JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 03 Issue 02
2022
Research Article
https://doi.org/10.56979/302/2022/76

A Systematic Analysis for Cardiovascular Disease Classification Using Deep Learning

Rabia Javed[1], and Ali Haider Khan[2, *]

[1]Department of Computer Science, TIMES Institute, Multan, 60000, Pakistan.
[2]School of Systems & Technology, Department of Computer Science, University of Management and Technology, Lahore, Pakistan.
[*]Corresponding Author: Ali Haider Khan. Email: s2018288001@umt.edu.pk.

Received: August 01, 2022 **Accepted:** September 12, 2022 **Published:** September 27, 2022.

Abstract: The processing of medical data has profited from automation and contemporary computing breakthroughs, which have given rise to several novel instructional approaches. In both traditional and cutting-edge disciplines, deep learning has emerged as a cutting-edge machine learning paradigm. Deep learning algorithms have developed into supervised, semi-supervised, and unsupervised modes for a variety of real-time applications. The technology has shown to be broadly applicable in image processing, computer vision, medical diagnostics, robotics, and control operation. Deep learning is essential in the field of medical science for recognizing various diseases and solving health issues. The deep learning revolution will significantly alter cardiovascular imaging within the next decade. To ensure that deep learning may meaningfully impact clinical practice, it is crucial for medical practitioners to stay up with these breakthroughs. This evaluation is intended to be a preliminary step in that process. In this study cardiovascular disease diagnosis and classification have been examined using different state-of-the-art deep learning approaches. Deep Neural Networks can be used to improve the classification of heart disease as a whole in a crucial field called heart illness. The classification process can be carried out using a variety of methods, such as DL, KNN, SVM, ANN Nave Bayes, Random Forest, SSD, DNN, and TDNN where DL exhibited maximum accuracy. Although deep learning-based automated cardiovascular classification algorithms have shown highly accurate results, they have not yet been widely used by healthcare professionals.

Keywords: Cardiovascular; Deep Neural Network; Classification; Healthcare.

1. Introduction

The phrase "cardiovascular disease" (CVD) refers to multiple conditions that can affect and damage the heart or blood vessels. In 2019, American Heart Association figures revealed that CVDs have surpassed all other causes of mortality worldwide. In excess of 17.6 million in 2016, there were deaths, and it is predicted that this number will by 2030 to 23.6 million [1]. Heart disease is without a doubt one of the main causes of illness and mortality among individuals throughout the world. One of the most significant problems in the discipline of medical data analysis is the prediction of heart illness. The medical sector uses a tremendous amount of data. Deep learning makes use of a vast array of data related to the natural healthcare system, including data that can be used to identify possibilities and projections [2]. Heart failure, which has a high morbidity and death rate as well as a high frequency of hospitalizations, continues to be a significant clinical and public health issue despite all scientific and medical advancements [3]. The majority of heart failure hospitalizations occur in cases of acute heart failure, which is described as "the fast onset of, or change in, symptoms and signs of Heart failure" in the 2012 ESC guidelines and recommendations for Acute and chronic heart failure diagnosis and therapy. [4] The duration between the development of symptoms and presentation and urgency can vary greatly; acute heart failure is not a disease but rather a syndrome with a variety of precipitants, causes, underlying illnesses, and acuteness. Heart failure is a fatal condition that affects 2% of the adult population [5], according to estimates. For patients suffering from acute heart failure, clinicians must identify the condition immediately and put the right management in place while providing initial care. Along with checking a 12-lead ECG for ischemia, arrhythmias, and other traits that can point to the cause or trigger of the current episode of acute heart failure, most guidelines [7, 8] call for widely available laboratory and radiographic testing during the ED examination. [9].

The risk of developing heart disease has increased as a result of several harmful behaviors including excessive cholesterol, obesity, an increase in triglyceride levels, hypertension, etc. [10] There are other symptoms that the American Heart Association [11] notes, such as people who have trouble sleeping, abnormal heartbeats, swelling in legs, and in some cases, weight gain that happens rather quickly.

Nowadays, it is widely acknowledged that artificial intelligence and machine learning are having a significant impact on the medical sector. To identify the condition, categorize the data, or forecast the outcomes, we can employ a range of deep learning and machine learning models. Using machine learning algorithms, a comprehensive examination of genomic data may be performed with ease. Medical records can be converted and thoroughly evaluated for better forecasts, and these models can be trained to anticipate pandemics [12].

The best way to improve CVD outcomes is by early and precise diagnosis. Making a diagnosis relies heavily on cardiovascular imaging. The majority of modern image analysis methods depend on qualitative visual evaluation of images and rudimentary quantitative measurements of heart shape and function. More sophisticated image analysis methods that permit deeper characterization of imaging phenotypes are required to optimize the diagnostic utility of cardiac imaging. Artificial intelligence (AI) technologies in medical imaging have rapidly advanced exponentially due to the growth of massive data and the availability of powerful computing resources. [13].

