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The application of neural networks in diagnosing heart disease: A review

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Abstract
One of the main factors that cause an increase in mortality annually as a result of heart disease is misdiagnosis on the part of doctors or ignorance on the part of the patient, so the aim of this review was to use more accurate, cost-effective, easy-to-use methods and physician support methods where computer-generated neural networks are used in medical diagnoses. Early diagnosis of heart disease can significantly enhance the long-term chances of survival in victims of the disease. Artificial neural networks are widely used to diagnose and predict diseases, so it was emphasized that in the near future completely new diagnostic equipment based on this new technology can be developed in the field of EG, EG, MACROSCOPIC and microscopic image analysis systems.

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1. Introduction

To gather the relevant papers on the classification of heart diseases with artificial neural networks, we conducted a search on well-known digital libraries: Scopus, PubMed, and the Web of Science. We identified sixty-one articles that met the inclusion and exclusion criteria. We use a data extraction format where methodological details are extracted in order to better understand the characteristic use of neural networks and to compare the designs and assumptions applied. The main result of our research was that, despite the large number of proposed architectures used for classification, feed forward and radial basis functions are the neural network architectures most frequently used for classification of heart diseases, as shown in 29.36% and 19.67%, respectively, of the 61 selected articles. These results are mainly affected by the studied dataset and the number of features. (Khan *et al*., 2021) [36] (Alkhodari & Fraiwan, 2021) [5] (Arooj *et al*.2022) [9].

Cardiovascular diseases are responsible for a large share of deaths worldwide and represent the primary cause of death in industrialized or developing countries, affecting both men and women. One of the most widespread cardiovascular diseases is ischemic heart disease, which may lead to a heart attack. Early detection may be possible by observing the fluctuation of indications like creation of the electrocardiograph (ECG) or detecting the cardiovascular murmurs on auscultation. These are often hard to measure consistently. Consequently, a number of machine learning-based methods have been proposed to detect heart diseases. The aim of our study is to review and analyze the most used models based on artificial neural networks and to identify the most suitable model. (Giovanni *et al*.2020) [30] (Roth *et al*.2020) [55] (Yuyun *et al*.2020) [83].

2. Understanding Heart Disease

If the heart is not functioning well, the body's well-being is put in jeopardy. There are many ways it can start to work badly. The coronary arteries, that supply oxygen and nutrients to the heart muscle tissue, may become clogged, preventing the blood supply to the heart. Such a condition can lead to two of the most severe heart afflictions: the myocardial infarction or heart attack, and angina pectoris, the latter coming before the first and acting as a warning signal.

If the patient's heart valves are not working perfectly, he/she may be short of breath, feel weak, or become easily fatigued. The heart may become enlarged and its failure to pump properly develops into congestive heart failure. Congenital defects can place extra burden on child hearts, and their little muscles might grow tired too soon. The solution might be a heart transplant. High blood pressure strains the heart, too, as well as complex cardiac arrhythmias. These afflictions may come and go - the situation is an ideal example of a complex system with multitudes of interdependencies. Their intensity can also depend on other factors such as stress and heredity. These considerations make the diagnosis of coronary artery disease difficult and intensive. (Shao *et al*.2020) [61] (Talebi *et al*., 2021) [70] (Fathima 2021) [25].

The heart has four chambers, two upper receiving chambers, the atria, and two lower pumping chambers, the ventricles. There is a valve between each of the atria and ventricles on each side which prevents blood from flowing back from the ventricles into the atria. At the base of two large blood vessels, the aorta is the body's main artery, and the pulmonary artery is the vessel that carries blood between the heart and the lungs. To be effective, the heart has to work perfectly. It delivers blood, filled with oxygen and nutrients to the rest of the body and takes in return the waste products to be removed in the lungs or excreted in the kidneys. (Al-Sakini, 2022) [6] (Christoffels and Jensen2020) [17] (Peate, 2021) [53].

