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Original Article

Analysis of Various Techniques and Methodologies for Heart Disease Prediction a Review

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Abstract: *One of the most important organs for the normal operation of our body is the heart. A WHO investigation revealed that cardiovascular diseases consistently account for 31% of deaths worldwide (CVDs). Additionally, low- and middle-income nations like India account for more than 75% of these deaths. Predicting whether or whether CVDs will occur inside a mortal body is the key challenge. There are many medical devices that can be used to diagnose heart diseases, but they have drawbacks such as being extremely expensive and not being able to accurately predict cardiac conditions (10). Age, coitus, blood pressure, cholesterol, blood sugar, and diabetes, as well as other lifestyle factors including rotundness, eating unhealthy foods, not exercising as much, smoking, drinking alcohol, etc. In this proposed research work the review of the different prediction techniques and methodologies have been enlightened with various research literatures. This will give the analysis of the different technologies*

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Keywords: *Heart Disease Prediction, Cardiovascular Diseases, Artificial Neural Networks (ANN), Deep Learning, Fuzzy Logic, Data Mining, Genetic Algorithm, arrythmia.*

I. INTRODUCTION

Heart is one of the most vital organs for the proper functioning of our body. According to a check by WHO, 31percent of the worldwide deaths every time occurs due to Cardiovascular conditions(CVDs). Also, further than 75 percent of these deaths occurs in low- and middle-income countries including India. The main challenge is to directly prognosticate the actuality of CVDs inside mortal body. Numerous medical instruments are available in the request for the vaticination of heart conditions but there are some downsides of these instruments like they're veritably expensive, they aren't effective enough for prognosticating heart conditions (10).

Age, coitus, Blood Pressure, Cholesterol, Blood Sugar, Diabetes and some life factors like rotundity, eating unhealthy food, lower physical exertion, smoking, consumption of alcohol etc. are some of the major threat factors that leads to heart conditions. utmost of the life threat factors are controllable. In the last many decades, medical wisdom has used the technological advancements veritably well to ameliorate the quality of healthcare. These advancements in technology have paved ways for accurate opinion and vaticination of conditions. Machine literacy could be a veritably good choice to achieve high delicacy for prognosticating heart conditions as it's suitable to assay large quantities of data and relating patterns & trends. also, machine literacy provides important faster and dependable results. There are other soft computing approaches as well similar as Artificial Neural Networks (ANN), Deep literacy, Fuzzy sense, Data Mining, inheritable Algorithm etc. that can put into effect for prognosticating heart conditions. The primary idea of this paper is comparing different advanced methods and soft computing ways that can prognosticate whether a person is suffering from Heart Disease or not grounded on a combination of threat factors(features).

II. BASICS OF TECHNIQUES ANALYSED

A. Machine Learning

Machine Literacy is a fashion that allows the computers to learn from the once data without being explicitly programmed. So, principally it's a discipline to prognosticate effects directly using statistical styles and algorithms. Machine literacy enables computers to manage new situations by assaying, tone training, compliances and gests. Machine literacy has set up its operation in multitudinous fields similar as healthcare, speech recognition, husbandry, banking, natural language processing, optimization, business analytics etc.

B. Deep Learning

Deep Literacy is a part of machine literacy that helps to educate computers to do what comes naturally to humans learn by exemplifications and compliances. Deep literacy is a type of machine literacy which is inspired by the structure and functioning of a mortal brain. Deep literacy came up into the picture when the processing power of ultramodern computers grew exponentially. operations of deep literacy involve automatic speech recognition, fraud discovery, healthcare etc.

C. Artificial Neural Network (ANN)

It is an effort to simulate the network of neurons that make up a human brain in order to enable computers to learn things and take decisions just like humans. It consists of many layers and each layer has many neurons. Initially, an ANN undergoes a training phase where it learns to observe and recognize patterns in dataset, whether visually, aurally, or textually. During this training phase, the network makes a comparison of its predicted output with actual output. The variation between both outcomes is adjusted using back propagation.

D. Data Mining

In general, data mining means selection and extraction of useful information from vast amount of available data. The outcome and result of data mining is the knowledge and patterns extracted from the given data. There are three major steps involved in data mining: Data Pre- Processing, Data Extraction and Data Presentation. It can be applied in various fields like education, healthcare, banking, e-commerce, scientific analysis, etc.

