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A Survey on Hybrid Deep Learning and Neural Fuzzy Inference Systems for Early Coronary Heart Disease Detection

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Abstract - *coronary heart disease (CHD) continues to be a primary cause of global mortality, highlighting the critical necessity for precise and early detection techniques to enable prompt management and prevention. Recent breakthroughs in ML and DL have demonstrated potential in improving diagnosis accuracy; yet, challenges remain regarding interpretability, computational complexity, and the management of ambiguous or unclear medical data. This survey examines advanced methodologies and investigates the possibility of hybrid frameworks that combine deep learning models with neural fuzzy inference systems (NFIS) for the identification and prevention of CHD. Hybrid techniques, which integrate the feature extraction and learning capabilities of deep learning with the interpretability and uncertainty management of neuro-fuzzy inference systems, provide a robust framework for enhancing early coronary heart disease diagnosis and risk evaluation. We offer an extensive comparison of modern machine learning, deep learning, and hybrid models, evaluating their performance across multiple measures, including accuracy, sensitivity, and computing demands. This paper examines upcoming topics such as transfer learning, multi-modal data integration, and explainable AI, emphasising the prospective applications of these systems in clinical environments. Our research indicates that hybrid DL-NFIS models possess considerable potential for improving CHD identification and, thus, augmenting patient outcomes in preventive healthcare.*

Keywords: *Coronary Heart Disease Detection, Hybrid Deep Learning, Neural Fuzzy Inference System, Medical Diagnostics, Early Detection and Prevention.*

1. INTRODUCTION

CHD is a predominant cause of global death, impacting millions and imposing a considerable strain on healthcare systems. CHD progresses incrementally as plaque accumulates in the coronary arteries, impeding blood flow to the heart and potentially resulting in serious consequences, including myocardial infarctions or abrupt cardiac arrest [1]. Given its progressive nature, early identification of CHD is essential for the implementation of preventative treatments that might decelerate or perhaps reverse disease progression. Timely intervention can significantly enhance patient outcomes, decrease healthcare expenditures, and ultimately preserve lives. Conventional techniques for identifying CHD, including electrocardiograms (ECGs), stress tests, and coronary angiography, are highly efficacious but frequently constrained by accessibility, expense, and invasiveness. These constraints have propelled the quest for automated, non-invasive, and more efficient diagnostic instruments capable of delivering precise and early identification of CHD. Recent breakthroughs in artificial intelligence (AI), particularly in ML and DL, have shown considerable promise in the analysis of medical data for diagnostic applications. These techniques may discern intricate patterns and correlations within extensive datasets, rendering them optimal for the creation of precise and prompt diagnostic systems [2].

Figure 1 depicts the numerous categories of CVDs), with "cardiovascular disease" at the centre, radiating outward to distinct particular varieties [3]. These categories encompass Angina Pectoris, characterised by chest pain resulting from diminished blood supply to the cardiac muscle, and Rheumatic heart disease, a condition arising from rheumatic fever that predominantly impacts the heart valves. Coronary Heart Disease, or coronary artery disease, entails the constriction or obstruction of coronary arteries, restricting blood flow to the heart. Ischaemic situations occur when blood flow and oxygen supply are limited to certain bodily regions, frequently affecting the heart. Myocarditis denotes the inflammation of the cardiac muscle, hindering its capacity to pump blood effectively. Congenital heart disease includes structural cardiac anomalies existing at birth. Cardiomyopathy encompasses disorders that impair the heart muscle, diminishing its ability to pump blood efficiently. Each distinct type of cardiovascular disease diverges from the central "cardiovascular disease" node, illustrating the numerous symptoms of this condition [4].

Furthermore, the cardiovascular epidemic in some populations, such as Indians, illustrates a complicated interaction between population-level alterations and intrinsic biological and genetic variables that elevate the biological risk for CHD. Six principal transitions contribute to this increased risk: epidemiological, demographic, dietary, environmental, socio-cultural, and economic as shown in Figure 2. The transitions are exacerbated by early-life factors and distinct genetic predispositions, highlighting the necessity for a holistic strategy in the detection and prevention of CHD. This intricate risk profile necessitates sophisticated models capable of managing complicated, interrelated elements, rendering hybrid frameworks, such as those integrating deep learning with neural fuzzy inference methods, very attractive for these applications [5].

