizing the mortality rate associated with heart disease. The study evaluates the predictive metrics for heart disease using six machine-learning algorithms, namely Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Gaussian Naïve Bayes (GNB), and k-Nearest Neighbor (kNN). In(Mutlu,2023) . The author explores assorted data mining methods applied within the healthcare sector. It delineates the issues encountered by health professionals in managing substantial volumes of data and elaborates on how data mining can facilitate the derivation of meaningful insights from such expansive datasets. The authors in (Ruben,2019) offer a comprehensive review of data mining's utility in the healthcare sector while shedding light on the prevailing difficulties and challenges tied to its implementation within this

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context. The authors delineate several data mining strategies, such as decision trees, artificial neural networks, and association rules, and explore their prospective uses within healthcare. The authors additionally tackle ethical and legal considerations linked with healthcare data mining, including issues related to patient privacy and data security. According to the authors, data mining could play a crucial role in elevating healthcare outcomes by identifying risk factors, forecasting diseases, and designing individualized treatment schemes.

In (Sa,2024) the authors explore the prospective use of data mining strategies in diagnosing and treating cancer. The authors undertake a thorough review of diverse data mining methodologies such as decision trees, artificial neural networks, and support vector machines, delving into their potential use in analyzing cancer-related data. The authors underscore the obstacles linked with the incorporation of data mining techniques in healthcare, which include concerns around the quality of data, privacy, and ethics. The primary aim of the article in(Aniruddha,2020)is to tackle the issue of constraining and summarizing various data mining algorithms utilized in the realm of medical prediction, with a specific focus on intelligent and efficient heart attack prediction. The authors offer valuable insights into the recent advancements in data mining techniques pertinent to heart disease prediction, potentially benefiting researchers and practitioners in this field.

Methodology

We undertook a systematic exploration to delve into the existing pool of knowledge concerning algorithms, their efficacy in disease prediction, the specific diseases they are applied to, and the datasets they employ. The initial step involved drawing the scope of this work, establishing unambiguous perimeters and focal points. The core aspects under scan included: the varieties of algorithms in question, their performance indicators, the spectrum of diseases these algorithms target, and the datasets deployed in such pursuits. Crafting this framework was quintessential for maintaining a focus and ensuring the relevance of the literature review to the research aims.

Upon articulating the scope, we formulated a blueprint for the research, choosing Google Scholar as the cornerstone source for scholarly literature. Owing to its rich repository of academic articles

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and research papers, Google Scholar was deemed an apt platform for a thorough examination.

To streamline the search, we employed a roster of targeted keywords and search phrases such as “Machine Learning” and “Disease Prediction” amongst others. These keywords proved pivotal in combing through the expansive database and pinpointing literature that sound with the subject matter.Subsequent to the search phase, a collection of academic literature emerged, prompting the onset of the selection process. This stage revolved around a discerning assessment of the titles, abstracts, and conclusions of each paper. This evaluation allowed for a preliminary understanding of each paper’s relevance to the study's objectives. Based on this evaluation, informed decisions were made concerning the inclusion or exclusion of each paper.

With a curated selection of papers in hand, an in-depth analysis ensued. Each paper was examined, with key information concerning the algorithms, their performance, the diseases in focus, and datasets being extracted. The analysis exceeded data extraction and included a critique of the research methods, inferences, and the ramifications of these findings. Documenting and discussing the outcomes entailed a structured presentation of the gleaned data from each paper. This encompassed an extensive analysis that did not merely chronicle the findings but rendered a critical evaluation of each study’s integrity, constraints, and consequences. Through this synthesis, interrelations among diverse studies were established, and patterns as well as anomalies in the existing body of work were elucidated.

Our aim is to deepen our understanding of the field. Thus, we aim to address several key questions:

Q1: Which heart disease types and the data sets are most frequently considered in the literature? Here, we aim to uncover the specific heart conditions that have garnered significant attention from researchers, offering insight into areas of focus and potential gaps in the research.

Q2: What are the primary machine learning (ML) algorithms employed for predicting heart diseases? This question seeks to identify the most prevalent ML methodologies and techniques used in the context of heart disease prediction.

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Q3: What key insights emerge from examining the above questions? By synthesizing the answers to these questions, we hope to gain a comprehensive understanding of the current state of heart disease prediction using ML, including trends, challenges, and areas for future exploration.

Machine Learning for Heart Disease Prediction

In this section, we will answer the aforementioned questions.

Disease types

In this section, our goal is to answer this research question: Which heart disease types and data sets are most frequently considered in the literature?