2.1. Types of Heart Disease

The problem of determining patient conditions without invasive procedures increases the need for a system capable of providing precise data for the guidance of health professionals. Additionally, such a system can speed up decision-making concerning the hospitalization or referral of individuals requiring further medical or surgical attention. In this scenario, the use of computational intelligence represents an interesting alternative, capable of providing high-quality information and support for decision-making by health professionals. (Secinaro *et al*.2021) [58] (Nasseef *et al*.2022) [51] (Giordano *et al*.2021) [29].

Nowadays, heart disease represents the leading cause of death worldwide. The disease can be defined as a state in which the heart is unable to carry out its functions effectively. It is important to note that heart diseases are not restricted to heart attacks; there are many types of heart-related problems. There are numerous types of heart diseases (arrhythmias, coronary heart disease, myocardial infarction, and malfunctions of the heart's valves and more), and the symptoms of heart disease are often difficult to obtain, requiring hospitalization and the use of invasive procedures for verification. (Bray *et al*.2021) [13] (Khan *et al*.2020) [37].

2.2. Risk Factors

It has been reported that raised blood cholesterol is the most important cause of atherosclerosis and that people with high cholesterol levels are more likely to have heart attacks. Data released by the World Health Organization (WHO) indicates that in those who are older than 25, every 1% reduction leads to a 2% reduction in the risk of ischemic heart disease. It is also established that patients who are hypertensive have, on average, a 1.5 to 2.5 times higher risk of developing coronary artery disease than people with normal blood pressure. High levels of low-density lipoprotein (LDL), which have a strong connection to heart disease and diabetes, are foremost targets of therapy. (Mortensen & Nordestgaard, 2020) [46] (Liu *et al*. 2022) [40].

Cumulative evidence has been gathered in the past four decades or so that points out that certain factors might contribute to atherosclerosis. It has been established from epidemiological studies such as the Framingham heart study, the determination of key risk factors like hypercholesterolemia and hypertension, and their possible connections to cardiovascular diseases, such as coronary disease and stroke. Established risk factors that contribute to vascular disease are hypercholesterolemia, high blood pressure, as well as cigarette smoking, diabetes, increasing levels of plasma homocysteine, low levels of high-density lipoprotein (HDL) cholesterol, male sex, and a family history of premature cardiovascular disease. It is believed that even modest weight loss of only 5 to 10 pounds through moderate nutritional modifications reduces the risk of coronary heart disease. (Fan & Watanabe, 2022) [24] (Verhaar *et al*., 2020) [74] (Duttaroy, 2021) [22].

3. Neural Networks in Healthcare

The pursuit of more detailed and accurate diagnostic information has also uncovered the necessity for better distributional methods to interpret data and for the new, complex electronic tools required to support some new technologies. Traditional methods for making a particular evaluation, quantifying the risks and making any essential repair recommendations depend upon a number of specific test results, the availability of a physician with enough systematic data from which to draw a plan about the reasons and the answer, and on the interpretation of such data by the physician forming appropriate judgmental assumptions. Such judgments are quite time-consuming and are open to manual failure. Due to this reason, there is now a concern and an interest in automating this judgment-making behavior to synthesize computer systems that are capable of making such diagnostic and predictive judgments from recorded institutional test data. (Zhao *et al*. 2021) [86] (Matabuena *et al*.2021) [42] (Sommerauer, 2022) [64].

Biotechnology has made significant progress and claimed numerous success stories since its inception. The healthcare sector is no exception: equipped with an array of state-of-the-art medicines and diagnostic techniques, biotechnology has become the most promising ally in battling everyday stress and tension that leads to a state of disease. A number of sources contribute to disease in human beings; contribution to cardiovascular disease is highest among them. Therefore, myocardial disease such as coronary heart attack has become a tremendous threat to human beings. It calls for formulation of an advanced, sensitive and common battery of diagnostic tests to detect and quantify the extent of disease. (Villagómez-Guzmán and Quiroz 2024) [76] (Donato *et al*.2023) [20].