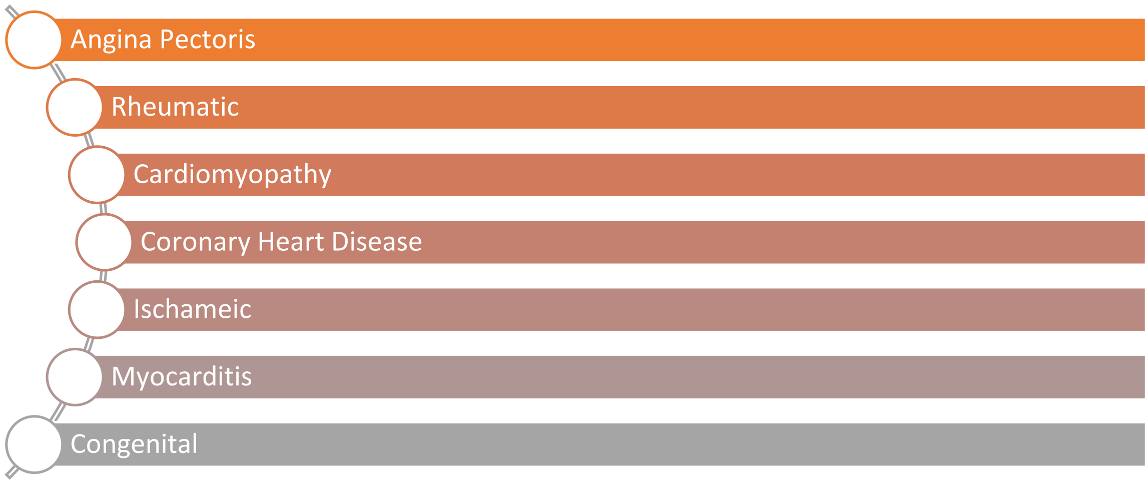

FIGURE 1. Types of CVDs

Nonetheless, although ML and DL models exhibit potential, they also include specific constraints. Deep learning models frequently operate as "black boxes," providing minimal interpretability, which is essential for establishing doctors' trust and facilitating informed medical decisions. Moreover, these models can encounter difficulties with unclear or imprecise data, which is prevalent in medical contexts where genetic predisposition, lifestyle, and environmental factors converge. Researchers are currently investigating hybrid methodologies that integrate the learning potential of deep learning with the interpretability of fuzzy inference systems, particularly via neural fuzzy inference systems (NFIS). These hybrid models seek to improve CHD detection by providing both high accuracy and a level of interpretability, thereby reconciling performance with clinical applicability.

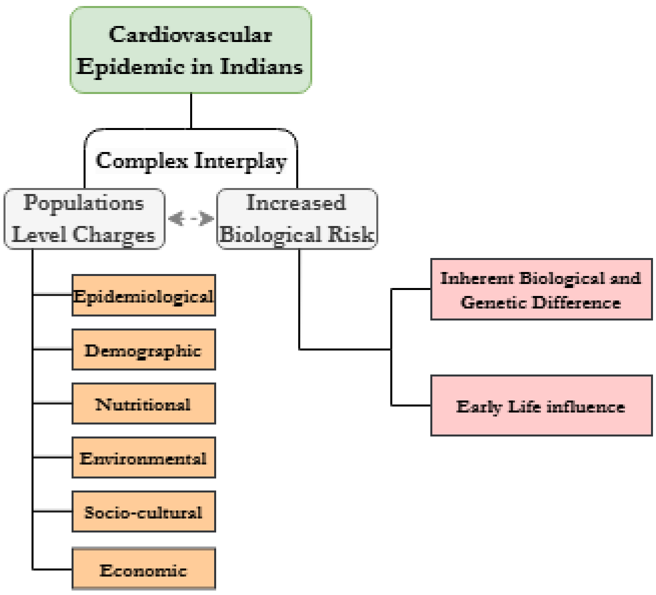

FIGURE 2. The surge in cardiovascular disease among Indians

This investigation seeks to investigate current progress in CHD detection utilising hybrid deep learning models and NFIS. We examine the current literature on machine learning, deep learning, and hybrid methodologies, evaluating their advantages and drawbacks while analysing their efficacy in coronary heart disease detection. Furthermore, we examine upcoming trends, such transfer learning and explainable AI, that may augment the potential of these systems in early diagnosis and preventive healthcare. This review aims to elucidate how sophisticated AI methodologies are influencing the future of CHD detection and emphasise the critical importance of hybrid models in enhancing patient outcomes [6].