Figure 1 shows how many articles on machine learning (ML) and cardiac imaging are published each year. This indicates a positive trend for upcoming research. A light grey bar shows how many publications are anticipated to be released in late 2019.

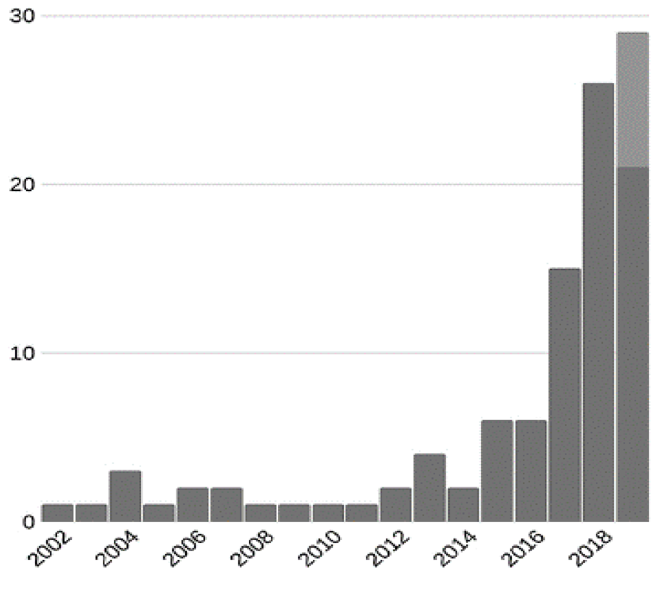

Figure 1. Annual publications in cardiac imaging and machine learning [13].

People are now able to perceive the good prospects of the integration of artificial intelligence (AI) and healthcare thanks to the growth of AI and the gradual commencement of AI research in the medical arena. One of these, the popular deep learning discipline, has demonstrated higher potential in uses like disease and treatment response prediction. The accuracy of medical disease prediction has consistently increased from the first logistic regression model to the machine learning model, and finally to the current deep learning model. Performance in all areas has been greatly improved [14].

As a result, it is now crucial for the precise and accurate prognosis of disorders associated with the heart. For this reason, a large number of academics from all around the world began focusing on using vast databases to forecast heart-related disorders. Numerous Deep learning techniques have the ability to analyze large datasets and produce insightful results. Since different methods are used by machine learning models, these algorithms have become crucial for accurately predicting whether or not heart problems will exist.

2. Research Objectives

This study's primary goal is to examine how cardiovascular disease categorization methods have changed through time, from 2012-2022 utilizing a machine learning and deep learning approach. The principal goals of this research study are:

1. To assess how practically implementable, the cardiovascular classification systems are.
2. To provide an overview of the current research investigations based on the advantages of cardiac disorder categorization and the direction of future research.
3. Based on the classification of cardiovascular disease, determine the most recent research trends and publication interests.

The below table 1, lists the inclusion and exclusion criteria for the study, which clearly presents the selection and rejection of articles.

Table 1. Inclusion and exclusion criteria of study.

Inclusion Criteria	Exclusion Criteria
In C: 1Publications that provide technological methods for the classification of cardiovascular disease using deep learning	Ex C: 1 Articles that just described Heart disease and didn't emphasize solutions based on deep learning/machine learning
In C: 2 Publications that provide technological methods for detecting cardiac disease using deep learning	Ex C: 2 Publications that do not provide technological methods for detecting cardiac disease using deep learning
In C: 3 Articles that have been authored in English	Ex C: 3 Articles that not have been authored in English.

3. Search String

("Cardiovascular disease" OR "Cardiovascular disease classification" OR "cardiac disease Prediction" OR "detection" OR "cardic disorder) AND ("deep neural network" OR "dnn" OR "deep learning" OR "neural network" OR "nn" OR "convolutional neural network" OR "cnn" OR "Machine learning" OR "ml")

Or

("Heart disease" OR "heart disease classification" OR "heart disease Prediction" OR "detection" OR "heart disorder) AND ("deep neural network" OR "dnn" OR "deep learning" OR "dl" OR "neural network" OR "nn" OR "convolutional neural network" OR "cnn" OR "Machine learning" OR "ml")

