

A NOVEL NEURAL NETWORK APPROACH FOR HEART DISEASE DETECTION

¹R.Vinitha, ²Viji Vinod

¹Research scholar, Department of Computer Science, Dr.M.G.R.Educational and Research Institute, Chennai, vinitharajan2701@gmail.com

²Professor, Faculty of Computer Applications, Dr.M.G.R.Educational and Research Institute, Chennai, vijivinod.mca@drmgrdu.ac.in

ABSTRACT

Heart disease remains a leading cause of morbidity and mortality globally, emphasizing the critical need for accurate and timely diagnostic methods. This review paper systematically explores the application of optimum methods for heart disease detection, offering a comprehensive survey of various algorithms employed in this domain. The paper begins by elucidating the significance of early detection and diagnosis in mitigating the impact of heart disease on public health. The review meticulously investigates and compares diverse algorithms utilized in heart disease detection, ranging from classical ML approaches to state-of-the-art DL techniques. These algorithms include but are not limited to decision trees, support vector machines, NNs, and ensemble methods. The study critically evaluates the strengths and limitations of each algorithm, considering factors such as computational efficiency, interpretability, and scalability. Additionally, the review highlights recent advancements in feature selection and extraction techniques that contribute to enhancing the performance of heart disease detection models. The discussion also delves into the integration of innovative technologies, such as wearable devices and internet of things (IoT), to facilitate continuous monitoring and early detection of cardiac anomalies.

Introduction

Heart Failure, characterized by the heart's diminished pumping efficiency, results from causes such as coronary artery disease, hypertension, or prior heart attacks, presenting symptoms like fatigue, edema, and difficulty exercising. Arrhythmias, irregular heart rhythms, whether fast, slow, or erratic, may be attributed to factors such as coronary artery disease, hypertension, or congenital defects, manifesting in palpitations, dizziness, fainting, and chest discomfort. Valvular Heart Disease involves damage or defects in heart valves, affecting blood flow and leading to fatigue, shortness of breath, and chest pain. Cardiomyopathy, affecting the heart muscle's structure, may result from infections, medications, or genetic factors, exhibiting symptoms like fatigue, swelling, and irregular heartbeats. Congenital Heart Defects, present at birth, vary widely in symptoms and causes, necessitating early detection. Inflammatory Heart Diseases, including myocarditis and pericarditis, arise from infections, autoimmune conditions, or medications, eliciting symptoms such as chest pain, fever, and fatigue. Understanding these diverse heart diseases is imperative for early detection, effective management, and prevention, particularly for individuals with risk factors, underscoring the importance of regular medical check-ups and a heart-healthy lifestyle.

Electrocardiograms (ECGs or EKGs) measure the heart's electrical activity, aiding in the detection of irregularities such as arrhythmias. Blood tests provide valuable information, including cholesterol levels and cardiac biomarkers, offering indications of heart damage or strain. Chest X-rays assess the heart's size and shape, identifying potential abnormalities in the lungs affecting cardiac function. Echocardiography employs sound waves to create detailed images, essential for evaluating heart valves, chambers, and overall cardiac performance. Stress testing, including exercise and pharmacological stress tests, evaluates the heart's performance under exertion, aiding in the identification of coronary artery disease and overall cardiovascular fitness. Holter monitoring, involving a portable device recording the heart's electrical activity over an extended period, is effective in detecting intermittent arrhythmias.

Fuzzy Logic Systems, accommodating uncertainty through degrees of truth, find application in modeling intricate relationships within heart disease prediction, particularly when faced with vague or incomplete information. Genetic Algorithms (GAs), drawing inspiration from natural selection, optimize features and parameters, enhancing the efficiency and accuracy of predictive models. Support Vector Machines (SVMs), adept at handling high-dimensional data, classify heart disease risk by discerning patterns in complex datasets, utilizing features such as age, gender, and clinical measurements. The ongoing evolution of soft computing applications in heart disease prediction showcases researchers' commitment to enhancing accuracy and interpretability in predictive models.