3.1. Fundamentals of Neural Networks

In the PNN classifier, a hyperplane is sought or drawn in the feature space to distinguish between patterns in different classes. This optimization of hyperplane in the feature space is achieved by modifying weights on the synapses according to the error between the desired and computed outputs. Furthermore, the hyperplane can be shifted from the origin point so as to be free from distance relation properly. PNN is the simplest multilayer network and is capable of efficiently discriminating between output classes, thus making it versatile and practical, rendering it suited for applications in pattern classification. (Sree Kala & Christy, 2021) [67] (Baroud *et al*. 2020) [10].

Another learning algorithm employed for the neural network is the Perceptron learning algorithm. Designed by F. Rosenblatt, the perceptron model became the original "big idea" which spurred a remarkable amount of research and development of Artificial Neural Network models. It learns by using a Credit Assignment procedure, in which a particular stimulus causes activation of one or more of the Output units. If the output unit responds amicably, the activation is propagated back through the network to the associated Input units to adjust the weights. (Hosseinzadeh *et al*.2021) [31] (Gajic *et al*.2021) [28].

In a neural network, the connections (synapses) change the connection strength, and thus they learn. The process by which the connection weight is changed is called adaptive learning. There are many learning algorithms commonly used in neural networks such as Back Propagation, Perceptron, PNN, etc. The major advantage of the back-propagation algorithm is that the architecture of the network has been kept very simple. Each network consists of an input and output layer of multilayers. The back-propagation is an iterative method for finding local minima of a functional. The functional in network theory is a cost function and in current literature shown as E. (Kaur *et al*., 2023) [35] (Kalta and Bhatt 2021) [34].

A neural network is a parallel computer, mimicking the human brain to some extent. The brain is trained to learn from inputs, and based on that learning, it acts on different inputs in different ways. A digital computer can be programmed to simulate all of these inputs. However, the process would be very slow since digital computers are sequential computers. The technique by which such a computer can operate in parallel is called plane-wise. By parallelizing the computer, the time of operation is greatly reduced. (Nwadiugwu, 2020) [52] (Dastres and Soori2021) [19].

3.2. Applications in Medical Diagnosis

As with other topics, the application of neural networks in medical diagnosis has a number of its specifics. In particular, possible limitations on the number of observations in medical areas and the amount of information about the patient in a particular task. These constraints determine the need for new ways to collect and process information. Since the information in the diagnosis of diseases means data from medical tests, analyses, etc., then the new methods can encompass a wider combination of various types of research data. The situation when solving practical medical problems can acquire a different purpose due to the diversity of diagnostic diseases and body deformation. The different peculiarities of medical diagnostic problems are due to differences in the organization and specificity of the diagnostic domain. (Abdou, 2022) [2] (Xu *et al*., 2020) [79].

It has been established that the use of an approach based on classification algorithms not only promotes a significant increase in the precision of solving problems in medical decision-making but also significantly improves the effectiveness of diagnosing various diseases. In addition to artificial neural networks, including approaches based on the use of combinations of classifiers, in particular boosting, Bayesian models, Bagging, Random Forest, and others, are also of great interest. With this in mind, the construction of artificial neural networks in thematic tasks of diagnosing diseases is one of the priority tasks in the field of work in which this method of machine learning is employed. (Ibrahim and Abdulazeez 2021) [33] (Senan *et al*. 2021) [59].

4. Neural Networks for Heart Disease Diagnosis

The purpose of this document is to build a general architecture and save practical patterns of the use of ANN diagnostics as a based data mining biomedical telemedicine system (patient). The diagnosis of heart disease rests on the concept of Big Data in medical information mining. This is achieved by assessing and incorporating existing ANN architectures according to specific architectural conditions that are prejudiced by the diagnosis of heart disease. The necessary effort is taken to guide the diagnostic-protective and diagnostic systems for high performance and robustness. (Muhammad *et al*., 2020) [47] (Du *et al*.2020) (Ahsan & Siddique, 2022) [3].

