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A Review on Heart Disease Detection Classification Based on Deep Learning Algorithm

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Abstract

Heart disease it is one of the main causes of death in the globe. Heart illness encompasses a spectrum of disorders that impact the heart, its blood arteries, and its overall functionality. Also referred to as cardiovascular disease. This paper investigates the potential benefits of deep learning (DL) architectures for improving diagnostic accuracy addressing the critical need for improved diagnosis of cardiac disease, and the difficulties associated with applying DL methods for heart disease identification. This survey study highlights the important role that DL plays in cardiovascular diagnostics from a number of tasks like as diagnosing, predicting, and classifying heart diseases. Convolutional Neural Networks (CNNs), a type of deep learning, are being used in the context of heart illness with the primary goal of creating accurate and dependable models for the identification, diagnosis, and prognosis of various heart-related disorders.

A. Introduction

Heart disease is one of the most complex and deadly illnesses that affect people worldwide One of the main causes of death nowadays is cardiovascular disease, which frequently causes additional illnesses like strokes, hypertension, heart failure, and arrhythmia [1][2]. A variety of disorders that affect your heart are referred to as heart diseases[3]. cardiovascular illnesses account for more than 17.9 million fatalities globally each year, making them the leading cause of death today[4].Many lives can be saved by early recognition of this illness, thus accurate diagnosis and clinical analysis are required [5]. Accurate detection is achieved and diagnostic costs are decreased through the use of machine learning and deep learning techniques numerous data mining methods have been investigated to comprehend and analyze data related to heart disease Neural Network techniques have also been employed to assess the degree of disease in individuals[6].Since the advent of medical big data and artificial intelligence technologies, there has been a growing emphasis on developing deep learning algorithms for the classification of cardiac disease in the past few years, papers on deep learning of medical imaging have increased significantly[7].Many Research proposed the use of deep learning architectures and artificial neural networks to identify cardiac irregularities through the analysis of ECG signals and heart sounds obtained from portable devices and digital stethoscopes[8].For several CNN has been used in computer vision for decades, analyzing images from MRIs, X-rays, medical data, pathological images, pattern recognition, electron transport proteins, and other sources[9]. An extensive overview of deep learning methods in cardiology is the focus of this review paper.[10]. This survey article's section will discuss several deep learning algorithms for heart disease and how they differ in terms of several factors. It also shows how deep learning algorithms may be used in the future to treat cardiac problems. The paper is organized as follows: Section B provides an explanation of the theoretical background. Section C examines case studies of practical applications, and Section D offers conclusions for the paper.

B. Research Method

This part compared the studies and research on deep learning, providing a basic introduction to the field, its types, and the most popular literature methodologies[11].

1. Detection of Heart Disease Using Deep Learning Model.

In order to detect heart disorders, they employed a convolutional neural network (CNN). Computer-based applications are necessary for data evaluation in systems that are mostly made up of techniques for computer aided diagnosis in worldwide [12]. The main problem in human life is heart disease. "Cardio" means "heart." Cardiologist disease is the category name for heart disease. The different forms of heart disease that can be detected include[13]:

- Congenital heart disease.
- Arrhythmia.
- Coronary artery disease.
- Dilated cardiomyopathy.
- Myocardial infarction.
- Heart failure.

- Hypertrophic cardiomyopathy.
- Mitral regurgitation

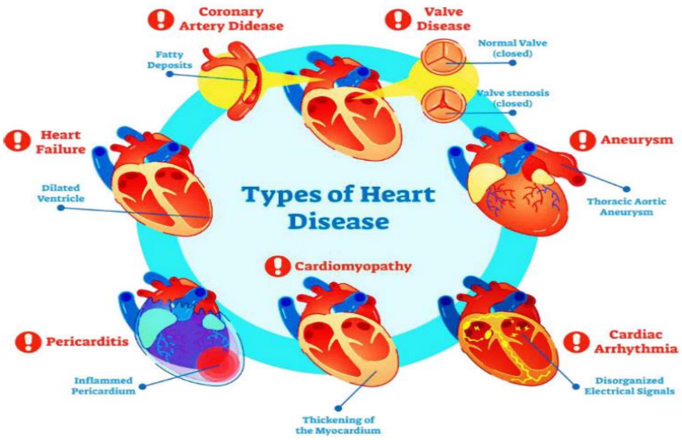

Figure 1. List of type heart disease.