As machine learning (ML) techniques have progressed, the use of data-driven methods for diagnosing heart diseases through electrocardiogram (ECG) signals has become more prevalent among researchers and practitioners. However, traditional diagnostic processes often result in delayed detection, as patients undergo various standard tests and typically consult a doctor only when symptoms worsen. On the other hand, ML-based methods enable early detection of heart conditions, allowing individuals to conduct regular self-diagnoses using affordable, compact sensors (Baitharu, et al., 2024).

Early detection of heart disease is possible through the analysis of heartbeat rhythms, which can be categorized into five types: non-ectopic, supraventricular ectopic, ventricular ectopic, fusion, and unknown beats. Abnormal heartbeats, known as arrhythmias, are significant because of their life-threatening potential. From the studies that we analyzed, most of them focused on arrhythmia due to its severe impact on health, as it is a leading cause of serious health issues and fatalities in heart patients. Consequently, prompt diagnosis and treatment are crucial for those with cardiac arrhythmia. For example, Yang et al. (2018) created a new method for detecting heart disease using a Linear Support Vector machine on imbalanced data as well as on clear ECGs. Romdhane et al. (2020) introduced a CNN-based method for heartbeat segmentation to identify arrhythmia. These studies utilized the MIT-BIH arrhythmia heart disease dataset. Additionally, Che et al. (2021) employed a CNN-based technique to analyze the temporal aspects of ECG signals with real-world data.

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The majority of researchers rely on tabular datasets for identifying various heart diseases through machine learning methods. Rather than focusing on specific conditions, many researchers broadly categorize their work under the umbrella term 'heart disease'. For example, both Nahar et al. (2023) presented their findings on heart disease using the Cleveland dataset. This dataset includes 13 attributes to determine the presence of heart disease in patients, without specifying particular types of heart conditions.

The study shows that “heart arrhythmia” and “cardiovascular disease” form the largest cluster compared to other heart-related diseases in terms of the number of studies. For example, Minou et al. (2020) developed a detection method for cardiovascular disease using Random Forest (RF) and Decision Trees (DT). Similarly, Kumar and Ramana (2021) introduced neural network-based methods for assessing the prognosis and severity of cardiovascular diseases. Additionally, other research has focused on conditions like cardiac arrest (Baral et al., 2021 Liu et al., 2022), coronary heart disease (Dutta et al.., 2020, and Myocardial Infarction (MI) (Wiharto et al., 2024, Sharma et al., 2020), all within the scope of machine learning-based heart disease detection methods.

Machine Learning Algorithms

In this section, we answer the following question: What are the primary machine learning (ML) algorithms employed for predicting heart diseases?

Based on the list of articles, it indicates a growing preference for deep learning (DL) algorithms over traditional machine learning techniques in the development of machine learning-based heart disease diagnosis models. Most of the studies have employed DL methods to create models for diagnosing heart disease. For example, Awan et al. (2019) utilized a Multi-layer Perceptron (MLP) to predict the likelihood of heart failure patients being readmitted within 30 days, achieving 48% sensitivity and 70% specificity in preliminary tests. Li et al. (2025) developed a Deep Neural Network (DNN) model called craftNet, which successfully identified handcraft features for cardiovascular disease detection with an accuracy ranging from 86.82% to 89.25%. Additionally, Dixit and Kala (2021) employed a 1D CNN model to detect heart disease in its early stages using cost-effective, compact ECG sensors, demonstrating that their model could accurately identify heart disease in 93% of cases based on data from 300 actual patients.

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Support Vector Machines (SVM) are the second most frequently used algorithm by researchers in the field. Liu et al. (2022), for instance, implemented SVM to devise intelligent scoring systems for predicting cardiac arrest within 72 hours. Similarly, Shah et al. (2020) evaluated SVM alongside Random Forest (RF), Ordinal Regression, Logistic Regression (LR), and Naive Bayes (NB) on the Cleveland dataset for heart disease detection, with SVM outperforming the others by reaching a 95% accuracy rate. In addition to SVM and CNN-based methods, other algorithms like ensemble learning (Wang et al., 2022), k-Nearest Neighbors (kNN) (Sharma et al., 2020), Decision Trees (DT), Linear Discriminant Analysis (LDA), and Bayesian Networks (BN) (Exarchos et al., 2014) are also commonly used in developing machine learning-based heart disease diagnosis models. Wang et al. (2021), for example, developed a novel GAN-based method named CAB, achieving a 99.71% classification accuracy for arrhythmia, while Rath et al. (2021) combined Long Short Term Memory (LSTM) with GAN for a model that could detect heart disease with 99.4% accuracy from the MIT-BIH dataset. To summarize it, the most utilized algorithm in the selected studies is CNN as the most popular, followed by SVM.