2. CHALLENGES IN EARLY DETECTION AND PREVENTION

CHD continues to be one of the most difficult disorders to identify early because of its intricate aetiology, silent development, and many risk factors. Early detection of CHD is crucial for minimising serious consequences and lowering mortality rates. Nevertheless, numerous significant obstacles impede the efficacy of early detection and prevention initiatives, despite progress in medical technology and diagnostic methods. A primary issue in the early identification of CHD is the absence of distinct and early symptoms. Coronary heart disease frequently progresses asymptomatically, with manifestations emerging only when considerable arterial obstructions have developed. The asymptomatic advancement complicates the identification of at-risk individuals before to key events, such as myocardial infarctions. Furthermore, initial manifestations of coronary heart disease, such moderate chest tightness or weariness, are frequently ambiguous and may be misinterpreted as less serious ailments. The vagueness of this symptom hinders identification and treatment, elevating the risk of negative effects.

The variability of risk variables hinders the early identification of CHD. The risk of coronary heart disease is affected by a confluence of hereditary, lifestyle, and environmental variables, with disparities in their interactions among various groups. Genetics may predispose individuals to CHD, whereas lifestyle variables, including nutrition, physical inactivity, and smoking, can expedite disease progression. Environmental factors, such as pollution and socioeconomic level, contribute to the exacerbation of cardiovascular risk. The intricate interaction of these factors, along with individual variability, complicates the development of standardised screening techniques that accurately detect CHD risk in varied populations.

Data constraints in healthcare provide a substantial obstacle to the early identification of CHD. Medical data is frequently fragmented, missing, or inconsistent, complicating the acquisition of a thorough understanding of a patient's health status. Moreover, acquiring high-quality data, particularly in areas with restricted healthcare access, presents a barrier. Consequently, numerous machine learning and deep learning models trained on incomplete datasets have difficulties in generalising effectively within clinical practice. Moreover, privacy and data-sharing limitations exacerbate the challenges associated with the collection and utilisation of extensive datasets that could enhance model accuracy and resilience in coronary heart disease detection.

The interpretability and trustworthiness of AI models employed in CHD detection continue to be significant issues. Although machine learning and deep learning models exhibit commendable accuracy in the analysis of medical data, their "black-box" characteristics hinder doctors' capacity to comprehend and trust their predictions. The absence of transparency is especially concerning in critical medical diagnoses such as CHD, where comprehending the rationale behind a model's diagnosis is vital for clinical decision-making. As a result, the use of AI-based CHD diagnosis systems in healthcare environments has progressed slowly, as both physicians and patients desire more comprehensible and dependable approaches.

Confronting these problems necessitates a thorough, multifaceted strategy that encompasses the development of interpretable AI models, the improvement of data quality, and the establishment of personalised screening processes that account for the distinct risk factors of various populations. By surmounting these challenges, there exists the potential to achieve substantial advancements in the early identification and prevention of coronary heart disease, thereby enhancing patient outcomes and alleviating the worldwide burden of cardiovascular disease.

3. FUZZY TECHNIQUE FOR RISK EVALUATION

Figure 3 depicts a conceptual model of a Neural Fuzzy Inference System for assessing the risk of CVD. This model seeks to assess the cardiovascular disease risk in individuals by integrating individualised clinical data with a fuzzy inference methodology, which emulates human thinking to analyse unclear or imprecise information. The procedure commences with the aggregation of patient clinical data, which includes diverse health indicators and biomarkers indicative of cardiovascular health. These data points function as the system's input, establishing the basis for precise and customised risk assessment.

The model initially preprocesses the patient's clinical data to guarantee it is in a standardised and functional format. Preprocessing is an essential phase in any data-driven model, since it eliminates noise, addresses missing values, and organises the data for efficient processing. Subsequent to preprocessing, the data undergoes feature selection to identify the most pertinent and influential properties. In the context of CVD, these characteristics may encompass measurements such as blood pressure, cholesterol levels, heart rate variability, age, and lifestyle factors. Choosing appropriate features is essential as it improves the model's efficacy, decreases computing complexity, and emphasises the most predictive variables [7].