2. Deep Learning

Deep learning is a component of machine learning that mimics the behavior of the human brain in that it is built on several learning levels and error reduction in intermediate layers. These methods use built-in computational models that include multiple hidden layers for data learning and prediction[14].

2.1 Deep Learning Model.

Deep learning has proven to be an effective technique. When it comes to the identification and diagnosis of cardiac disease. Deep learning models have the ability to analyze intricate patterns in medical data, specifically in electrocardiogram (ECG) signals and heart sound recordings, by utilizing advanced neural network architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs)and long -Term memory (LSTM)[15].

2.2.1 Convolutional Neural Networks (CNN):

CNN It is composed of three distinct convolutional layer blocks, each of which is succeeded by a dense layer, activation function[16][17]. As seen in Figure 2, CNN are increasingly used in diagnosing and interpreting medical images like MRI scans, angiograms, and echocardiograms for the identification and treatment of cardiac diseases[18][19]. Convolutional pooling and fully connected layers make up CNN's structure. The CNN is divided into two sections: feature extraction which involves connecting each neuron's input to the local receptive field of the layer before it, and feature mapping[20]. The embedded sequences are further processed by the CNN's convolutional layers to extract abstract patterns and features at different granularities[21]. CNN combines extraction and classification into a single step, as opposed to traditional recognition algorithms that need intricate extraction procedures[22].

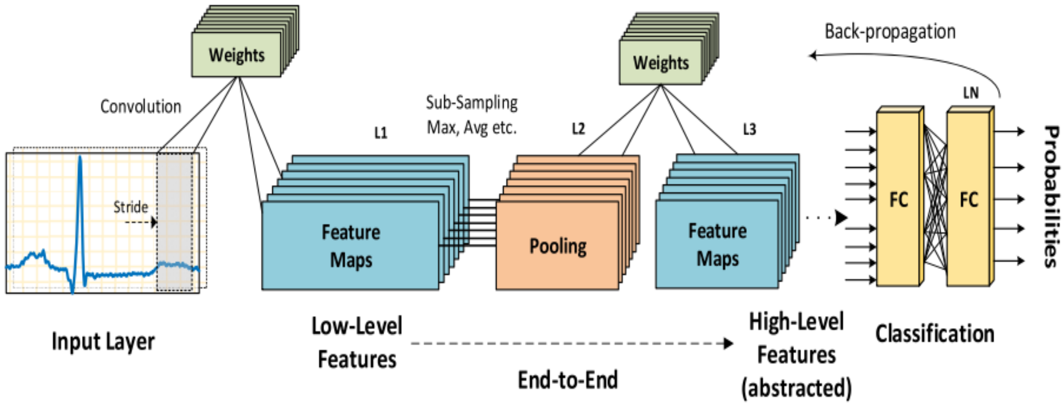

Figure 2. CNN Structure [23]

2.2.2 Recurrent Neural Networks (RNNs):

The sequential strategy of RNN makes it a unique deep learning algorithm with links between hidden layers. It repeatedly duplicates the hidden layer, applying the same weights and biases to the inputs at each time step. The network will execute the procedure in a loop, updating and modifying its hidden state while storing the data in its internal memory. By training on the appropriate data, the RNN will construct its model[24], [25]. It is capable of storing the most pertinent data.[26][27].

2.2.3 Long Short-Term Memory (LSTM):

Using a gated design, one of the most often used RNN variations is Long Short-Term Memory (LSTM), which can handle sequential data. The temporal irregularity and dependence problems outlined above are beyond the capabilities of ordinary LSTM networks.[28][29]. The major goal is to build up an intelligent system based on LSTM technique for heart disease prediction in order to make an appropriate decision to avoid and monitor heart disease and stroke. LSTM approaches are accurate and have additional factors for prediction in heart disease.[30]

2.2.4 Generative Adversarial Networks (GANs):

Generating and reconstructing images using GAN is comparable to filling in missing data. It can learn complex associations and learns the distribution of data without making explicit assumptions. Since GAN employs extra data to improve the generated data, larger data sets result in higher accuracy.[31], [32] . A backpropagation algorithm is used to continually tune both the discriminant and generative networks, leading to reciprocal improvement. The discriminant network discerns between produced and actual data, whereas the generative network learns the distribution of samples.[33]

3. Heart Disease Dataset.

Research and analysis about heart disease can be performed using a variety of databases. Here are some datasets that have been the most popular dataset used by the researchers frequently used in this field is:

a. Cleveland Heart Disease Dataset.

b. Hungarian Heart Disease Dataset.
c. Switzerland Heart Disease Dataset.
d. MIT-BIH Arrhythmia Database.
e. PhysioNet.