Machine learning (ML) has occurred as a promising tool for heart disease prediction, leveraging intricate patterns within medical data to enhance diagnostic accuracy. ML models are adept at analyzing diverse datasets, identifying key risk factors, and predicting the likelihood of heart disease. Decision Trees create interpretable tree-like structures to analyze patient data and predict the likelihood of heart disease. SVM find hyperplanes to classify heart disease, especially useful in high-dimensional datasets. K-Nearest Neighbors (KNN) classifies data points based on similarities with neighboring points in feature space. NNs, particularly DL models, analyze a range of features, including clinical, imaging, and genetic data, for heart disease prediction. Gradient Boosting Algorithms like XGBoost iteratively refine predictive models, enhancing accuracy based on previous errors. Ensemble Learning methods, such as bagging and boosting, combine individual models for a more robust and accurate prediction. The selection of a specific ML algorithm depends on dataset characteristics, the nature of the problem, and desired model interpretability. Hybrid models or combinations of algorithms are often employed to achieve superior results in heart disease prediction. The continual progress in ML and healthcare technology contributes to the ongoing enhancement and refinement of predictive models for heart disease.

DL, a subset of ML, has proven to be highly successful in diverse medical applications, particularly in the realm of heart disease detection. DL models, exemplified by NNs with multiple layers, exhibit the capability to autonomously learn hierarchical representations from intricate datasets. Recurrent NNs (RNNs), designed for sequential data, analyze time-series data like ECG signals to identify patterns associated with heart conditions, including arrhythmias and ischemic events. Autoencoders, unsupervised learning models, contribute to heart disease detection by extracting meaningful features from diverse data types, including imaging and clinical data, aiding in the understanding of complex cardiac structures. Generative Adversarial Networks (GANs), with a generator-discriminator architecture, generate synthetic medical

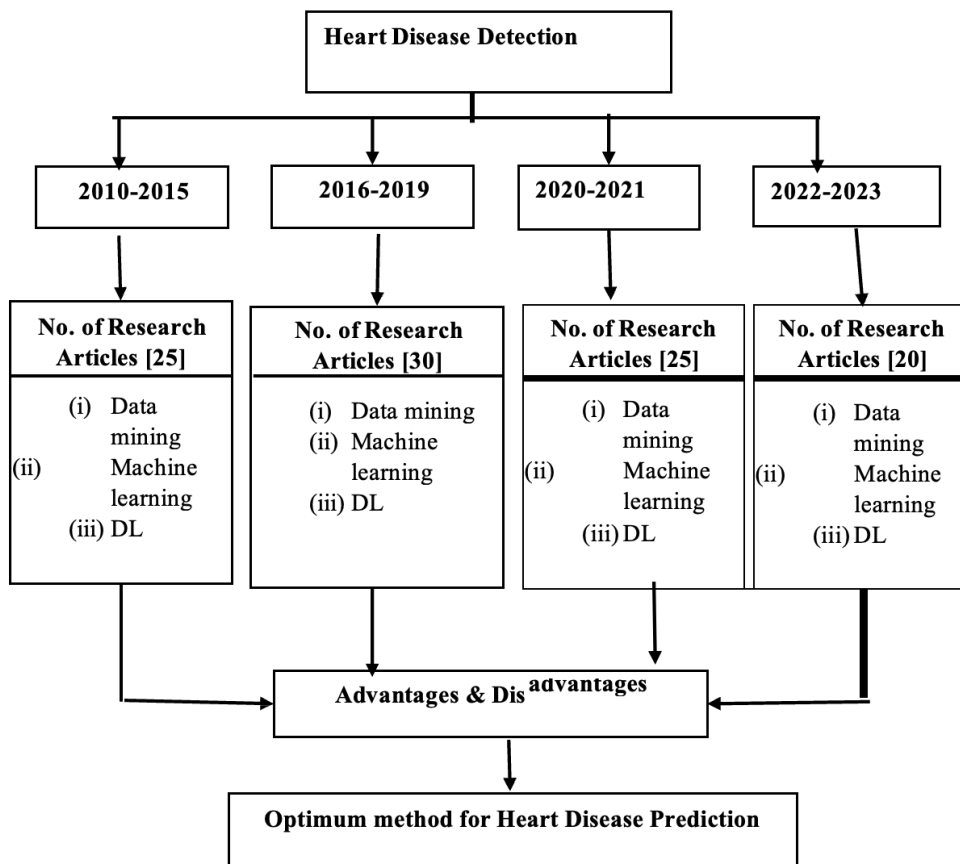
images or augment datasets, particularly useful when large datasets are scarce. Hybrid Models, combining the strengths of CNNs and RNNs, prove effective in tasks involving both spatial and temporal information, such as the analysis of 4D cardiac imaging data. Attention Mechanisms enhance the interpretability of DL models for cardiac imaging, allowing models to focus on specific regions in medical images or segments in time-series data. Transfer Learning, involving pre-training on a large dataset and fine-tuning on a smaller, task-specific dataset, proves beneficial when labeled data for heart disease detection is limited, leveraging pre-trained models on general medical imaging tasks for specific cardiac applications. The field of DL in heart disease detection is dynamically evolving.