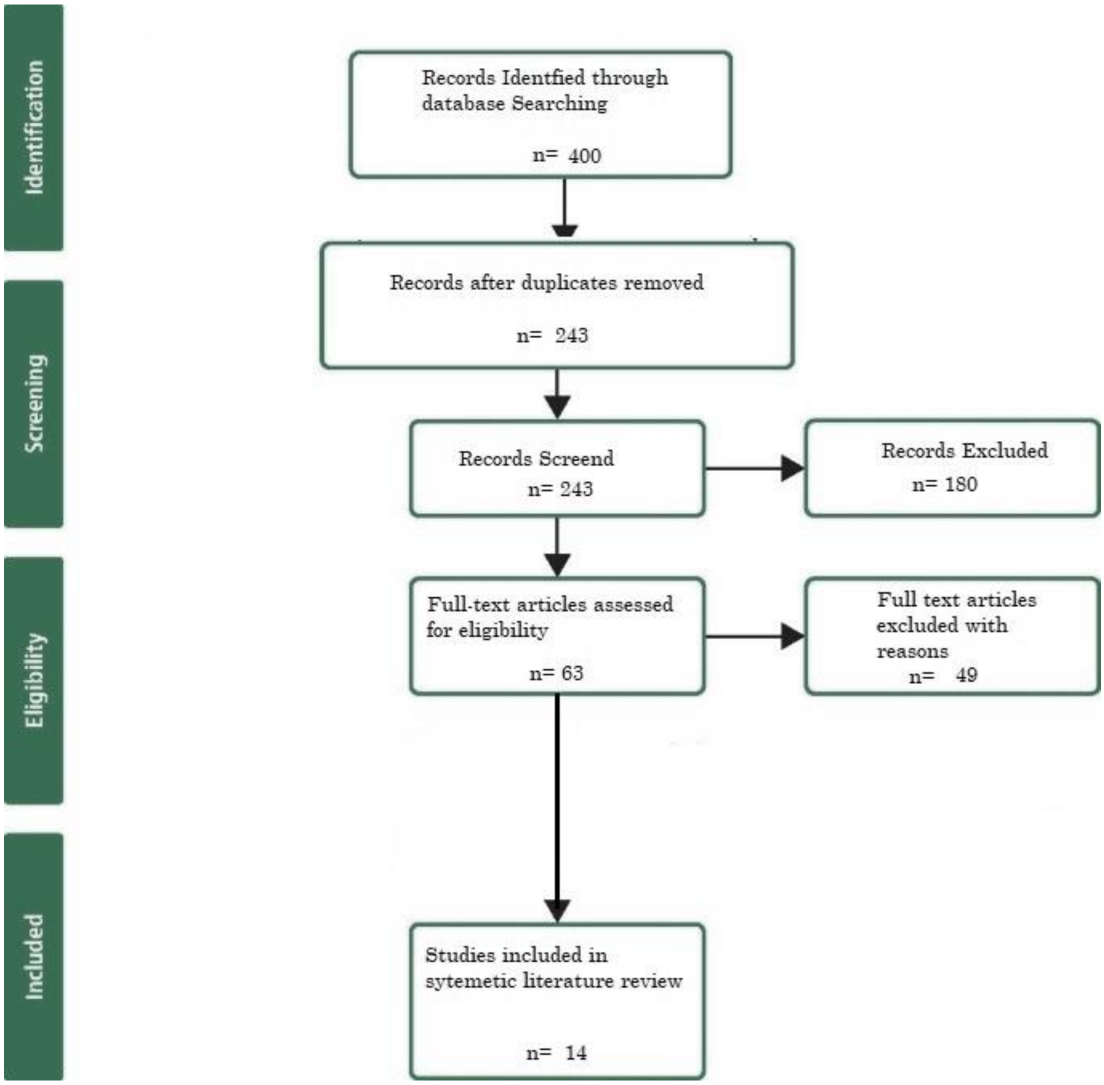

Figure 2. Systematic Research Methodology.

Figure 2 provides a pictorial representation of the process of selection of articles that have been analyzed in the study.

4. Deep Learning Methodologies

Deep learning is applied to monitor patients as a whole, study disease progression, and create individualized treatment plans. In this chapter, the construction and operation of deep neural networks are covered, with an emphasis on how they might be used to diagnose and treat various diseases.

Deep learning, which is based on a machine learning approach, deals with complex input-output mappings. Deep neural networks are a popular technique for processing and analyzing medical data because of their reliability and resemblance to how human functions [15]. With little manual engineering required, Computer models are enabled by deep learning that is made up of many processing layers to discover data representations at various levels of abstraction [16].

4.1. K-Nearest Neighbors

The KNN model, one of the easiest and most used supervised classification algorithms, was proposed by Fix and Hodge. It operates by determining its closest neighbors by computing the distance between the tests and training data points. The class of the new sample's closest neighbor is then chosen. K denotes the number of nearest neighbors in KNN. [17] According to the results, there are considerable differences in how well KNN classifiers perform depending on the distance employed [18]. Figure 3, depicts the K-nearest neighbor algorithm.