Table 1 displays the main characteristics along with the corresponding ranges.

4. Heart Disease Diagnosis.

Heart conditions are a serious medical problem that are becoming more deadly. Automated techniques employing heart signals and pictures are being developed, and early detection can stop or lessen their effects. Researchers have found that advanced learning approaches which include CNN improve disease presentation when compared to older methods.[34][35]. The diagnosis of heart disease includes a wide range of disorders that affect the heart and blood vessels. Popular varieties include as shown in the figure 3.

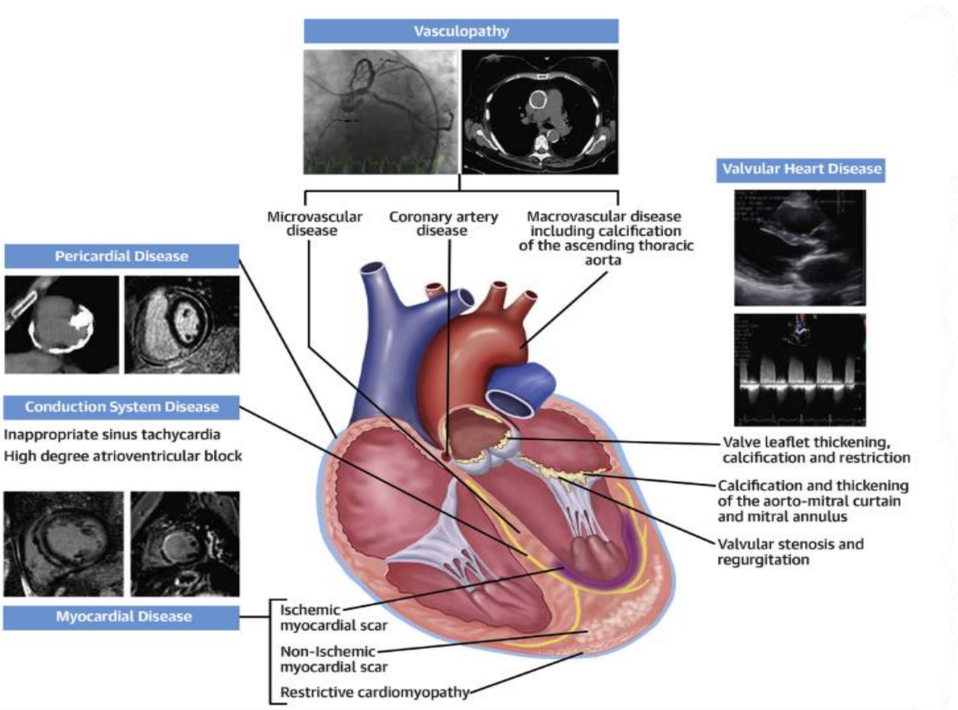

Figure1. Types Of Heart Disease Disorders.

C. Literature Review

In [36], proposed an automatic framework for ECG diagnosis without manual feature extraction, handling imbalanced data effectively through resampling the 1D-CNN model for ECG classification achieved high accuracy of 97.36% and an impressive F1 score of 99.83%.

In [37] The paper discussed a deep learning approach using a Hybrid Alexnet-SVM architecture for classifying ECG signals, particularly focusing on Arrhythmia, Congestive Heart Failure (CHF), and Normal Sinus Rhythm (NSR) ECG signals. The study achieves high accuracy of 96.77% in classifying ECG signals. LSTM models are utilized for processing ECG data series, showcasing promising results in classification accuracy.