Methodology

This block diagram illustrates the distribution of research articles related to Heart Disease Detection over the span of three years: 2010-2020, 2020-2021, and 2021-2022, with partial data for 2022-2023.

Each category represents the number of research articles published within the specified time frames, focusing on key technologies and methods employed in heart disease prediction.

The diagram aims to highlight the technologies and methods prevalent in heart disease detection research within each time frame. Additionally, it suggests a shift towards more advanced techniques like DL, NNs, and optimization methods in recent years. The advantages and disadvantages of these methods would be essential to consider for determining the optimum approach for heart disease prediction.



Heart disease detection using Datamining

In our endeavor to improve the effectiveness and efficiency of home monitoring, we put forth a platform that leverages data mining for early detection of any deterioration in a patient's condition. This research involves a survey of recent techniques employed in knowledge discovery for heart disease prediction. Moreover, we introduce a novel prediction method aimed at enhancing accuracy. Our goal is to develop a data-mining system specifically designed for assessing risk factors related to heart events, with a primary focus on reducing Coronary Heart Disease (CHD) occurrences [1-10].

| S. NO | Year of publication | Author Name | Proposed work | Advantages | Disadvantages |
|-------|---------------------|--------------------|---------------|---------------------------------|---------------------------|
| 1 | 2011 | Leandro Pecchia | Data mining | Potentially insightful | Lower sensitivity |
| 2 | 2017 | Meenal Saini | Data mining | Automatically identify features | Heavily dependent on data |
| 3 | 2010 | Minas A. Karaolis, | Data mining | early detection | Larger datasets needed |

Interferences

Several limitations are intrinsic to health data, given its dynamic nature, susceptible to changes over time. The utilization of data mining applications, while beneficial for analysis, brings about privacy concerns that warrant careful consideration. In our study, a dataset comprising 528 cases from the Paphos district in Cyprus was collected, predominantly featuring individuals with more than one event. Despite this valuable dataset, inherent disadvantages include lower sensitivity, indicating a potential trade-off in detection accuracy. The effectiveness of data mining applications is heavily contingent on the quality of the input data, highlighting the need for meticulous data curation. To bolster the robustness of our findings, further investigation with larger datasets is deemed essential, recognizing the importance of scalability and comprehensive data representation in refining the applicability of our research outcomes.

Heart disease detection using ML

This study encompasses a spectrum of innovative approaches for heart disease prediction and diagnosis. The proposed Heart Disease Prediction Model (HDPM) within a Clinical Decision Support System (CDSS) integrates Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to detect and eliminate outliers, a hybrid Synthetic Minority Over-sampling Technique-Edited Nearest Neighbor (SMOTE-ENN) for balancing training data distribution, and XGBoost for accurate prediction. Simultaneously, a low-complexity solution is introduced, employing a multiclass convolutionalNN for the automated recognition and classification of