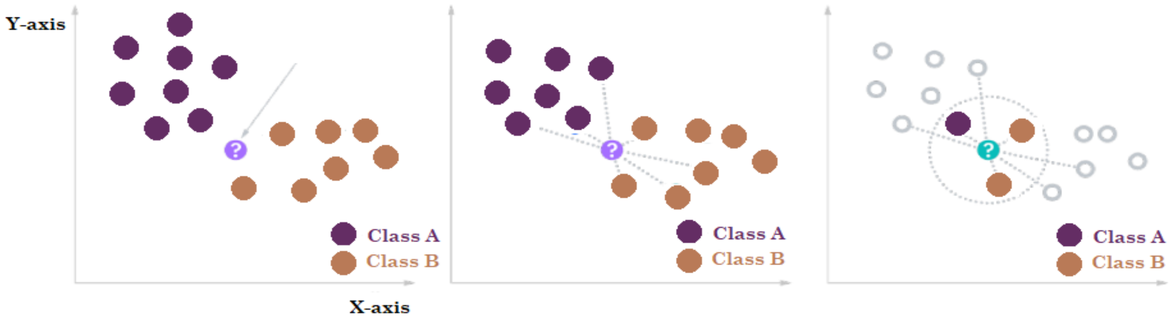

Figure 3. K-Nearest Neighbor.

4.2 Support vector machine

SVM is a powerful technique for classifying data. [19], nonlinear function estimator [20] or fast iterative algorithm [21]. It uses supervised machine learning to learn from training sets of target labelled tuples in an effort to identify the best hyper-plane. Finding the hyper-plane that can observe different classes is the goal. Multiple hyper-planes be capable of doing this task, but the objective is to find the hyper-plane with the largest margin that minimizes the distance between classes. Using the aforementioned hyper-plane, the new and latest data point that needs to be classified can be classified and categorized easily [22] Figure 4, represents SVM.

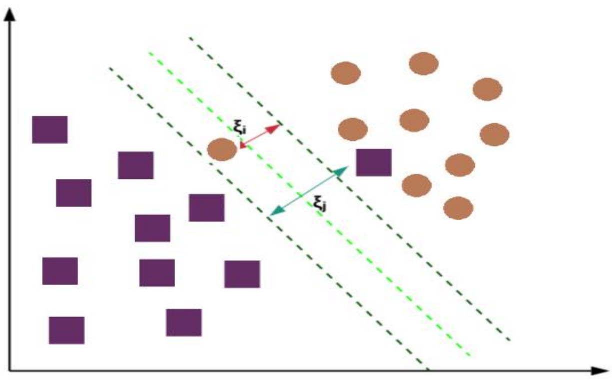

Figure 4. Support vector machine.

4.3 Artificial Neural Network

Artificial neural networks (ANNs), are a powerful tool for classification tasks as well as critical problem-solving tasks like signal amplification, signal identification, and signal and factor prediction. It imitates brain functioning [23, 24]. The adaptability of ANNs is a key characteristic. This makes it possible for them to be used in situations where it is impossible to develop a formal numerical model [25], but when there is a large enough sample size [26]. Figure 5, represents an artificial neural network.

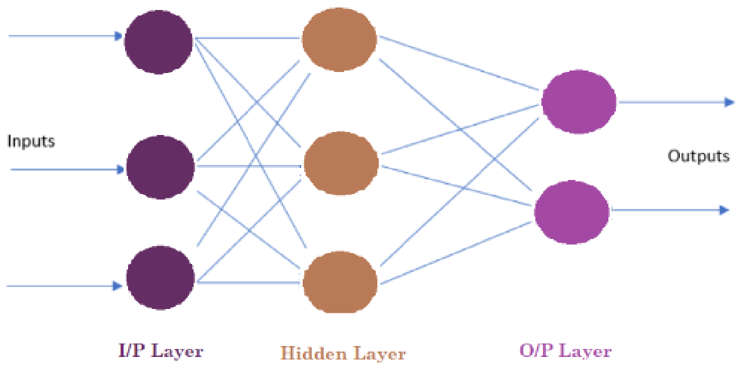

Figure 5. Artificial Neural Network.

4.4 Long Short-Term Memory (LSTM)

RNN architecture [27] which is frequently applied in deep learning is replicated by LSTM. Neurons typically have forward connections in feedforward systems, however, LSTMs have reversible feedback connections. Like pictures, LSTM processes data points. When the input gap is significant, RNNs made up of the sigma cells lack the capacity to learn the pertinent information from the input sources. Long-term dependencies could be effectively managed by the long-short-term memory (LSTM) by integrating gate operations to the cell's structure. [28] For jobs requiring the precise measurement or production of time intervals, LSTM is a potential approach [29] Figure 6, represents the architecture of LSTM.