In [38], the authors the implemented of an IoT framework for heart disease prediction using a modified deep convolutional neural network (MDCNN) classifier, Deep learning techniques like (CNN) and (LSTM) are employed for accurate disease prediction, the stages of the diagnosis process, researcher used (UCI, CHD, and Public Health) dataset

In [39] focused on classifying normal and abnormal heart sounds using a dataset from PhysioNet/Computing in Cardiology Challenge 2016. and a (CNN) model with a (GAP) layer was designed for classification. Class weights were adjusted to address class imbalance, improving sensitivity and specificity.

In [40], presented on developing a deep learning model for classifying ECG signals using a CNN- BiLSTM architecture, high specificity in identifying arrhythmias, accurate ECG signal classification and automated cardiac diagnosis.

In [41] The paper used ECG signals from 15 CHF patients and 18 healthy individuals to automatically detect Congestive Heart Failure (CHF) using a hybrid deep learning algorithm. Results show significant differences between CHF and NSR patients, proving feasible for CHF detection and prediction.

In [42] ,presented on developing a DL-based multiclass instance segmentation model for accurate detection of septal defects in fetal US images. The proposed model utilizes the Mask R-CNN (MRCNN) architecture, extending the Faster R-CNN (FRCNN) model for improved segmentation and object detection using dataset consists of 764 fetal heart images, including ASDs, VSDs, AVSDs, and normal conditions, achieved high mean average precision (mAP) of 99.48% for MRCNN and 82% for FRCNN, indicating accurate defect detection.

In [43] researchers successfully implemented an enhanced deep learning-assisted convolutional neural network (EDCNN) on the Internet of Medical Things platform for accurate heart disease diagnosis and prediction, achieving 99.1% precision. The dataset used for the Enhanced Deep Convolutional Neural Network (EDCNN) system is from the UCI repository.

In [44] researchers focused on utilizing the 'MIMIC-II Care (MIMIC-II)' database from the Physionet repository for signal processing and deep learning model validation in healthcare monitoring applications. The proposed PP-Net model, a combination of LSTM RNN and CNN layers, aims to estimate DBP, SBP, and HR simultaneously. The model achieved high accuracy with NMAE of 0.059, NRMSE of 0.090, and a correlation coefficient of 0.9902.

In [45] the paper discussed a heart disease prediction model using structured data from hospital records. It involves data collection, cleaning, and machine learning algorithms like Naive Bayes and CNN for prediction. The model achieves high accuracy levels of 85-88% using Convolutional Neural Networks (CNN).

In [46] researcher proposed the development of deep CNN for categorizing valve diseases and sounds. Feature extraction methods such as mel-frequency cepstral coefficients and discrete wavelet transform were employed. The models achieved high precision with F1 scores over 98.2% and specificities over 98.5%.

In [47] **,** the paper (CNN) models are used in this study to categorize numerical data related to heart failure in the medical domain. The research predicts patient survival following heart failure using the HFCR dataset, which includes 12 medical features. demonstrating the applicability of the ResNet18 model, which achieved the greatest accuracy of 95.13%.

In [48] the paper proposed introduces a new (DL) approach for automated identification of Congestive Heart Failure (CHF) and Arrhythmia (ARR) using ECG. The algorithm combines Convolutional Neural Network (CNN) with Constant-Q Non-Stationary Gabor Transform (CQ-NSGT). The CQ-NSGT algorithm transforms 1-D ECG signals into 2-D time-frequency representations, fed to a pre-trained CNN model called AlexNet. The proposed approach outperforms existing techniques in terms of accuracy 98.82%, sensitivity 98.87%, specificity 99.21%, and precision 99.20%.

In [49] the paper presented a novel dilated inception CNN-LSTM network for fetal heart rate estimation, enhancing accuracy and reliability of monitoring during pregnancy and labor.Our method achieved 97.3% agreement on labor dataset and 99.6% on 2013 Physionet/ Computing in Cardiology Challenge, surpassing top-performing algorithms, potentially improving fetal HR extraction accuracy.

In [50] researchers in this paper presented on automated detection and localization of myocardial infarction (MI) using electrocardiogram (ECG) signals. It employs deep learning models like CNN and LSTM, achieving over 99% accuracy with the SMOTE + Tomek link sampling technique. The study utilizes MITDB and PTBDB datasets, emphasizing data preprocessing, balancing, and model training.

In [51] researchers developed CardioXNet, a lightweight deep learning framework for cardiovascular disease classification, combining 1D squeeze excitation and CRNN networks, achieving high accuracy, precision, recall, and F1 score on PhysioNet dataset.