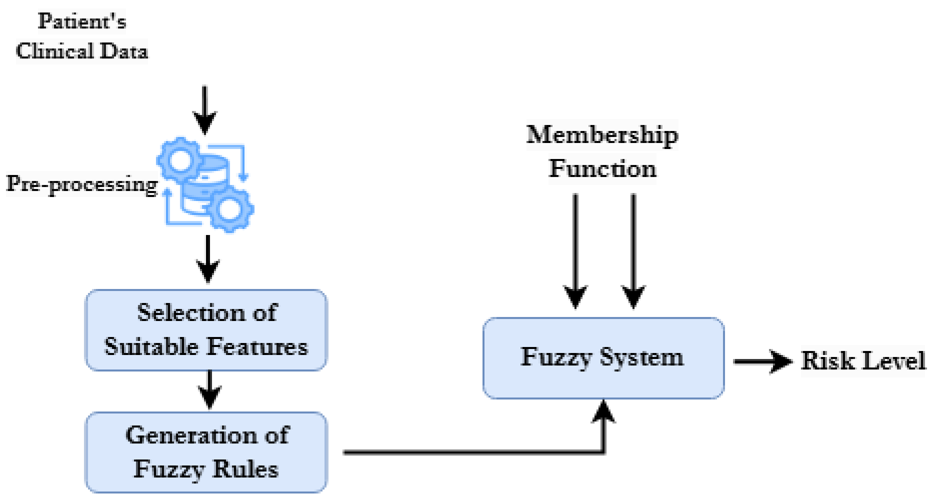

FIGURE 3. Conceptual Model for the fuzzy inference system.

Subsequent to feature selection, the model produces fuzzy rules. The rules establish the foundation of the fuzzy inference system, correlating input variables to risk levels through if-then logic that accommodates imprecision and ambiguity in human health indicators. For instance, guidelines may indicate that if a patient exhibits elevated cholesterol and hypertension, their likelihood of cardiovascular disease is presumably high. By incorporating these fuzzy criteria, the system may identify risk levels more adaptively and intuitively than conventional models, catching nuanced fluctuations in health data that inflexible threshold-based systems may overlook.

The fuzzy system incorporates a membership function that assigns each input feature a degree of membership across different risk categories, including low, medium, or high. The ultimate result of this fuzzy inference method is a detailed risk assessment for cardiovascular disease, customised for each patient according to their own clinical characteristics. This methodology utilises a Neural Fuzzy Inference System, integrating the advantages of neural networks (data-driven learning) with fuzzy logic (managing uncertainty and imprecision), hence providing an effective instrument for the early identification and individualised risk evaluation of CVD. This method has the potential to improve preventive healthcare by facilitating prompt interventions for patients at risk.

4. LITERATURE REVIEW

This section discusses contemporary CVD detection and diagnosis technologies, highlighting AI and ML advances that have altered the area. Traditional machine learning algorithms, deep learning, and hybrid models improve CVD detection accuracy and reliability. Each method uses massive datasets, medical imaging, and patient records to forecast CVD risk and discover early disease signs. The section outlines its benefits and weaknesses. It also addresses interpretability, computational complexity, and data quality difficulties in clinical adaptations of these models.

Elsedimy et al [8] introduce an innovative approach for heart disease diagnosis that integrates quantum-behaved particle swarm optimisation (QPSO) with a support vector machine (SVM) classification model to enhance predictive accuracy. The QPSO-SVM model enhances feature selection and parameter optimisation, adeptly balancing exploration and exploitation using a self-adaptive threshold method. Upon evaluation using the Cleveland heart disease dataset, the model demonstrated elevated sensitivity, specificity, accuracy, and F1 scores, surpassing other models. This approach illustrates the efficacy of QPSO in managing high-dimensional data and improving SVM performance; however, the study recognises drawbacks, such as insufficient testing on alternative datasets, which may affect its generalisability. Additional study is advised to assess the model's resilience in actual clinical environments, where data may exhibit greater variability and imbalance, underscoring the necessity for ongoing advancements in CVD detection techniques.

V. V. Paul and J. A. I. S. Masood [9] provide a survey of predictive methodologies for CVD, emphasising a hybrid deep neural network (HDNN) approach aimed at enhancing the accuracy of heart disease predictions. This HDNN model amalgamates various neural network architectures, notably merging convolutional neural networks (CNN) and long short-term memory (LSTM) networks with supplementary dense layers, to capitalise on the advantages of each methodology. The paper assesses the HDNN model against conventional approaches utilising publically accessible datasets, including the Cleveland heart disease dataset, and analyses performance through metrics such as sensitivity, Matthews Correlation Coefficient (MCC), F1 score, accuracy, precision, AUC, and specificity. The HDNN model demonstrates improved accuracy relative to traditional methods; however, the report highlights possible avenues for further investigation, including the model's scalability and its application in practical clinical environments. Furthermore, it underscores the potential to enhance the model's functionalities by evaluating its efficacy across various demographic cohorts or including real-time patient data for adaptive prediction, thereby addressing a significant deficiency in personalised cardiovascular disease risk evaluation.