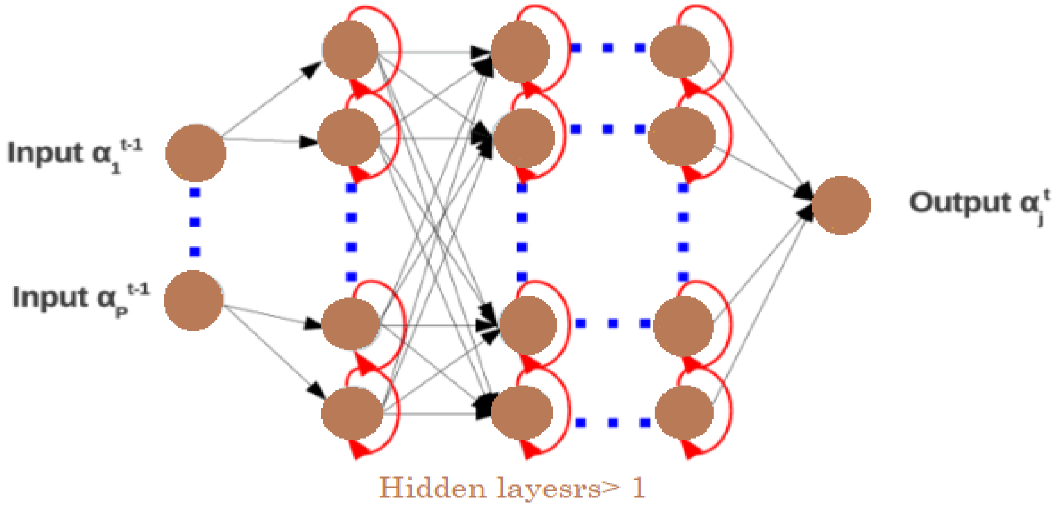

Figure 6. Long Short-Term Memory.

5. Related work

Sahrma et al. [30] proposed a Talos-optimized deep learning neural network (DNN). Talos optimization is a brand-new technique for DNN optimization. With 90.76% accuracy, Talos outperforms other optimizations. It is used to find the rate predictions for datasets on heart disease. The Talos optimization is used to construct and deploy a Keras model.

R. Sharmila et al. [31] recommended employing data approaches to make enhancements in the dataset for the prediction of heart disorders. SVM offered a better and more effective accuracy of 85%. Sequential SVM is less accurate than parallel SVM in SVM.

MAlnajjar et al. [32] provided a paradigm for deep learning that can categorize heart sounds and identify heart disease symptoms. The predicted approach would act as a preliminary cardiac disease screening that can aid in identifying heart disease symptoms the screening results can be used by a doctor using a digital stethoscope in a hospital setting or by a patient at home to diagnose pathologies. Our Heart Sounds classification model employs Deep Learning (DL) methods using spectrograms, converting audio data to visuals that make use of the benefits of Mel-Frequency Cepstrums (MFC), which are used to extract perceptual information (MFCC).

Sharan Monica et al. [33] proposed an analysis of cardiovascular disease. In order to anticipate the sickness, this research suggested data mining techniques. It is intended to present an overview of the most recent methods for extracting data from datasets, which will be helpful to healthcare professionals. The decision tree for the system's performance can be built in a certain amount of time. The main goal is to forecast the disease with the fewest possible attributes.

Ajam, N. et al. [34] suggested an artificial neural network for detecting heart illness Feedforward, backward, and Propagation learning approaches have been used to evaluate the model's performance. 20 neurons in the buried layer and 88% classification accuracy were achieved by taking appropriate functions into account. An important outcome for the prognosis of heart disease is shown by ANN.

Ghaemmaghami, H et al. [55] suggested an approach that uses audio recordings of heartbeats recorded by Stethee to automatically identify the endpoints of temporal events connected to particular cardiac cycles. Systole, diastole, first heart sound (S1), second heart sound (S2), or undesirable noise are all automatically assigned to the detected events.

Acharya et al. [36] developed a deep convolutional neural network (CNN) model with 11 layers for diagnosing CHF. The preprocessing of ECG signals for the suggested CNN model is minimal, neither artificial features nor categorization are necessary. Cardiologists can use the proposed CNN model in practice as a diagnostic help by using it to evaluate ECG signals more quickly and objectively.

Beyene, C et al. [37] suggested a technique that employs J48, Naive Bayes, and Support Vector Machine algorithms to forecast the development of heart disease for speedy results retrieval and early automatic diagnosis that contribute to providing high-quality services and lowering expenses to save a person's life.

Miao, K et al. [38] created a model using 303 clinical examples drawn from Cleveland Clinic Foundation patients with coronary heart disease were used to create a prediction model for identifying new patient cases and a model for classifying the data using training data The test results revealed that the diagnostic precision of the DNN classification and prediction model was 83.67%., generated DNN classification and prediction models provided reliable and accurate clinical diagnoses of coronary heart disease.

Atkov, O. et al. [39] proposed a diagnostic model using an artificial neural network for coronary artery heart disease prediction. By varying the inputs of the artificial neural network the model. In this model, the accuracy of diagnosis depends on the type of artificial neural network.