Despite the substantial adoption and exploration of AI techniques in the field of medical diagnosis, the search for additional efficient heart disease diagnostics will continue. Meanwhile, an impressive level of statistical classification performance of artificial neural networks (ANNs) in solving the task of recognizing a range of diseases (including those of the heart) has already been achieved. As general forms of adaptive learning, there are several reasons for using artificial neural networks for diagnostic purposes, such as their natural representation of knowledge in a distributed way, learning from examples (experience), fault tolerance, nonlinearity, and generalization skills. Recently, a great increase in interest in using artificial and hybrid expert systems to diagnose heart disease has been apparent. The opportunities to promote anatomical decision support for clinical files and to permit physiologically interpreted diagnostic support have received the most interest. (Mehmood *et al*.2021) [43] (Arooj *et al*.2022) [9] (Samir *et al*. 2021) [57].

4.1. Challenges and Limitations

Our interpretation about the relevance of the selected data is that it is insufficient for a comprehensive diagnosis, but it is sufficient to understand the presence of some diseases. The observed limitations and the current easy access to NN-based machine learning tools could encourage other research teams towards a better understanding of the data to develop compliant and validated medical devices suitable for routine patient use. The detected limitations from the analysis of our vision and the review offered by investigators indicate several items worth considering to ease reaching it. For practical implementation, one will face the challenge of providing non-invasive, seamless, and non-occlusive measurements to avoid patient discomfort. (Mehmood *et al*. 2021) [43] (Sharma and Parmar 2020) [62] (Arnaout *et al*. 2021) [8].

Though the application of temperature measurements to identify cardiovascular diseases is currently impossible, the identified results are encouraging. It is worth noting the authors' vision on practical implementation, which is to provide the measurements as non-invasive, seamless, and non-occlusive. We also share the opinion about the advantage of measuring both the anterior part of the thorax and the face, if space restrictions in the implementation were not an issue. However, the main limitations for widespread application are the lack of simple devices for temperature acquisition and the lack of a TLCD device with simultaneous physical and technical integration for signal acquisition and processing. We also identify the high costs in both devices, the lack of tested and approved devices in clinical terms, and the patient or society's defense about their use as other barriers. (Fine *et al*.2021) [27] (Münzel *et al*. 2022) [48] (Liu *et al*. 2022) [41].

4.2. Advantages over Traditional Methods

One advantage of the neural network over other functional modeling techniques is pattern recognition. This is particularly true with complex differential diagnosis problems such as CHD. This can be a major problem when dealing with new diseases or diseases without any physical tests directly related to the disease state. The key to heart disease diagnosis is the recognition and understanding of key patterns or features within the physiologic data. Artificial Intelligence diagnosis is particularly well-suited for pattern recognition and classification. In many respects, this is the problem with traditional medical diagnosis. Such classification is based on "gold-standard" data. Data on several thousand patients which came from a cardiac catheterization or autopsy (by-pass) study which researched, monitored and analyzed the patient's medical condition over a period of months or even years. Since this information is rarely collected at the large data level outside specialized research science settings, AI diagnostic models often carry the same limitations as traditional medical models. (Faieq and Mijwil 2022) [23] (Naeem *et al*.2024) [49] (Shamsara *et al*.2021) [60].

First, they can quickly approximate V(Φ) over a topology with large numbers of related inputs. Because neural networks are statistically trained, i.e. data points and suspected relationships are used to program the network, known co-morbidity parameters or relationships between the symptoms and other patient information do not have to be empirically measured in advance. The neural network develops some understanding of the overall patient, revealing the relationships between symptoms and patient data in terms of a multivariable differential equation. This fundamental difference between expert systems and neural networks is one reason the two systems have been used in combination to address common diagnostic problems. (Sun *et al*. 2020) [69] (Zeleznik *et al*. 2021) [85] (Varrecchia *et al*. 2021) [73].