Mondal et al. [9] introduce an innovative dual-stage stacked machine learning model for assessing heart disease risk, utilising a dataset including 1,190 individuals with eleven essential attributes [27]. The research employed five machine learning classifiers, optimising hyperparameters via RandomizedSearchCV and GridSearchCV, to ascertain the most effective models. The models were further enhanced by a stacking ensemble technique, attaining an accuracy of 96%, a recall of 0.98, and a ROC-AUC score of 0.9623. The model's exceptional stability and repeatability indicate its potential for precise and prompt heart disease diagnosis, which could significantly mitigate global mortality linked to cardiovascular disease.

Subramani et al. [10] concentrate on the prediction of CVD by machine learning and deep learning methodologies, highlighting the significance of artificial intelligence (AI) in forecasting outcomes for CVD patients. Their model utilises a stacking methodology featuring base and meta-learner layers, incorporating classifiers such as Random Forest, Logistic Regression, Multilayer Perceptron, Extra Trees, CatBoost, and Gradient Boosting Decision Tree. They employ the SHAP approach for feature selection to identify significant variables. The study attained almost 96% accuracy, demonstrating the benefits of AI-based technologies in enhancing CVD prediction precision compared to conventional statistical models. Future objectives involve investigating IoT integration to improve predictive capabilities in clinical environments and acquiring additional data from various medical institutions to strengthen deep learning frameworks.

Sarra et al. [11] emphasise the progress in machine learning for predicting cardiac disease, specifically utilising Support Vector Machine (SVM) in conjunction with a chi-squared ($\chi 2$) feature selection technique to enhance accuracy. The suggested SVM model mitigates the danger of overfitting by pertinent feature selection, consequently improving predictive performance across measures such as accuracy, sensitivity, specificity, and F1-score. The research highlights the significance of precise and timely diagnosis to reduce worldwide heart disease mortality rates. Nevertheless, although the SVM model exhibits improved prediction skills, the authors recognise the necessity for additional assessment across a broader range of datasets to validate its efficacy.

Rahim et al. [12] introduce the MaLCaDD framework, which employs machine learning methodologies to forecast CVD, tackling challenges such as absent data via mean substitution and data imbalances through SMOTE. The framework integrates feature importance for efficient feature selection, minimising computational complexity while preserving accuracy. The study indicates that, despite its thorough methodology for data preparation and prediction, enhancements could be achieved by including real-time data analysis using wearable health monitoring devices for ongoing cardiovascular disease risk evaluation. DeGroat et al. similarly concentrate on utilising AI and machine learning for CVD by creating the Clinically Integrated Genomics and Transcriptomics (CIGT) framework, which amalgamates transcriptomic, clinical, and demographic data for precise prediction [13]. The study employs feature selection techniques, including recursive feature elimination, Pearson correlation, chi-square, and ANOVA, to identify essential biomarkers, which are further validated through literature review and clinical data cross-referencing. This model illustrates the capability of incorporating intricate data types to improve cardiovascular disease prediction.

Kresoja et al. [14] offer cardiologists an extensive manual on employing ML to forecast the prognosis of cardiovascular illnesses. The study highlights the capacity of machine learning algorithms to analyse and comprehend intricate clinical data, facilitating clinical decision-making, especially given the overwhelming volume of medical data that exceeds human analytical capacities. The study seeks to equip medical practitioners and researchers for the difficulties presented by ML technologies by elucidating underlying principles, potential hazards, and contemporary applications in cardiology, including omics, imaging, and basic science. The study differentiates ML and AI and conventional statistical methods, emphasising ML's predictive potential while acknowledging its compromise in interpretability. It examines many ML approaches, encompassing supervised and unsupervised learning, and details their particular applications in cardiology, serving as a significant resource for physicians aiming to integrate machine learning insights into their practice.

Miao et al. [15] created an ensemble machine learning model employing adaptive boosting (AdaBoost) to forecast cardiac disease using four distinct datasets. Their model attained an average accuracy of 85.27%, although encountered overfitting, evidenced by a greater error rate during testing compared to training. This limitation indicates that although AdaBoost effectively enhances prediction accuracy, it may necessitate modifications to prevent overfitting, especially in varied real-world datasets. The research elucidates the application of ensemble learning in cardiovascular prediction and underscores the necessity for ways to improve generalisability. Rajagopal and Ranganathan performed a comparative investigation of five distinct dimensionality reduction strategies in conjunction with a multilayer perceptron (MLP) classifier for the detection of cardiac arrhythmia [16]. The study utilised Fast Independent Component Analysis (Fast-ICA) with a minimal threshold of ten components, resulting in a remarkable F1 score of 0.99, so illustrating the efficacy of dimensionality reduction in improving model performance. Their findings underscore the significance of feature engineering, especially in managing high-dimensional data for heart disease prediction. The study demonstrates that optimising input data through dimensionality reduction approaches can markedly enhance the accuracy of cardiac risk prediction algorithms.