heart disease through Phonocardiogram (PCG) signals. In a distinct model named DGACNN, the best performance in recognizing FHD is achieved at a rate of 85%, addressing the challenge of insufficient training datasets. The Enhanced DL assisted ConvolutionalNN (EDCNN) aims to improve patient prognostics, aligning with the broader trend in utilizing DL for intelligent automated systems in conjunction with the CAD. Another proposal involves the Recursion enhanced random forest with an improved linear model (RFRF-ILM) for heart disease detection, seeking key features through ML techniques. Support vector regression (SVR) models, applied to estimate Left Ventricular Ejection Fraction (LVEF) from ECG-derived heart rate variability (HRV) data, contribute valuable insights from the Intercity Digital ECG Alliance (IDEAL) study. Mechanocardiography (MCG) emerges as an effective approach for cardiovascular disease (CVD) detection, monitoring translational and rotational chest movements. Additionally, a blockchain-enabled contextual online learning model under local differential privacy is proposed for CHD diagnosis in mobile edge computing, emphasizing collaborative information sharing among edge nodes. The selective integration of multiple ML algorithms and feature selection methods with personal clinical information is explored for more nuanced predictions. The utilization of a new local feature and deep belief network for ventricular information extraction and contour coordinates regression is presented as an efficient means of identifying heart disease. The article also introduces an accurate system for heart disease diagnosis based on ML techniques, emphasizing the role of ML and large-scale big data in developing precise prediction models for cardiovascular disease. IoT framework with a Modified Deep ConvolutionalNN (MDCNN) attached to a smartwatch and heart monitor device is proposed for more accurate heart disease evaluation. The application of ML methods to body surface ECG data for automated diagnosis of CAD is gaining interest. The introduction of an optimally configured and improved deep belief network named OCI-DBN addresses challenges and enhances system performance. Contrast-enhanced cardiac computed tomography angiography (CTA) is acknowledged as a prominent non-invasive imaging modality for diagnosing cardiovascular diseases, offering a comprehensive assessment of coronary artery patency and structural features of the heart and great vessels. In a unique approach, ML algorithms are employed to classify patient-reported outcomes (PROs) using activity tracker data in patients with stable ischemic heart disease (SIHD). The study identifies gaps in heart disease diagnosis and treatment research, proposing a model to systematically close those gaps by applying data mining techniques to treatment data for reliable performance. Lastly, the review delves into the current status of automatic echo analysis, discussing challenges and the need for robust systems suitable for efficient clinical use or point-of-care testing [11-40].

| S. NO | Year of publication | Author Name | Proposed work | Advantages | Disadvantages |
|-------|---------------------|-----------------|---------------|----------------------------------|--|
| 1 | 2020 | N. L. Fitriyani | SMOTE-ENN | Capturing intricate interactions | Required significant computational resources |

| | | | | | |
|----|------|----------------------------|---------------------|------------------------------|----------------------------------|
| 2 | 2020 | R. Avanzato | CNN | Automatically learn | Challenging to interpret |
| 3 | 2020 | Y. Gong <i>et al.</i> | DGACNN | Non-linear relationships | limitation for settings |
| 4 | 2020 | Y. Pan | EDCNN | Versatile | Intensive |
| 5 | 2020 | C. Guo | RFRF-ILM | Handle categorical features | Black box |
| 6 | 2020 | M. Alkhodari | SVR | Perform well | Time complexity |
| 7 | 2020 | S. Mehrang <i>et al.</i> , | ML | Accuracy | Crucial |
| 8 | 2020 | X. Liu | Blockchain | Enhance the security | Scalability |
| 9 | 2020 | J. Wang <i>et al.</i> , | ML | Responsible | Collaboration |
| 10 | 2020 | C. Xiao | Deep belief network | Complex | Specialized hardware |
| 11 | 2020 | J. P. Li | ML | Handle large amounts of data | Computationally intensive |
| 12 | 2020 | G. Joo | Machine learning | stays relevant | Challenging prediction |
| 13 | 2020 | M. A. Khan | MDCNN | Timely interventions | Quality |
| 14 | 2020 | L. Yao <i>et al.</i> , | ML | Communication | Challenging prediction |
| 15 | 2020 | S. A. Ali <i>et al.</i> , | OCI-DBN | Suitable for capture | Posing challenges |
| 16 | 2020 | V. Bui <i>et al.</i> , | CTA | Well-suited for tasks | Crucial |
| 17 | 2020 | Y. Meng <i>et al.</i> , | Machine learning | Continuously updated | Security |
| 18 | 2020 | Mai Shouman | Data mining | Discover hidden patterns | Complex |
| 19 | 2020 | Ankur Gupta | ML | Timely intervention | Heavily dependent on the quality |
| 20 | 2020 | Ghada Zamzmi | ML | Versatile | Inaccurate predictions |