In [52] Researchers used CNNs to analyze cardiac sound waves for early detection and prevention of cardiovascular illnesses. The study used preprocessed data, CNN for heart sound categorization, and U-net for segmentation. The algorithm was validated using data from the 2016 PhysioNet/CinC Challenge, with the following outcomesw ith a sensitivity of 0.781 and specificity of 0.873, the results provide good accuracy rates in segmentation and classification.

In [53] they focused on exploiting electrocardiogram (ECG) signals to diagnose heart failure (HF). It suggests models for classification that are based on Support Vector Machine (SVM) and Convolutional Neural Network (CNN), with above 99% specificity, sensitivity, and accuracy. The models don't require engineering features, have a smaller architecture, and require little pre-processing. The collection includes signals from databases maintained by BIDMC and MIT-BIH. As compared to the CNN-SVM model, which achieves 99.26% accuracy, 99.37%

sensitivity, and 99.11% specificity, the CNN model yields result of 99.73% accuracy, 99.58% sensitivity, and 99.83% specificity.

In [54] ,they analysis of MCG data is done using a deep learning technique called Residual Network (ResNet) with transfer learning. It achieves an accuracy of 90.02%, demonstrating a great potential for CDVM classification.

In [55] researchers present in this paper feature-based fusion using CNN for lung and heart sound classification, utilizing deep learning methods and data augmentation techniques to improve accuracy. The FDC-FS model demonstrated excellent performance in detecting lung and heart conditions, with accuracies 89% to 97%.

In [56] ,presented a method for classifying heart sounds using deep learning algorithms and interpolation methods, utilizing heartbeats from both public and clinical trials using tow dataset. first dataset Set_a 99.63%, the accuracy, second dataset Set_b 97.19%

In [57] **,t**he study suggested employing deep learning and machine learning models, namely the hybrid CNN-LSTM technique, to predict cardiac disease. they talks about h important it is to make accurate predictions in the healthcare industry and shows findings for various datasets with high accuracy scores of 97.75% and 98.86%.

In [58] ,they used of DL models to categorize heart valve disorders using audio inputs was covered in this study. Feature extraction methods were employed in the investigation. Using a unique dataset, the models were able to classify cardiac illnesses with high accuracy (F1 = 98.2%) and specificity (98.5%) in both binary and multiclass settings.

In [59] ,presented a deep learning-based Clinical Decision Support System (CDSS) for predicting heart disease using a dataset. The accuracy achieved was 93.28%.

In [60] ,the improved accuracy of the Conv-DeiT model is highlighted in the paper's discussion of the application of the DeiT model in heart sound classification. It exhibits greater performance when compared to DeiT-small, DeiT-base, Conv-DeiT w/o att, and Conv-DeiT. The technological originality of the study is highlighted with regard to VHD classification and medical imaging

In [61] ,the Myocardial Infarction Detection System (MIDs) for PCG signal heart attack detection is introduced in this research. It compares MIDs with other CNN transfer learning models and makes use of transfer learning using CNN models.

In [62] ,the study described a unique deep learning architecture that uses echocardiogram videos to identify Hypoplastic Left Heart Syndrome (HLHS). A collection of ultrasound videos from nine control participants and thirteen HLHS subjects, divided up by the cardiac cycle at various gestational time points, was used in the study.

In [63] the authors proposed Using an RF classifier and a CNN-based squeeze net model, valvular heart sounds were classified into many classes. To increase classification accuracy, the proposed IoT-based model integrates the RF classifier and squeezing net model. On several test datasets, the Conv-RF approach produced results with a high sensitivity and specificity of 99.37% accuracy.

In [64],the paper presented a novel framework for early detection and prevention of Coronary Heart Disease (CHD) in individuals with diabetes. The proposed approach combines a hybrid deep learning model, O-SBGC-LSTM, with a Neural Fuzzy Inference System.

In [65] used the Cleveland Heart Disease dataset, the authors presented a unique hybrid model of CNN and LSTM for heart disease classification. The paper showed accuracy and creativity. The amazing model accuracy of 96.66% was achieved through careful data preparation and hyperparameter optimization methods such as grid search and random search.