Khalil, M. et al. [40] Suggested a method consisting one Dimensional Convolutional Neural Networks that are the basic foundation of the suggested study (1D-CNN). A new Multi-Level Wavelet Convolutional Neural Networks (ML-WCNN) is presented to automatically recognize various forms of cardiac arrhythmias, in contrast to the conventional CNN models-based categorization. The suggested method combines the Stationary Wavelet Transform with the One D-CNN model to simultaneously extract distinctive differentiating traits from the unprocessed ECG signal and numerous wavelet sub-bands.

Liu, T. [41] presented a bidirectional-convolutional long short term memory (Bi-CLSTM) method that is used in the DL segmentation structure, which combines an intra-slice information compression residual convolution neural network. The segmentation maps have also been used to perform automatic disease diagnoses. The automatic cardiac diagnostic challenge (ACDC) experimental findings demonstrate the efficacy of our heart segmentation structure and disease diagnosis techniques.

Mehmood et al. [42] proposed a strategy that focuses on modeling temporal data while applying CNN for early HF prediction. We constructed the heart disease dataset, compared the outcomes using cutting-edge techniques, and got good findings. According to experimental findings, the proposed method performs better than the current methods in terms of performance evaluation measures.

Khan, A. H et al. [43] suggested a method for processing ECG data in all formats. Cardiovascular disease detection was performed using Single Shoot Detection (SSD), a Deep Neural Network architecture based on MobileNet v2. The study's main goal was to identify major cardiac anomalies.

6. Discussion

We have conducted a thorough analysis of literature studies that use deep learning to diagnose cardiovascular disease. As a result, this section will explore existing limitations and potential future possibilities for deep learning in cardiovascular disease diagnosis as well as the deep learning approach itself. Almost all facets of cardiovascular imaging, from echocardiography to intraoperative fluoroscopy, are now covered by deep learning applications. For diagnosis or prognosis, the majority of apps can automatically extract pertinent clinical information from cardiovascular images. For instance, heart failure patients can be identified and their EFs can be computed using machine learning-based segmentation of the left ventricular cavity in MRI. Different deep learning approaches have been incorporated for the classification of cardiovascular disease, which includes Deep Neural networks, support vector machines, Artificial neural network, convolutional neural network, K-nearest neighbor, single shoot detection model, classification and regression trees, time delay neural network.

The findings of this research demonstrate the widespread application of deep learning and machine learning in the classification and prediction of cardiovascular disease. While many algorithms are still in the early stages of research, they are being used in therapeutic settings. As a result, it's imperative to view

Machine learning and deep learning as approaches to improving patient diagnosis, prognosis, and therapy rather than as a danger.

Table 2. Algorithm Accuracy comparison.

Ref.	Algorithm	Accuracy
[30]	DNN	90.76%
[31]	SVM	85%
[32]	DL	100%
[33]	CART	92.2%
[34]	ANN	88%
[35]	TDNN	95%
[36]	CNN	98.97%
[37]	KNN and DTT	98.99%
[38]	DNN	83.67%
[39]	ANN	94%
[40]	ML-WCNN	99.57%
[41]	CNN	-
[42]	CNN	97%
[43]	SSD	98%

The above table 2, presents a brief comparison of algorithms that have been used for the classification of heart disorders, deep learning has shown higher accuracy than the other approaches. However, it is also crucial to be aware of unproven accusations that are frequently leveled against deep learning-based image analysis tools, particularly as many are currently tested on small, single-center datasets. It is expected that this research would help to better comprehend the various cardiovascular diseases classification algorithms that are available as well as the elements necessary for a successful clinical application.

7. Conclusion

The development of deep learning for heart disease diagnosis is examined, and developed methods with their methods of processing are described in this study. It's been observed that the advancement of deep learning has the higher benefit of delivering trustworthy and accurate diagnoses in automated decision-making for quicker and more accurate diagnoses in the processing of medical data. This study's main objective is to comprehend deep learning methods for error-free diagnostics. Deep learning classification and prediction models can decrease the frequency of false positives for coronary heart disease diagnostics and can deliver extremely reliable and accurate diagnoses that may endanger patients. The models can therefore be used to support patients and healthcare workers around the world in improving public health and global health, especially in locations with limited resources and developing countries, where there are fewer cardiac specialists available. The latest improvements demonstrate the need for additional work in the areas of feature representation, dimensional reduction, and low processing overhead in order to reach the goal of quicker and more accurate processing. To utilize DL to its fullest extent, however, The scientific community needs to do more than only perform retrospective validation studies and offer solid proof of the additional clinical value of DL-based tools in contrast to routine care in real-world scenarios. Recent developments in deep learning, such as recurrent neural networks, deep convolutional neural networks, long short-term memory neural networks, deep auto-encoder and limited Boltzmann machine-based deep brief networks [44, 45] may also improve the precision with which patients are diagnosed with cardiovascular disease.