Ravaji and Moghe [17] created a deep maxout network optimised by a hybrid cat swarm and chimp optimisation algorithm (CSChO) for the diagnosis of heart disease. Following preprocessing that included missing data imputation and log transformations, the study employed the Kendall tau distance metric alongside a deep belief network classifier for feature fusion. The CSChO-enhanced deep maxout network applied to the Hungary dataset attained a testing accuracy of 0.948, sensitivity of 0.949, and specificity of 0.919. Notwithstanding its encouraging outcomes, the study advocates for additional research to investigate various risk assessment methodologies, with the objective of improving clinical applicability.

Longato et al. [18] developed a deep learning model (DLM) to predict major adverse cardiovascular events (MACE) in a cohort of 214,676 diabetic patients from the Veneto area of Italy. Employing a multi-label, multi-outcome classification methodology, they integrated pharmaceutical claims, hospitalisation data, and patient demographics to forecast outcomes such as heart failure, myocardial infarction, stroke, and mortality over a five-year duration. While the approach facilitates early prediction of MACE in diabetic patients, obstacles in data collecting and evaluation hinder wider institutional adoption.

Sarmah presented an IoT-based system combined with deep learning neural networks (DLMNNs) for the real-time monitoring and diagnosis of cardiac events [19]. This system utilises authentication techniques, including encryption and SHA-512, for security and depends on sensor devices affixed to patients to collect physiological data. The DLMNN categorises data into normal and abnormal classifications, providing diagnostic and medication management assistance via cloud storage to enhance accessibility in healthcare environments.

The NFIS model attained a 94% accuracy rate, illustrating its efficacy in predicting heart disease through intricate, rule-based fuzzy logic. Swapna et al. employed convolutional neural networks (CNNs) and CNN-LSTM models to identify cardiac anomalies without conventional feature extraction techniques [20]. The study attained a maximum test accuracy of 90.9% with the integration of CNN and LSTM. Nonetheless, the model encounters obstacles pertaining to data quality, bias, and interpretability, which constrain its utility in clinical environments. Ghasemieh et al. utilised supervised machine learning methods to forecast diabetes and coronary heart illnesses, examining the feature overlaps between the conditions that may influence prognosis [21]. The research utilised the NHANES dataset to assess several methods, culminating in the creation of a weighted ensemble model to improve predictive accuracy.

The authors in [22] examines the intricate, nonlinear interactions among CVD risk variables by introducing a methodology that integrates various ML techniques to improve diagnostic precision. The authors employ support vector regression (SVR), multivariate adaptive regression splines, the M5Tree model, and neural networks for training, in addition to adaptive neuro-fuzzy inference systems (ANFIS) and statistical classifiers, including nearest neighbour and naive Bayes, to forecast seventeen cardiovascular disease risk factors. The study seeks to enhance prediction reliability for cardiovascular disease risk by utilising mixed-data transformation and classification techniques to manage both categorical and continuous variables. The sensitivity study, conducted on an actual hospital dataset, identifies critical parameters such as age, cholesterol, and glucose levels, with ANFIS attaining a superior prediction accuracy of 96.56%, followed by SVR at 91.95%. This complete methodology exhibits enhanced performance relative to conventional statistical and machine learning models, highlighting its efficacy in cardiovascular disease categorisation and risk evaluation.

B. Ramesh et.al [23] introduced an Optimal Scrutiny Boosted Graph Convolutional LSTM (O-SBGC-LSTM) model, augmented by the Eurygaster Optimisation Algorithm (EOA) for hyperparameter optimisation, to boost early diabetes prevention and detection. The O-SBGC-LSTM technique identifies distinguishing features by examining spatial configurations and temporal dynamics, investigating co-occurrence correlations between these domains. Furthermore, it implements a temporal hierarchical architecture to broaden the temporal receptive fields of the upper SBGC-LSTM layer, hence improving the model's capacity to acquire high-level semantic representations while minimising computing expenses. The model exhibited strong performance, with over 98% accuracy in the majority of studies and constantly surpassing traditional machine learning techniques in comparative analyses. Additionally, fuzzy inference techniques were incorporated to improve preventive strategies, offering a recommendation table to facilitate early intervention and control of diabetes.