Inferences

Various challenges and considerations surround the application of ML in healthcare. One significant hurdle is the limited availability of training data, particularly challenging in medical domains due to privacy concerns and data scarcity. CNNs may encounter difficulties in detecting small or subtle lesions, especially in noisy or low-resolution medical images. Ethical concerns, including privacy, security, and responsible data handling, arise with the use of NNs in healthcare. Random Forest's performance may be limited when extrapolating beyond the training data range, and SVMs, while effective, may lack interpretability, particularly with complex non-linear kernels. Overfitting is a concern that necessitates mitigation efforts, and the transparency of blockchain, while offering secure data storage, raises privacy concerns. Successful implementation in healthcare requires collaboration with professionals, as

misinterpretation or reliance on incorrect predictions can have severe consequences. Obtaining datasets for ML models in medical domains is challenging due to privacy concerns, and adapting to dynamic health situations requires regular updates and retraining. Ensuring compliance with regulatory standards is essential but poses challenges. The translation of model performance from controlled environments to real-world clinical settings is complex, as health conditions evolve over time and new information emerges. It's crucial to recognize that correlation does not necessarily establish causation, and rigorous testing and validation studies are imperative for heart disease detection. While ML holds promise in improving healthcare, there are disadvantages to consider, such as the requirement for significant computational resources, the black-box nature of CNNs, and the computational intensity of training and optimizing NNs. Achieving scalability while maintaining decentralization is an ongoing concern, and collaboration between domain experts is essential. Training DL models can be computationally intensive, posing challenges for smaller healthcare facilities. Understanding the reasoning behind specific predictions is crucial in medical applications, but it can be challenging, especially when dealing with complex or small datasets. The quality, representativeness, and size of training data heavily influence model performance, and incomplete data may lead to inaccurate predictions, emphasizing the importance of addressing these issues for the successful integration of ML in healthcare.

DL and heart disease prediction

The development of a valvular heart disease screening system integrates DL for fitting models and analysis. A novel approach is introduced to enhance the prediction of heart disease and patients' survival, incorporating supervised infinite feature selection (Inf-FSS), Improved Weighted Random Forest (IWRFF), and Bayesian optimization for hyperparameter tuning. CardioXNet, an end-to-end CRNN architecture, is proposed for automatic detection of cardiac auscultation classes using raw PCG signals, leveraging representation learning and sequence residual learning. The study focuses on feature selection improvement, presenting an enhanced squirrel search optimization algorithm with a meta-heuristic approach for picking salient aspects of heart illness. An efficient prediction method for coronary heart disease risk is introduced, based on two deepNNs trained on well-ordered datasets. ML algorithms, including LR, KNN, SVM, and GBC, are employed for cardiac disease prediction, utilizing a 5-fold cross-validation technique for verification. An intelligent system model for coronary heart disease diagnosis integrates a feature selection model considering examination cost, developed using a genetic algorithm and support vector machine. The proposed NN, VideoCAD, comprises PulseCAD and ImageCAD modules for facial and pulse-related features to predict coronary artery disease. Introducing computer-aided techniques for heart disease treatment, the study proposes a ML-based prediction model for binary and multiple classification heart disease prediction simultaneously. An AI-based device is proposed for automatic real-time diagnosis of cardiac diseases using DL techniques. Furthermore, the article presents a time-frequency-domain DL (TFDDL) framework for automatic detection of heart valve diseases (HVDs) using Phonocardiogram (PCG) signals, emphasizing the significance of early detection to minimize complications. Another study analyzes heart failure survivors, aiming to identify significant features and effective data mining techniques to boost the accuracy of cardiovascular patient survivor prediction. Overall, these contributions underscore the evolving

landscape of ML applications in cardiac healthcare, providing insights and advancements across various diagnostic and predictive modalities [41-70].

| S. NO | Year of publication | Author Name | Proposed work | Advantages | Disadvantages |
|-------|---------------------|-------------------|--|------------------------------------|---------------------------|
| 1 | 2021 | Y. -S. Su | DL | Continuous monitoring | Ensuring secure data |
| 2 | 2022 | A. Abdellatif | IWRF | Parallelizable | Memory-intensive |
| 3 | 2021 | B. Shuvo | Representation learning and sequence residual learning | Performance | Regularization techniques |
| 4 | 2022 | D. Cenitta | Improved squirrel search optimization algorithm | Beneficial recognition | Privacy |
| 5 | 2021 | T. Amarbayasgalan | DeepNNs | Complex | Interpret decision |
| 6 | 2021 | D. Bertsimas | Machine Learning | Accuracy | Require hardware |
| 7 | 2022 | G. N. Ahmad | Machine Learning | Quick analysis | Raise ethical concerns |
| 8 | 2022 | Wiharto | Genetic algorithm | Dealing with high-dimensional data | challenging to interpret |
| 9 | 2022 | X. Liu | Neural network | Learn complex patterns | Complexity |
| 10 | 2022 | G. Wang | Computer-aided techniques | Machine learning | Computationally intensive |
| 11 | 2022 | J. Karhade | TFDDL | eliminate manual feature | Large Dataset |
| 12 | 2021 | Abid Ishaq | Data mining | Improving efficiency | Biased |
| 13 | 2022 | R. C. Joshi | Artificial intelligence (AI) | Improving efficiency | Substantial resources |
| 14 | 2022 | X. Yuan | ML | Tailoring interventions | Irrelevant |