Amin et al., (2019) explored a variety of data mining methodologies for the purpose of heart disease prediction. The considered techniques encompass Decision Tree, Random Forest, K-Nearest Neighbor (KNN), Naïve Bayes, Support Vector Machine (SVM), and Vote. According to their findings, the data mining techniques demonstrating the highest predictive accuracy were Vote, Naïve Bayes, and Support Vector Machine. Soni et al., (2024), observed that the Naïve Bayes algorithm emerged as the most accurate in heart disease prediction, boasting a correctness rate of 86.53%. While the Neural Network algorithm trailed closely with a negligible difference of less than 1%, Decision Trees excelled in predicting cases with no heart disease, achieving an effectiveness rate of 89%. The evaluation of Deb et al., (2022) reveals that the random forest has demonstrated the greatest accuracy to date, while logistic regression has yielded the lowest accuracy. Additionally, the Decision Tree exhibited a slightly enhanced performance after employing the Bagging Ensemble technique. SVM displayed the least accuracy when a 10-fold cross-validation was implemented. In contrast Phasinam et al., (2022) show that SVM outperforms the other algorithms. In the study of Sarah et al., (2022), several

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algorithms were employed, namely Logistic Regression, Decision Tree, Naive Bayes, SVM, K-Nearest Neighbors, and Random Forest. Among these, Logistic Regression emerged as the top performer in terms of accuracy.

Arumugam et al., (2023) optimized the Decision Tree model to achieve peak performance in predicting the likelihood of heart disease in diabetic patients, as it consistently, according to them, surpassed the naive Bayes and Support Vector Machine models in performance.

Discussion

In this section, we answer this question: What key insights emerge from examining the above questions?

An in-depth analysis was conducted to gain a comprehensive understanding of the current trends and methods employed in diagnosing heart disease using imbalanced datasets. This detailed examination involved a large number of referenced studies and focused on several key aspects: types of heart disease, applications, machine learning algorithms, and solutions for handling data imbalances.

From the comprehensive analysis, it appears that arrhythmia is the most extensively researched condition in the context of Machine Learning-based heart disease diagnosis. However, other studies have also focused on cardiac arrest, Myocardial Infarction (MI) (Daraei & Hamidi, 2024), among others. It's important to note that cardiac arrest remains a significant challenge in intensive care units, characterized by low survival rates. Accurate screening for cardiac arrest using deep learning and traditional machine learning methods is difficult due to low sensitivity and high rates of false alarms (Baral et al., 2025). This underscores the need for researchers and practitioners to broaden their focus to encompass all types of heart diseases, rather than primarily concentrating on arrhythmia.

The majority of machine learning-based models for heart disease detection focus on feature selection, image segmentation, and classification. Two widely used datasets in this research are the Cleveland dataset and the MIT-BIH arrhythmia dataset, chosen for their accessibility and the challenges they present with data imbalance. Some studies have also incorporated real-world data (Che et al., 2021; Yan et al., 2021). This inclusion leads to variability in model performance, as seen in study results comparing

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open repository data with real-world data. It's crucial to recognize that models tested with real-world data tend to yield more authentic performance insights. Thus, using real-world data over open repository data is essential for a more accurate evaluation of machine learning models.

The limited effectiveness of Clinical Decision Support Systems (CDSS) is often due to model instability. Clinical systems require constant updates and cannot solely depend on outdated patient data. Continuous model refinement and development, based on new patient data, are crucial for the effective and accurate operation of CDSS. Collecting and training machine learning models with real-time data, especially in critical settings like emergency operation theaters and ICU patient care, poses significant challenges.

Numerous machine learning algorithms, including SVM, KNN, ANN, CNN, and GAN, have been utilized in developing machine learning-based heart disease diagnosis models. However, CNN-based models have garnered significant interest among researchers for their strong performance and ability to manage complex datasets. Additionally, GAN has gained prominence in recent literature for its exceptional ability to create synthetic data closely resembling real data, effectively addressing issues of data imbalance.

The analysis of various studies highlighted key challenges related to the datasets used in research. A significant issue was the inaccessibility of many datasets referenced, which restricts opportunities for independent verification and replication of research findings. Additionally, the dimensions of the datasets were often small, raising concerns about the generalizability of the study outcomes. Such limited-scale datasets may not adequately represent the broader population, affecting the diversity and scope necessary for applicable inferences. There was also a noticeable lack of clarity in the selection of dataset attributes for analysis, with many studies failing to explain their choice of specific attributes. This absence of transparency complicates the ability of other researchers to compare and build upon existing findings. These challenges underscore the need for enhanced transparency and thoroughness in dataset documentation and attribute selection, which are crucial for the advancement and credibility of research in this field.