The authors in [24] integrates the Adaptive Neuro-Fuzzy Inference System (ANFIS) with a Genetic Algorithm (GA) and the DenseNet-201 model for disease assessment as shown in Figure 4. Initially, DenseNet-201 is utilised for feature extraction, improving classification accuracy with its deep learning capabilities. The Whale Optimisation Algorithm (WOA) is utilised for feature selection to eliminate redundancy, preserving only the most pertinent qualities. The parameters of ANFIS are optimised by Genetic Algorithms, resulting in enhanced predictive performance. The model is assessed using metrics like RMSE, MSE, STD, and R^2, exhibiting enhanced performance compared to the traditional ANFIS model, underscoring its potential for dependable disease identification.

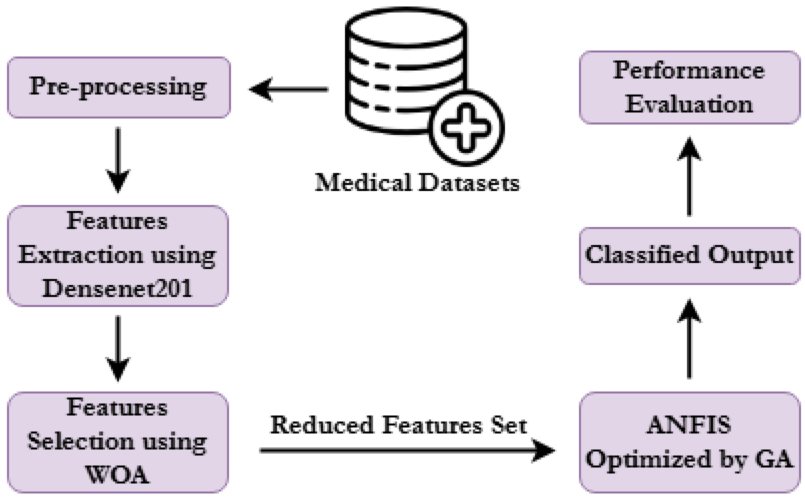

FIGURE 4. The work flow of disease prediction [24]

5. FUZZY LOGIC AND NEURO-FUZZY SYSTEMS

Fuzzy logic is acknowledged as an effective instrument in artificial intelligence for managing complicated and ambiguous information, rendering it especially appropriate for the detection of CHD and CVD. In contrast to conventional Boolean logic, which limits values to 0 or 1, fuzzy logic utilises a multivalued framework where truth values can vary between 0 and 1, hence addressing the complexities inherent in medical data. This adaptability allows fuzzy logic to convert qualitative verbal statements, such as "high risk" or "moderate probability," into a mathematical framework through fuzzy sets and membership functions. In CVD prediction, fuzzy logic enhances decision-making by accommodating intermediate degrees of truth, reflecting the often-ambiguous nature of real-world diagnostic processes.

In a fuzzy model, linguistic variables—such as age, cholesterol level, or blood pressure—are delineated with term sets, establishing the foundation of a fuzzy inference system (FIS). The fuzzification process converts precise numerical inputs into degrees of membership, facilitating the interaction of these variables inside the system. The FIS employs a rule-based framework, informed by expert knowledge, to evaluate CVD risk. Membership functions (MFs) are essential in these models, dictating the impact of various inputs on the system's outputs. An effectively constructed FIS can forecast the probability of CVD incidence by integrating various input components and their corresponding membership functions, offering a versatile but resilient framework for diagnosis.

A notable development in this field is the Adaptive Neuro-Fuzzy Inference System (ANFIS), which integrates the learning abilities of neural networks with the comprehensibility of fuzzy logic. ANFIS models are engineered to enhance the parameters of a fuzzy inference system through training data, resulting in increased prediction accuracy. Research has shown that ANFIS is successful in predicting cardiovascular disease risk, with classification accuracy rates of up to 92.3% by utilising variables such as age, cholesterol levels, and ECG signal data. ANFIS promotes reliability by utilising techniques such as k-fold cross-validation, especially in the assessment of heart disease severity or the comparison of electrocardiogram (ECG) signal feedback. This hybrid methodology offers significant accuracy and control, rendering ANFIS an essential instrument in the creation of diagnostic systems for cardiovascular disease risk evaluation [25].

To tackle the issues of data imbalance and non-linear interactions among categorical and quantitative risk indicators, techniques such as the Gifi transformation are utilised. This method facilitates the incorporation of categorical factors (e.g., gender and family history) alongside continuous variables (e.g., cholesterol levels and BMI) by transforming them into quantifiable formats that preserve intricate interconnections. The transformation of Gifi is crucial for preserving data integrity and avoiding oversimplification, so enabling the system to appropriately represent the complex interrelations among risk variables. Consequently, it facilitates a balanced representation of input data, thereby augmenting the prediction capacities of fuzzy-based and neuro-fuzzy systems.