Inferences

The utilization of IoT devices in healthcare, while providing valuable data, may fall short in offering a comprehensive understanding of complex heart conditions that demand in-depth diagnostic testing or specialized medical imaging. Random Forest, while deterministic in output, lacks inherent probabilistic predictions, and the adherence to regulatory standards and approval processes for deploying deepNNs in healthcare can be intricate. Developing and deploying deepNNs for healthcare applications necessitate ongoing considerations, as health

conditions evolve over time, requiring effective communication of uncertainties, particularly in medical decision-making. Compliance with regulations, amidst privacy concerns and data scarcity, poses challenges, and validating the clinical utility of DL models is crucial. Identifying and correcting errors made by these models can be challenging, requiring collaboration between AI algorithms and healthcare professionals. Trust and effective communication between human experts and AI systems are paramount for meaningful impact. On the flip side, ensuring secure data transmission, storage, and processing is essential to safeguard patient information. Memory-intensive nature of Random Forest models, especially with a large number of trees, may limit their use in resource-constrained environments, necessitating regularization techniques and careful model tuning. The demand for specialized hardware in the training and deployment of sophisticated AI models can be computationally intensive, posing challenges for smaller healthcare facilities and raising ethical concerns around responsible AI use in healthcare. This complexity calls for diligent consideration of ethical implications, emphasizing the importance of careful interpretation of decision-making processes, especially for largeNNs.

Hybrid algorithms and Heart disease prediction

This paper makes a significant contribution by designing a robust Heart Disease (HD) prediction system using Hybrid DeepNNs (HDNNs), which involves combining multipleNN architectures to extract and learn relevant features from the input data. Additionally, the development of a contact microphone-driven screening framework for the diagnosis of coexisting valvular heart diseases (VHDs) is presented, employing a sensitive accelerometer contact microphone (ACM) to capture heart-induced acoustic components on the chest wall. The hyperparameters of the prediction model are optimized using the advanced hyperparameter optimization framework OPTUNA, with an improved focal loss (FL) function. The study evaluates a prediction model using CHD data from the Framingham Heart Institute. Furthermore, an investigation into cardiovascular diseases (CVDs) for early prediction is conducted using DL-based regression analysis on a dataset of 2621 medical records from UAE hospitals. A long short-term memory-based deepNN is proposed for early prediction of CVDs by leveraging regression analysis. The research activity focuses on the precise diagnosis of heart illness, employing a Keras-based DL model to compute results with a denseNN. ML technologies are actively utilized in the biomedical, healthcare, and health prediction industries, contributing to innovative treatment and management of cardiovascular diseases through medicine, personalized hemodynamic modeling, and modern imaging. The study aims to improve heart failure detection at its early stages using nine ML-based algorithms for comparison and proposing a novel Principal Component Heart Failure (PCHF) feature engineering technique to enhance performance. Additionally, the review article assesses clinical and research possibilities, gaps, and jeopardies involved in cardiac anomalies detection using ECG measurement, highlighting the potential for advancements in the field [71-100].

| S. NO | Year of publication | Author Name | Proposed work | Advantages | Disadvantages |
|-------|---------------------|-------------|---------------|------------|---------------|
|-------|---------------------|-------------|---------------|------------|---------------|