Funding: This research received no external funding from any organization for this work.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Benjamin, E. J., Muntner, P., Alonso, A., Bittencourt, M. S., Callaway, C. W., Carson, A. P., ... & American Heart Association Council on Epidemiology and Prevention Statistics Committee and Stroke Statistics Subcommittee. (2019). Heart disease and stroke statistics—2019 update: a report from the American Heart Association. Circulation, 139(10), e56-e528.
2. Desale, K. S., & Shinde, S. V. (2022). Addressing Concept Drifts Using Deep Learning for Heart Disease Prediction: A Review. In Proceedings of Second Doctoral Symposium on Computational Intelligence (pp. 157-167). Springer, Singapore.
3. Roger, V. L. (2013). Epidemiology of heart failure. Circulation Research, 113(6), 646-659.
4. McMurray, J. J., Adamopoulos, S., Anker, S. D., Auricchio, A., Böhm, M., Dickstein, K., ... & Ponikowski, P. (2012). Task Force for the Diagnosis and Treatment of Acute and Chronic Heart Failure 2012 of the European Society of Cardiology; ESC Committee for Practice Guidelines. ESC guidelines for the diagnosis and treatment of acute and chronic heart failure 2012: The Task Force for the Diagnosis and Treatment of Acute and Chronic Heart Failure 2012 of the European Society of Cardiology. Developed in collaboration with the Heart Failure Association (HFA) of the ESC. Eur J Heart Fail, 14(8), 803-869.
5. McMurray, J. J., & Stewart, S. (2000). Epidemiology, aetiology, and prognosis of heart failure. Heart, 83(5), 596-602.
6. Solomon, S. D., Dobson, J., Pocock, S., Skali, H., McMurray, J. J., Granger, C. B., ... & Pfeffer, M. A. (2007). Influence of nonfatal hospitalization for heart failure on subsequent mortality in patients with chronic heart failure. Circulation, 116(13), 1482-1487.
7. Yancy, C. W., Jessup, M., Bozkurt, B., Butler, J., Casey, D. E., Drazner, M. H., ... & Wilkoff, B. L. (2013). 2013 ACCF/AHA guideline for the management of heart failure: a report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines. Journal of the American College of Cardiology, 62(16), e147-e239.
8. Moe, G. W., Ezekowitz, J. A., O'Meara, E., Lepage, S., Howlett, J. G., Fremes, S., ... & White, M. (2015). The 2014 Canadian Cardiovascular Society heart failure management guidelines focus update: on anemia, biomarkers, and recent therapeutic trial implications. Canadian Journal of Cardiology, 31(1), 3-16.
9. Cleland, J. G., Chattopadhyay, S., Khand, A., Houghton, T., & Kaye, G. C. (2002). Prevalence and incidence of arrhythmias and sudden death in heart failure. Heart failure reviews, 7(3), 229-242.
10. World Health Organization. (2013). Health topics: Cardiovascular diseases. Fact Sheet. Available online: http://www. who. int/cardiovascular_diseases/en/(accessed on 11 December 2020).
11. American Heart Association, Heart Failure, American Heart Association, Chicago, IL, USA, 2020, https://www.heart.org
12. Shalev-Shwartz, S., & Ben-David, S. (2014). Understanding machine learning: From theory to algorithms. Cambridge university press.
13. Martin-Isla, C., Campello, V. M., Izquierdo, C., Raisi-Estabragh, Z., Baeßler, B., Petersen, S. E., & Lekadir, K. (2020). Image-based cardiac diagnosis with machine learning: a review. Frontiers in cardiovascular medicine, 1.
14. Xie, S., Yu, Z., & Lv, Z. (2021). Multi-disease prediction based on deep learning: a survey. CMES-Computer Modeling in Engineering and Sciences.
15. Kaul, D., Raju, H., & Tripathy, B. K. (2022). Deep learning in healthcare. In Deep Learning in Data Analytics (pp. 97-115). Springer, Cham.
16. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. nature, 521 (7553), 436-444. Google Scholar Google Scholar Cross Ref Cross Ref.
17. Swain, D., Pani, S. K., & Swain, D. (2019). An efficient system for the prediction of coronary artery disease using dense neural network with hyper parameter tuning. Int. J. Innov. Technol. Explor. Eng, 8(6), 689-695.
18. Surya, V. B., Haneen, P., Ahmad, A. A., Omar, B. A., & Ahmad, L. (2019). Effects of Distance Measure Choice on KNN Classifier Performance-A Review. Mary Ann Liebert.
19. Pouriyeh, S., Vahid, S., Sannino, G., De Pietro, G., Arabnia, H., & Gutierrez, J. (2017, July). A comprehensive investigation and comparison of machine learning techniques in the domain of heart disease. In 2017 IEEE symposium on computers and communications (ISCC) (pp. 204-207). IEEE.
20. Huang, S., Cai, N., Pacheco, P. P., Narrandes, S., Wang, Y., & Xu, W. (2018). Applications of support vector machine (SVM) learning in cancer genomics. Cancer genomics & proteomics, 15(1), 41-51.
21. Wang, H., & Hu, D. (2005, October). Comparison of SVM and LS-SVM for regression. In 2005 International conference on neural networks and brain (Vol. 1, pp. 279-283). IEEE.
22. Vishwanathan, S. V. M., & Murty, M. N. (2002, May). SSVM: a simple SVM algorithm. In Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02 (Cat. No. 02CH37290) (Vol. 3, pp. 2393-2398). IEEE.
23. Obenshain, M. K. (2004). Application of data mining techniques to healthcare data. Infection Control & Hospital Epidemiology, 25(8), 690-695.
24. Agatonovic-Kustrin, S., & Beresford, R. (2000). Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. Journal of pharmaceutical and biomedical analysis, 22(5), 717-727.
25. Zou, J., Han, Y., & So, S. S. (2008). Overview of artificial neural networks. Artificial Neural Networks, 14-22.
26. Maind, S. B., & Wankar, P. (2014). Research paper on basic of artificial neural network. International Journal on Recent and Innovation Trends in Computing and Communication, 2(1), 96-100.
27. Sharma, S., & Parmar, M. (2020). Heart diseases prediction using deep learning neural network model. Interna-tional Journal of Innovative Technology and Exploring Engineering (IJITEE), 9(3), 124-137.

28. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-1780.
29. Yu, Y., Si, X., Hu, C., & Zhang, J. (2019). A review of recurrent neural networks: LSTM cells and network architectures. Neural computation, 31(7), 1235-1270.
30. Gers, F. A., Schraudolph, N. N., & Schmidhuber, J. (2002). Learning precise timing with LSTM recurrent networks. Journal of machine learning research, 3(Aug), 115-143.
31. Sharmila, R., & Chellammal, S. (2018). A conceptual method to enhance the prediction of heart diseases using the data techniques. International Journal of Computer Science and Engineering, 6(4), 21-25.
32. MAlnajjar, M. K., & Abu-Naser, S. S. (2022). Heart Sounds Analysis and Classification for Cardiovascular Diseases Diagnosis using Deep Learning.
33. Sharan Monica, L., & Sathees Kumar, B. (2016). Analysis of CardioVasular disease prediction using data mining techniques. International Journal of Modern Computer Science, 4, 55-58.
34. Ajam, N. (2015). Heart diseases diagnoses using artificial neural network. IISTE Network and Complex Systems, 5(4).
35. Ghaemmaghami, H., Hussain, N., Tran, K., Carey, A., Hussain, S., Syed, F., ... & Sperling, J. (2017, December). Automatic segmentation and classification of cardiac cycles using deep learning and a wireless electronic stethoscope. In 2017 IEEE Life Sciences Conference (LSC) (pp. 210-213). IEEE.
36. Acharya, U. R., Fujita, H., Oh, S. L., Hagiwara, Y., Tan, J. H., Adam, M., & Tan, R. S. (2019). Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals. Applied Intelligence, 49(1), 16-27.
37. Beyene, C., & Kamat, P. (2018). Survey on prediction and analysis the occurrence of heart disease using data mining techniques. International Journal of Pure and Applied Mathematics, 118(8), 165-174.
38. Miao, K. H., & Miao, J. H. (2018). Coronary heart disease diagnosis using deep neural networks. international journal of advanced computer science and applications, 9(10).
39. Atkov, O. Y., Gorokhova, S. G., Sboev, A. G., Generozov, E. V., Muraseyeva, E. V., Moroshkina, S. Y., & Cherniy, N. N. (2012). Coronary heart disease diagnosis by artificial neural networks including genetic polymorphisms and clinical parameters. Journal of cardiology, 59(2), 190-194.
40. Khalil, M., & Adib, A. (2020). An end-to-end multi-level wavelet convolutional neural networks for heart diseases diagnosis. Neurocomputing, 417, 187-201.
41. Liu, T., Tian, Y., Zhao, S., Huang, X., & Wang, Q. (2020). Residual convolutional neural network for cardiac image segmentation and heart disease diagnosis. IEEE Access, 8, 82153-82161.
42. Mehmood, A., Iqbal, M., Mehmood, Z., Irtaza, A., Nawaz, M., Nazir, T., & Masood, M. (2021). Prediction of heart disease using deep convolutional neural networks. Arabian Journal for Science and Engineering, 46(4), 3409-3422.
43. Khan, A. H., Hussain, M., & Malik, M. K. (2021). Cardiac disorder classification by electrocardiogram sensing using deep neural network. Complexity, 2021.
44. Hinton, G. E. (2012). A practical guide to training restricted Boltzmann machines. In Neural networks: Tricks of the trade (pp. 599-619). Springer, Berlin, Heidelberg.
45. Le, Q. V. (2015). A tutorial on deep learning part 2: Autoencoders, convolutional neural networks and recurrent neural networks. Google Brain, 20, 1-20.