The utilisation of fuzzy logic and ANFIS in cardiovascular disease diagnosis demonstrates the capability of AI-driven techniques to tackle the complex characteristics of cardiovascular diseases. These systems employ linguistic variables, membership functions, and data transformation techniques to create a robust framework for evaluating cardiovascular disease risk, considering many aspects such as age, blood pressure, cholesterol levels, and lifestyle choices. This method improves the interpretability of diagnostic models and meets the requirements of healthcare professionals, who need tools that provide detailed insights into patient risk profiles [26].

6. EMERGING TRENDS AND FUTURE DIRECTIONS

Recent breakthroughs in the field of CVD detection emphasise the growing utilisation of hybrid models and ensemble methods that integrate the advantages of various ML and DL techniques. Hybrid methodologies, which integrate optimisation algorithms with conventional classifiers, have demonstrated potential in improving feature selection and parameter adjustment, leading to increased model accuracy and stability. Nonetheless, a disparity persists in the generalisability of these models, as numerous instances have not been evaluated across varied datasets. Future directions entail enhancing hybrid methodologies to integrate diverse and representative clinical data, thereby mitigating this restriction and assuring model resilience in practical environments.

A notable trend is the utilisation of deep neural network (DNN) architectures that incorporate models adept at capturing both spatial and temporal data attributes. Hybrid DNNs, which integrate convolutional layers with recurrent layers such as LSTMs, seek to enhance prediction accuracy by proficiently analysing intricate patient records and imaging data. However, scalability and flexibility to personalised treatment continue to pose significant obstacles. Subsequent research may concentrate on enhancing these hybrid DNNs to include real-time patient data, facilitating adaptive and more individualised CVD risk evaluations. This will address a significant deficiency in existing diagnostic paradigms by facilitating comprehensive, personalised healthcare treatments for varied patient populations.

Ensemble approaches and stacking models have gained prominence, especially for their capacity to enhance predictive accuracy by integrating classifiers such as Random Forest, Logistic Regression, and Gradient Boosting. These ensemble methods, together with feature selection strategies, enhance interpretability, mitigating a recognised constraint in the clinical applicability of complicated models. In the future, combining these ensemble frameworks with Internet of Things (IoT) functionalities may provide real-time monitoring and dynamic cardiovascular disease risk evaluation. IoT-enhanced models offer a potential approach for ongoing cardiovascular health monitoring, particularly beneficial in hospital and remote patient environments.

The focus on data quality and dependability is a rising issue in cardiovascular disease detection research. Mitigating data imbalances, addressing missing values, and reducing noisy inputs is crucial for ensuring robust model performance. Contemporary frameworks employ approaches such as SMOTE to address data imbalance and utilise diverse imputation algorithms for managing missing data; nonetheless, real-time data integration is still inadequately developed. Future developments may include the integration of wearable health devices that provide continuous and accurate data collecting, hence supporting the seamless incorporation of real-time analysis and feedback into patient treatment.

Dimensionality reduction and feature engineering are essential for improving model efficiency, particularly with high-dimensional datasets prevalent in medical applications. Methods that optimise input data while preserving critical attributes mitigate computing demands and avert overfitting, a prevalent issue in extensive machine learning models. Future research should investigate advanced feature extraction and dimensionality reduction techniques specifically designed for cardiovascular data, facilitating efficient and precise CVD prediction while maintaining model efficacy. The trends in hybridisation, real-time data integration, ensemble learning, data preparation, and dimensionality reduction indicate a promising future for cardiovascular disease detection models. Rectifying these deficiencies will facilitate the development of more dependable, comprehensible, and adaptable diagnostic instruments that can enhance personalised cardiovascular treatment and prompt intervention.

7. CONCLUSION

This survey highlights the progress in hybrid deep learning and neural fuzzy inference systems for the early detection of CHD, demonstrating the efficacy of integrating deep learning models with fuzzy inference and optimisation methods. Although these methods enhance accuracy, interpretability, and adaptability, problems related to generalisability, real-time data integration, and dimensionality reduction continue to restrict clinical usefulness. Future endeavours will concentrate on executing an efficient approach inside this hybrid framework, with the objective of creating a robust, interpretable, and adaptive model for accurate, real-time CHD risk evaluation. This technique will facilitate personalised and preventative healthcare, addressing essential requirements in the early identification of CHD. Further, we concentrate on executing an effective approach inside this hybrid framework, prioritising feature selection to improve model interpretability and efficiency. Integrating novel data types, including genetic sequences and environmental factors, could enhance early CHD risk assessment, facilitating personalised preventative healthcare treatments.

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