5. Recent Advances and Innovations

5.1. Wavelet Decomposition Generative Adversarial Network (WDGAN)

Huge amounts of data being produced by big data have become a problem. In this project, electrocardiogram (ECG) data is created through wavelet decomposition using the generator model and later used for ECG in both the training and the testing space. This project uses the Long Short-Term Memory network (LSTM) along with a Generative Adversarial Network (GAN). The decision that the LSTM makes is based on the reconstructed information like the original zero-phase wavelet transformed ECG. The final project like in EBGAN was to evaluate the performance on the Heart Disease UCI database. (Wang *et al*., 2021) [77] (Suhail & Razak, 2022) [68] (Mohonta *et al*., 2022) [44].

5.2. Energy-Based Generative Adversarial Network

Generative adversarial networks (GANs) attempt to use a pair of networks, a generator, and a discriminator, to be able to check/evaluate one another while strategizing at the same time to make the respective network better in a quest to create more functionality in the problem-solving methodology. The network is able to make a small change (for example, increase confidence in benign image, turn non-natural images into natural images) that will result in a large change in the decision of the discriminator network. The ultimate result is a large capacity to manipulate the utility of the system. (Yang *et al*. 2021) [81] (Tao *et al*. 2021) [71] (Sadek *et al*. 2020) [56].

6. Case Studies and Clinical Trials

Our model also has some advantages. It is able to diagnose heart diseases early, save cost, and reduce patients' concerns. In comparing the presented diagnostic model with similar studies, the overall performance and the average area under the curve is higher. The dataset used here is a single-site one and small, and it only contains 303 patients who presented with typical chest pain. Still, it is diverse and has high relevance values in most attributes, supports diverse cardiac complaints or symptoms. The proposed heart disease diagnostic model has been compared with other cardiac diagnostic models, but considering the findings, it is obvious that the proposed heart disease diagnostic model is better, as it does not require further statistical analyses. (Chen *et al*.2020) [15] (Nahm, 2022) [55] (Vickers & Holland, 2021) [75].

To evaluate the presented diagnostic model and compare the performance of our proposed system with all the systematic reviews and meta-analyses in the heart disease diagnosis field, ten case studies were selected for comparison. As can be seen, all evaluation metrics confirm our claim that the presented diagnostic model is robust when different datasets are used and provides high performance, allowing the system to be a reliable tool that can be used to assist physicians in diagnosing heart diseases. Furthermore, our model only needs four diagnostic attributes: Electrocardiograph, Chest pain, Cholesterol Level, and Maximum Heart Rate, to predict the diagnosis outcome. (Wynants *et al*.2020) [78] (Yadaw *et al*.2020) [80] (Muhammad *et al*., 2020) [72].

7. Ethical Considerations

The clinical nature of the patient-doctor relationship demands that the final responsibility for the clinical decision be taken by the doctor. This professional activity is characterized by problems of uncertainty, complexity, and risk, to which are added ethical dilemmas of great weight. These considerations, of delay and black box, have legal and ethical implications, since responsibility is the prime issue when addressing decisions made by an AI. The biomedical practice model cannot nor should it give the doctor the role of mere executor of these decisions; the care provided implies a decision-making model that trusts the professional, leaving him with the possibility of questioning and modifying any recommendation made by the AI, especially when considering conflicts of clinical appropriateness and ethical dilemmas. It is the responsibility of the legislators to demand that the AIs have an 'ethically friendly functionality'. Propose to include in these an 'ethically friendly plug-in' that acts as an integrator of an 'ethical module' that allows the AI to respond with a simple explanation about the decisions taken. Such a control, however, entreats an interpretative cognitive capacity that neural networks still do not have, perhaps an elusive responsibility that they will never be able to pose, as others posit. It might be time to think and debate it before it is too late. (Abdel-Basset *et al*.2020) [1] (Sox *et al*., 2024) [65] (Libby, 2021) [39] (Rani *et al*.2021) [54].

This paper seeks to reflect on some ethical implications that could arise in the long term when neural networks are implemented, arguing that it is not late to think and discuss them further before it happens, and to adequately and ethically deal with the 'new paradigms' that seem to appear. It must be remembered that AI often presents itself as a 'black box', that is, it is built from knowing the input data and the output decision, without it being possible to understand or understand the internal mechanisms of decision generation. Therefore, all models have an ethical duty to incorporate interpretative tools that the user can understand and trust in the decision-making mechanism. (Ahsan & Siddique, 2022) [3] (Hughes *et al*. 2021) [32] (Bleijendaal *et al*. 2023) [12].