Table 1. An Analysis Of Studies Conducted Using Deep Learning On Many Datasets To Predict Heart Disease

No	Name	Year	Pros	Cons	Method	Dataset	Result
1	Mayank Chourasia et,al[36]	2020	Appropriate for autodiagnosis in real-time in clinical settings, saving time and effort.	CNNs and other deep learning models can be computationally demanding and resource-intensive.	CNN	MIT-BIH	97.36%
2	Ahmet Çınar & Seda Arslan Tuncer[37]	2020	The LSTM model offers a dependable and precise method for classifying ECG signals, medical diagnostics and healthcare	More labeled data might be required for the hybrid approach to enable effective feature extraction and classification.	LSTM CNN SVM	MIT-BIH	96.77%
3	Mohammad Ayoub Khan[38]	2020	MDCNN classifier to increase diagnosis, efficiency, and accuracy in disease prediction	raise privacy and security concerns due to the risk of compromised or misused health data	CNN and LSTM	UCI dataset, (CHD) dataset, and Public Health dataset	98.2%
4	Fan Li et,al[39]	2020	improves classification performance for normal and abnormal heart sounds by setting different class	potential insufficient deep learning utilization, and unsatisfactory performance in recognizing abnormal sounds.	CNN	PhysioNet/ Computing	86.8%, 87%, 86.6% and 72.1% respectively
5	Yongbo Liang et,al[40]	2020	Effective feature extraction CNN extracts features from ECG signals, enabling the model to learn effectively and improve classification accuracy.	The CNN-BiLSTM model is able to accurately interpret large data sets due to its specific requirements for specific ECG signal lengths.	CNN and BiLSTM	(MIT-BIH)from Beth Israel Hospital	85% and RBBB F1 94.3%.
6	Wenlong Ning et,al[41]	2020	Detection of congestive heart failure using ECG signals, enhancing the complexity of feature extraction and improving accuracy and reliability.	It may not fully meet the need for shorter time ECG data in clinical settings.	CNN ,RNN	ECG	accuracy 99.93%, sensitivity 99.85% and specificity 100%
7	Siti	2020	MRCNN offers high	the model need for	Mask-	Consists of	99.48% for

	Nurmaini et,al[42]		inference speed, accuracy, and ease of implementation for septal defect detection in fetal images.	diverse training data, robustness concerns, generalization challenges, and scope extension to work with additional cardiac views.	RCNN (MRCNN) And FRCNN	764 fetal heart images, including ASDs, VSDs, AVSDs, and normal conditions	MRCNN And 82% for FRCNN
8	Yuanyuan Pan et,al [43]	2020	Early detection of heart disorders, reduces human errors, achieves high sensitivity and specificity, and accurate diagnosis	EDCNN system faces limitations, data quality, bias, imbalance, privacy concerns, and insufficient data size	EDCNN	(EDCNN) from the UCI repository	99.1%
9	Madhuri Panwar et,al[44]	2020	The PP-Net model proving useful in clinical applications, feature extraction and real-time monitoring in hospitals	Poor PPG resulting from finger or hand movement can potentially affect signal accuracy and accuracy.	LSTM CNN AND PP-Net	MIMIC-II	NMAE of 0.09 (DBP) and 0.04 (SBP) mmHg for BP, and 0.046 bpm
10	VirenViraj Sh ankar et,al[45]	2020	the model provides a reliable method for early detection and risk assessment of heart diseases	One potential disadvantage of the heart disease prediction model is that its accuracy may decrease when medical data is incomplete	CNN	Hospital Data	between 85% to 88%.
11	Mohanad Alkhodari and Luay Fraiwan[46]	2021	can potentially aid in rapid and accurate diagnosis of heart diseases, serving as a valuable tool for healthcare professionals.	DL model may require significant computational resources and expertise, and its complex algorithms	CNN-BiLSTM And RNN	open-access dataset (VHD), (AS), (MS), (MR), and (MVP).	accuracy 97.87%, sensitivity 99.32%, specificity of, 98.30%, and 99.58%resp ectively
12	Muhammet Fatih Aslan et,al[47]	2021	This method allows for successful diagnosis of heart failure disease using deep learning techniques	The manual feature extraction method may result in information loss	CNN	HFCR	95.13 %
13	Ahmed S. Eltrass et.al[48]	2021	The system enhances cardiac condition diagnosis accuracy, performance, and specificity by eliminating R-peak detection,	Further research may be needed to evaluate the scalability and generalizability of the method	CNN And CQ-NSGT	MIT-BIH NSR db, BIDMC CHF db, and MIT-BIH ARR db.	accuracy 98.82%, sensitivity 98.87%, specificity 99.21%, and precision 99.20%.
14	E Fotiadou et,al[49]	2021	The CNN-LSTM network improves fetal heart rate	Complex CNN-LSTM required a large number of	CNN and LSTM	Private dataset and PhysioNet	97.3% and Physionet/ Computing