Currently, there is no universally agreed-upon standard or protocol that researchers, particularly those from multidisciplinary or non-medical backgrounds, are required to adhere to. This lack of

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standardization extends to the presentation of study reports. For example, some research focuses primarily on accuracy to highlight their findings , while others base their claims of model superiority on metrics like AUC, ROC, sensitivity, and specificity (Awan et al., 2019; Daraei & Hamidi, 2024; López-Martínez et al., 2020). Although these performance measurement tools are widely used to demonstrate the statistical outcomes of most machine learning classifiers, there is still a need for a proper guideline to report study results effectively and consistently. In this context, a recent study offers some useful recommendations for addressing this gap (Schwendicke & Krois, 2021).
Most machine learning algorithms, particularly those in the realm of Deep Learning, are still being scrutinized for the transparency of their decision-making processes. Despite recent proposals for explainable or interpretable methodologies, these ML-based models often fall short in offering satisfactory explanations that enhance the trustworthiness and interpretability of their outcomes (Ahsan et al., 2021). Notably, among the extensive collection of studies reviewed, none provided clear explanations on the reliability of their model's predictions. Such explanations are crucial, especially in clinical diagnostic systems where models frequently make decisions in critical scenarios, potentially involving life-and-death situations (Manjurul et al., 2023). This is particularly concerning given that many users of these applications, including doctors, nurse practitioners, and non-experts, may rely on them in clinical settings, where operating without a thorough understanding of the model's reasoning can be hazardous.

Ensuring reliable diagnoses is a major concern in machine learning-based clinical diagnostic systems. Factors like geographical location, data samples, and types of heart diseases can significantly influence the effectiveness of these models. For instance, a machine-learning model designed for diagnosing arrhythmia might not be suitable for detecting cardiac arrest. Consequently, developing ML-based clinical diagnosis systems for different diseases might require separate models, as the training data will vary from one source to another. Creating a versatile model capable of diagnosing multiple diseases in real-time is, therefore, a complex task. Another critical factor for secure diagnosis is the stability of the model when there are changes in parameters or updates to the model based on user feedback and experiences.

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Through the examination of various studies, we also identified that there is an inconsistency in the conclusions regarding the effectiveness of algorithms used in disease prediction. While some studies indicate, for example, Decision Tree algorithms as being particularly effective, others point to Naive Bayes as being superior. One notable inconsistency is in the evaluation of the Support Vector Machine (SVM) algorithm, where it is lauded as the best in some studies, while others sharply critique it for low accuracy. This inconsistency in findings necessitates a critical look into the possible factors that could contribute to such disparate results. A plausible explanation for this divergence could be rooted in the datasets used in these studies. The choice of datasets and how they are preprocessed might be influencing the performance of the algorithms. For instance, certain datasets might inherently be more suitable for a particular type of algorithm due to the nature of the data, or the way the data has been cleaned and prepared could advantage one algorithm over another. Another factor that requires attention is the size of the datasets used in these studies. It is acknowledged within many of these research papers that the size of the dataset poses a threat to the validity of the conclusions. They suggest that testing the algorithms with larger datasets is necessary to provide more reliable insights into their efficacy. In summary, the discord in the results of these studies could be attributed to various factors including the selection and preprocessing of datasets, and the scale of data used. As such, it is crucial that future research considers these elements to produce more reliable and consistent finding.

Conclusion

As we arrive at the conclusion of our comprehensive exploration, we endeavor to encapsulate the quintessential takeaways from our scrutiny into the application of data mining techniques in the realm of healthcare for predicting diseases. Our journey, spanning across an array of techniques, their efficacy in predicting various diseases, employing an assortment of datasets, and our analytical comparison, has furnished a holistic view of this burgeoning domain. In this final section, we synthesize our key findings, underscore the significance of our revelations, and spotlight the possible ramifications of emerging trends. In conclusion, we reflect on the future paths highlighted in the earlier section. The analysis of various studies revealed significant inconsistencies in the performance of

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algorithms for disease prediction. The discrepancies may be attributed to factors such as the choice of dataset,feature selection, preprocessing steps, and dataset size. To achieve a better understanding of algorithm performance, it is essential to critically examine the methodologies, and consider evaluating the algorithms with larger datasets.

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