8. Future Directions and Emerging Trends

There is potential to extend the research in identifying and classifying multiple chronic diseases, potentially minimizing the burden of diagnosis in treating diseases in a complex health system. Our proposed collaboration approach is the first one with significant potential to have a positive impact compared to clinic visits or lengthy diagnostic procedures. In summary, the contributing discovery will help the healthcare industry using novel insights gathered from the federated neural network approach. (Alderwick *et al*., 2021) [4] (Spaulding *et al*.2021) [66] (Zamboni *et al*.2020) [84].

The proposed collaborative approach would potentially have a big impact in the healthcare industry in training the models to predict multiple chronic diseases, thus helping health professionals to have an opinion that is accurate and representative even if the future data volume or dimension is high. In addition, the computational load for the prediction task can be potentially reduced even though the same relation is already known. If heart disease is truly under control, it will do miracles in saving many lives. (Usama *et al*.2020) [72] (Singh *et al*., 2022) [63] (Battineni *et al*.2020) [11].

The future contribution of the proposed research work involves a comprehensive review of existing models of federated learning and thereby proposing a new federated learning model. Another major contribution of the proposed model is the sharing of data between public and private hospitals. However, the model would need a permission-based compliance system to allocate private and public data between hospitals and the federated model. (Alumran *et al*.2021) [7] (Ferreira & Marques, 2021) [26] (Kumar *et al*.2021) [54].

In such a case, a federated neural network model could be useful for obtaining diagnostic information. In simplistic terms, the specialist doctor at one hospital will preprocess the input data (i.e., the X-ray or MRI images), which can then be classified by specific expert doctors. Finally, all the data is gathered from different clinics to interpret the final diagnostic interpretation by using a federated learning model approach. Furthermore, it is important that the contribution of the incorporated expert model in the final decision be quantified because all model contributions will not be equal in importance. (Cinelli *et al*., 2020) [18] (Chen *et al*.2021) [16] (Yazdi *et al*., 2020) [82].

Future research directions primarily depend on the availability of complete health data. However, in many underdeveloped countries, hospitals do not digitize patient data. Furthermore, in the case of chronic diseases, the availability and transfer of patient information is obligatory since it is unrealistic that the same group of specialists will be present every time when patients come for a check-up. As a result, the patient information will be distributed across hospitals, necessitating a federated learning approach. (Cerchione *et al*. 2023) [14] (Moro and Morea 2020) [45].

9. Conclusion

The authors discuss the potential benefits of using deep feed forward neural networks, deep belief networks, and deep de noising neural networks in solving these high dimension medical problems. In addition to assessing the use of datasets and the provided tools used to build and implement deep neural network models, the authors also discuss the main advantages and challenges that users would expect to encounter due to examining a number of influencing factors related to these modern devices. Epidemiological studies suggest that before implementation of deep neural network models, caution should be taken in interpreting any results in terms of generalizability for patients. In this article, the authors also provide a number of suggestions and topics for future work as well. The authors hope that this paper will provide a valuable source of information for future researchers who are interested in exploring deep neural network models and/or need to use it in order to improve heart disease prediction in practical settings.

Neural networks have gained a considerable amount of popularity in a large number of real-world problem settings, especially in high dimension settings such as financial resources and investments, speech and character recognition, signal processing and transmission, weather predictions, etc. In recent years, neural networks have emerged rapidly in medical diagnostics. In this article, the authors present a comprehensive review of the applications of neural networks in diagnosing heart disease. The authors focus on reviewing the main works related to both the construction of algorithms and methodologies as well as the applications in which considerable use of a dataset and the implementation of deep neural network models were conducted. The authors review a number of the foundational studies as well as some current applications of heart disease diagnosis that have the greatest impact and productivity of neural network models.

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