| | | | | | |
|----|------|----------------|---|---|------------------------------|
| 1 | 2023 | M. S. A.Reshan | HDNNs | Automatically extract relevant features | Challenging privacy concerns |
| 2 | 2023 | A. Shokouhmand | Hybrid algorithm | Comprehensive understanding | Maintain over the long term |
| 3 | 2023 | H. Yang | OPTUNA | Lead optimization | Effectiveness |
| 4 | 2023 | S. Ghorashi | DL-based regression | Capture complex patterns | limitation in real-time |
| 5 | 2023 | T. Rahman | DL models | Deal complex patterns | Biases in the data |
| 6 | 2023 | S. N. Ali | Deep encoder-decoder-based denoising architecture | Scalable | Regularization techniques |
| 7 | 2023 | A. A. Almazroi | Keras-based DL | Automatically learn | Require privacy |
| 8 | 2023 | A. Noor | Machine Learning | Recognize relationship | Lack interpret |
| 9 | 2023 | M. Kadem | Machine learning | Tailored individual | Fail to generalize |
| 10 | 2023 | S. C. Patra | ML | Higher accuracy | Computationally intensive |
| 11 | 2023 | S. Das | HLSTM | Time series | Require careful tuning |
| 12 | 2023 | A. M. Qadri | Machine learning | Improves accuracy | Quantity |
| 13 | 2023 | S. I. Joy | AI | Versatile | Time complexity |

Inferences

The utilization of deepNNs in healthcare raises ethical concerns related to data privacy, security, and the responsible use of AI. Inaccuracies in predictions may arise from natural variations in health parameters, necessitating techniques like resampling or adjusting class weights to address this limitation. Suboptimal model performance may occur if relevant features are excluded or irrelevant features are included. Obtaining datasets in medical domains can be challenging due to privacy concerns and data scarcity, emphasizing the need for robust clinical trials and validation studies. Diagnosing and correcting errors made by DL models can be challenging. Collaborative efforts between data scientists and healthcare professionals are essential for successful implementation, and the integration of ensembles may face challenges if components are of low quality or highly correlated. Handling irregularities or anomalies in the data may require additional preprocessing steps, and predictions often come with a certain level of uncertainty. The practical adoption of AI in clinical settings requires seamless integration. Challenges include privacy concerns, limited data availability, the need for expert annotations, and potential difficulties in maintaining patient engagement and motivation over the long term. The choice of parameters, biases in the data, and the need for specialized

hardware can impact the effectiveness of models, especially in real-time or resource-constrained applications. Interpretability remains a challenge, particularly for complex models like deepNNs, and models may perform well on training data but struggle to generalize to new populations. The computationally intensive nature of models like LSTMs and the necessity for careful tuning further contribute to the complexity of implementation.

Conclusion

Health data, with its dynamic nature and susceptibility to changes, poses intrinsic limitations. The use of data mining applications, while beneficial for analysis, raises privacy concerns, and our study on a dataset from the Paphos district in Cyprus reveals inherent disadvantages, including lower sensitivity. Data mining effectiveness depends on input data quality, emphasizing the need for meticulous curation. Larger datasets are essential for robust findings, recognizing scalability and comprehensive representation importance. ML in healthcare faces challenges like limited training data availability, issues with CNNs in detecting subtle lesions, ethical concerns with NNs, and limitations of models like Random Forest and SVMs. Overfitting and privacy concerns persist, requiring collaboration to avoid misinterpretations. Obtaining datasets is challenging due to privacy concerns, dynamic health situations require updates, and regulatory compliance is challenging. Model translation to real-world settings is complex, and rigorous testing is imperative. ML benefits healthcare but demands significant resources, raises concerns about transparency, and challenges in achieving scalability and decentralization. IoT devices in healthcare provide valuable data but may fall short for complex heart conditions. DeepNNs introduce ethical concerns, necessitate ongoing considerations, and demand trust and communication between experts and AI systems. Ethical implementation requires addressing limitations, ensuring data security, and interpreting decision-making processes carefully.