			estimation accuracy and reliability by combining deep learning techniques with physiological measurements	parameters and computational resources for training and deployment			99.6%
15	Hari Mohan Rai and Kalyan Chatterjee[50]	2021	efficacy of the proposed DL models and data preprocessing techniques in accurately detecting myocardial infarction from ECG signals	Complexity in Oversampling	CNN and LSTM	PTBDB and MIT-BIH	99.82 %, 99.88 %, and 99.89 %
16	Samiul Based Shuvo et.al[51]	2021	CardioXNet excels in CVD classification tasks with high accuracy, precision, recall, and F1 score, and efficiently extracts features	CardioXNet performance is limited by its inability to handle diverse phonocardiogram datasets	CRNN, CNN, LSTM and CardioXNet	PhysioNet	99.60% accuracy, 99.56% precision, 99.52% recall, 99.68% F1 And 86.57%
17	Yi He et.al[52]	2021	CNN classifier use for heart sound segmentation and classification enabling accurate identification of abnormalities potentially aiding early cardiovascular condition detection	the complexity of DL models like the CNN classifier, which often require significant processing power, memory, and training time.	CNN	PhysioNet	between 0.997, and 0.781
18	Jad Botros et,al[53]	2022	CNNs outperform traditional machine learning methods due to their automatic feature identification without human intervention	complex (CNNs), the high computational cost of training and testing these methods, which can hinder understanding of decision-making processes	CNN and SVM	MIT-BIH and BIDMC	CNN-SVM 99.26% accuracy, 99.37% sensitivity, 99.11% specificity
19	Zhenghui Hu et,al[54]	2022	high diagnostic specificity and sensitivity, using data analysis to find new information.	CNNs pose significant challenges in medical settings due to their high data dependency and complexity	CNN And ResNet	MCG	90.02%
20	Zeenat Tariq et,al[55]	2022	high accuracy, comprehensive evaluation, effective data augmentation, and clear presentation	may be complex and require specialized knowledge in signal processing and machine learning	CNN	lung sound	89% to 97%
21	Muhammed Yildirim[56]	2022	method is successfully applied for dataset enhancement, improving model accuracy and efficiency	lacking specialized interpolation techniques, insufficient dataset information	CNN	Set_a And Set_b	99.63% And 97.19%

22	Mana Saleh Al Reshan et.al[57]	2023	efficient DL and ML models for heart disease prediction, showing encouraging outcomes for medical decision support systems.	Reliability and accuracy of the system could be impacted by datasets that contain a large number of missing values.	HDNN and CNN-LSTM	Cleveland HD And Comprehen sive HD	97.75% And 98.86%
23	Randa I. Aljohani [58]	2023	accurately diagnose heart valve problems using DL models, specifically CNN, for quick and accurate diagnosis.	The quality and consistency of recorded heart sounds may vary when using electronic stethoscopes for data gathering	CNN	Private dataset	F1 98.2% and specificities 98.5%
24	Abdulwahab Ali Almazroi et, al[59]	2023	this model for heart disease prediction that outperforms individual models and ensemble approaches in terms of accuracy, sensitivity, and specificity	complex CC require more time	CNN And ML	Cleveland, Hungarian, Long Beach, and Switzerland.	93.28%
25	Talit Jumphoo [60]	2023	model Conv-DeiT, which combines SE-attention mechanism and convolutional blocks, performs better than conventional techniques.	in order to guarantee the generalizability of the suggested Conv-DeiT model, additional validation on a variety of datasets is required, with a focus on the HSM database.	CNN and Conv-DeiT	HSM	97.44% accuracy, Conv-DeiT 99.44%.
26	Satria Mandala et,al [61]	2023	Using CNN models with transfer learning, the Myocardial Infarction Detection System (MIDs) is a revolutionary technique that improves accuracy for identifying heart attacks in PCG data.	thorough explanation of potential difficulties is lacking	CNN	particular dataset	sensitivity of 97.4%, specificity of 96.0%, and accuracy of 96.7%.
27	Tawsifur Rahman et.al [62]	2023	presented a groundbreaking DL framework for detecting Hypoplastic Left Heart Syndrome (HLHS) using echocardiography films	The paper may have limitations in terms of sample size	CNN-LSTM	Private dataset	accuracy, precision, sensitivity, F1 score, and specificity of 90.5%, 92.5%, 92.5%, 92.5%, and 85%,
28	Tanmay Sinha Roy Et.Al[63]	2023	This model outperforms real-time heart sound analysis. It also exhibits	Unavoidable background noise that could compromise the	CNN	Heart Sound, Kaggle and	99.37%