REFERENCES

- [1] Y. -S. Su, T. -J. Ding and M. -Y. Chen, "DL Methods in Internet of Medical Things for Valvular Heart Disease Screening System," in *IEEE Internet of Things Journal*, vol. 8, no. 23, pp. 16921-16932, 1 Dec.1, 2021, doi: 10.1109/JIOT.2021.3053420.
- [2] N. L. Fitriyani, M. Syafrudin, G. Alfian and J. Rhee, "HDPM: An Effective Heart Disease Prediction Model for a Clinical Decision Support System," in *IEEE Access*, vol. 8, pp. 133034-133050, 2020, doi: 10.1109/ACCESS.2020.3010511.
- [3] R. Avanzato and F. Beritelli, "Heart Sound Multiclass Analysis Based on Raw Data and ConvolutionalNN," in *IEEE Sensors Letters*, vol. 4, no. 12, pp. 1-4, Dec. 2020, Art no. 7004104, doi: 10.1109/LSENS.2020.3039366.
- [4] M. S. A. Reshan, S. Amin, M. A. Zeb, A. Sulaiman, H. Alshahrani and A. Shaikh, "A Robust Heart Disease Prediction System Using Hybrid DeepNNs," in *IEEE Access*, vol. 11, pp. 121574-121591, 2023, doi: 10.1109/ACCESS.2023.3328909.
- [5] Y. Gong et al., "Fetal Congenital Heart Disease Echocardiogram Screening Based on DGACNN: Adversarial One-Class Classification Combined with Video Transfer Learning," in *IEEE Transactions on Medical Imaging*, vol. 39, no. 4, pp. 1206-1222, April 2020, doi: 10.1109/TMI.2019.2946059.
- [6] Y. Pan, M. Fu, B. Cheng, X. Tao and J. Guo, "Enhanced DL Assisted ConvolutionalNN for Heart Disease Prediction on the Internet of Medical Things Platform," in *IEEE Access*, vol. 8, pp. 189503-189512, 2020, doi: 10.1109/ACCESS.2020.3026214.

- [7] C. Guo, J. Zhang, Y. Liu, Y. Xie, Z. Han and J. Yu, "Recursion Enhanced Random Forest With an Improved Linear Model (RERF-ILM) for Heart Disease Detection on the Internet of Medical Things Platform," in *IEEE Access*, vol. 8, pp. 59247-59256, 2020, doi: 10.1109/ACCESS.2020.2981159.
- [8] M. Alkhodari, H. F. Jelinek, N. Werghi, L. J. Hadjileontiadis and A. H. Khandoker, "Estimating Left Ventricle Ejection Fraction Levels Using Circadian Heart Rate Variability Features and Support Vector Regression Models," in *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 3, pp. 746-754, March 2021, doi: 10.1109/JBHI.2020.3002336.
- [9] S. Mehrang et al., "Classification of Atrial Fibrillation and Acute Decompensated Heart Failure Using Smartphone Mechanocardiography: A Multilabel Learning Approach," in *IEEE Sensors Journal*, vol. 20, no. 14, pp. 7957-7968, 15 July 2020, doi: 10.1109/JSEN.2020.2981334.
- [10] X. Liu, P. Zhou, T. Qiu and D. O. Wu, "Blockchain-Enabled Contextual Online Learning Under Local Differential Privacy for Coronary Heart Disease Diagnosis in Mobile Edge Computing," in *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 8, pp. 2177-2188, Aug. 2020, doi: 10.1109/JBHI.2020.2999497.
- [11] J. Wang et al., "A Stacking-Based Model for Non-Invasive Detection of Coronary Heart Disease," in *IEEE Access*, vol. 8, pp. 37124-37133, 2020, doi: 10.1109/ACCESS.2020.2975377.
- [12] C. Xiao, Y. Li and Y. Jiang, "Heart Coronary Artery Segmentation and Disease Risk Warning Based on a DL Algorithm," in *IEEE Access*, vol. 8, pp. 140108-140121, 2020, doi: 10.1109/ACCESS.2020.3010800.
- [13] S. B. Shuvo, S. N. Ali, S. I. Swapnil, M. S. Al-Rakhami and A. Gumaiei, "CardioXNet: A Novel Lightweight DL Framework for Cardiovascular Disease Classification Using Heart Sound Recordings," in *IEEE Access*, vol. 9, pp. 36955-36967, 2021, doi: 10.1109/ACCESS.2021.3063129.
- [14] J. P. Li, A. U. Haq, S. U. Din, J. Khan, A. Khan and A. Saboor, "Heart Disease Identification Method Using ML Classification in E-Healthcare," in *IEEE Access*, vol. 8, pp. 107562-107582, 2020, doi: 10.1109/ACCESS.2020.3001149.
- [15] T. Amarbayasgalan, V. -H. Pham, N. Theera-Umpon, Y. Piao and K. H. Ryu, "An Efficient Prediction Method for Coronary Heart Disease Risk Based on Two DeepNNs Trained on Well-Ordered Training Datasets," in *IEEE Access*, vol. 9, pp. 135210-135223, 2021, doi: 10.1109/ACCESS.2021.3116974.