			superior resolution, sensitivity, and specificity.	classification's accuracy.		Physio Net	
29	B.Ramesh And Kuruva Lakshmanna et.al[64]	2024	early CHD identification and prevention, emphasizing the potential to enhance patient outcomes and lower medical expenses.	the absence of comprehensive details regarding the particular datasets that were utilized to train and evaluate the suggested model.	CNN-LSTM AND LSTM (O-SBGC-LSTM), SBGC-LSTM	Private dataset	>98%
30	Ahmad Alaik Maulani[65]	2024	innovative approach, exceptional accuracy, and rigorous methodological rigor	Cleveland Dataset, such as its size, source, and potential biases, the study's transparency could be increased.	CNN and LSTM	Cleveland	96.66%

D. Discussion

Several notable themes and patterns have been shown by the multiple investigations carried out by different researchers in the field of heart disease diagnosis utilizing deep learning models.The table illustrates the effective utilization of various deep learning architectures, notably convolutional neural networks (CNNs), across diverse domains in heart disease identification. This diversity in technology underscores the versatility of deep learning in detecting and diagnosing heart diseases.The continuous high accuracy these models exhibit across several experiments is a noteworthy trend. The accuracy rates of over 98% were reported by authors like Mayank Chourasia et,al. (2020), Mohanad Alkhodari and Luay Fraiwan. (2021), Jad Botros et,al. (2022),Randa I. Aljohani .(2023), and B.Ramesh And Kuruva Lakshmanna et. (2024). This demonstrated the resilience of deep learning techniques in addressing the difficulties related to the detection heart disease, including how they can potentially aid in the rapid and accurate diagnosis of heart diseases, serving as a valuable tool for healthcare professionals.

Furthermore, the use of a variety of datasets, such as MIT-BIH, open-access dataset (VHD), (AS), (MS), (MR), and (MVP),MIT-BIH and BIDMC , and others, illustrates the efforts made to valuable tool for medical diagnostics and healthcare, heart disease prediction. This diversity suggests that the subject is maturing, as scholars focus on certain facets of valuable tool for medical diagnostics and healthcare, heart disease prediction. Although most research on heart disease focuses on early detection of heart disease, VirenViraj Shankar et,al(2020) research on early detection and risk assessment of heart diseases.

E. Conclusion

In conclusion, based on a thorough examination of numerous papers and research findings, this review paper investigates the application of convolutional neural networks (CNNs) in the detection, diagnosis, and prediction of cardiac disease. CNNs are useful for identifying cardiac illness because they can identify, evaluate, and forecast patterns from complicated medical data, such as pictures, echocardiograms, and ECGs, assisting medical professionals in making precise diagnosis and treatment decisions.

Furthermore, CNN models facilitate early identification of high-risk patients and focused therapies by supporting risk assessment, prognostic prediction, and individualized healthcare planning for heart disease.

Overall, the review's findings highlight how deep learning CNNs have the potential to completely change the field of cardiovascular care. Despite the notable advancements, more study is necessary to overcome the obstacles and constraints that still remain, such as the lack of data, the interpretability of the models, and the generalizability of the results across a range of patient populations. We can lead the way toward more efficient and individualized heart disease management by developing and upgrading deep learning techniques further, which will ultimately improve patient outcomes and quality of care globally.

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