E. Fuzzy Logic

Fuzzy logic was first introduced by Dr. Lotfi Zadeh. It is an approach to generalize the standard logic, in which the degree of truth can be any value between 0.0 and 1.0. Fuzzy models or sets can be understood as mathematical way of representing ambiguity and imperfect information. These models have the ability of identifying, representing, changing, interpreting, and making use of data and information that are ambiguous and uncertain.

F. Genetic Algorithm

Genetic Algorithm is a subdivision of evolutionary algorithms used for search-based optimization. It is based on the concept of genetics and natural selection. Optimization means finding the input values for which we get the best output. Here “best” means maximum or minimum. Feature selection is a very crucial step for predictive analysis, especially for larger datasets. Genetic algorithm is one of the most advanced methods for feature selection.

III. METHODOLOGIES USED

A. Electrocardiogram

The technique used to measure electrical potentials is called an ECG of the heart to identify issues relating to the heart [61]. It is non-invasive, simple to get, and offers an effective stand-in for diagnosing disease. Using MITDB to detect arrhythmias: CNNs have been utilized to detect arrhythmias using MITDB. Using a non-linear modification, Zubair et al. [54] identified the R-peak and created a beat segment around it. In order to train a three-layer 1D CNN with variable learning rate based on mean square error, they first used the segments, and the results were superior to previous state-of-the-art. Li et al. [55] removed the Then, using the SDAE encoder and a SoftMax, they developed a classifier for four arrhythmias, attaining an overall accuracy of 97.5%. In [59], the authors used a low-pass, band stop, and median filter to denoise the signals. They segmented/resampled the heartbeats after utilizing the Pan-Tomkins technique to find R-peaks. A SDAE was utilized to extract features from the heartbeat signal, and a FNN was employed to categorize the heartbeats into 16 different forms of arrhythmia.

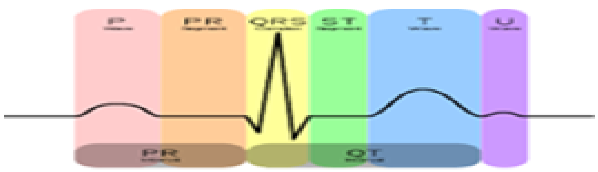

Figure 1: ECG (Electrocardiogram Signal)

It was possible to attain performance that was comparable to that of earlier feature engineering methods. Normalizing the ECG before feeding it to a Stacked Sparse AE (SSAE), which they then tweaked, was the method used by Yang et al. They classify six different forms of arrhythmia with a 99.5% accuracy rate while also proving the method's resistance to noise.

a) Arthymia Detection

Using databases other than MITDB:CNNs have been utilized to identify arrhythmias using databases other than MITDB. In order to categorize four different types of arrhythmias, the authors of [56] built a two-layer CNN utilizing the DeepQ [41] and MITDB. Denoising filters (median, high-pass, low-pass, and outlier elimination) are used to significantly preprocess the signals before they are segmented to 0.6 seconds around the R-peak.

They are then given to the CNN for training along with the RR interval. In order to produce customized outcomes and enhanced precision, the authors additionally use an active learning methodology. In both datasets, they achieve high sensitivity and positive predictivity. Rajpurkar et al. created a wearable ECG dataset that includes more unique patients (30000) than any other dataset. It was then combined with prior datasets to train a 34-layer CNN using residuals. Their approach outperforms the typical cardiologist in detecting a broad spectrum of arrhythmias across a total of 14 output classes.

Acharya et al. [59] trained a four-layer CNN using the databases AFDB, MITDB, and CREI in their article to distinguish between normal, atrial fibrillation (AF), atrial flutter, and ventricular fibrillation. They outperformed earlier state-of-the-art techniques based on R-peak identification and feature engineering without being able to detect the QRS. The same authors have also trained the prior CNN architecture to distinguish between shockable and non-shockable ventricular arrhythmias [62], identify CAD patients using FAN and INDB [63], classify CHF with CHFDB, and identify patients with other diseases using FAN and INDB.

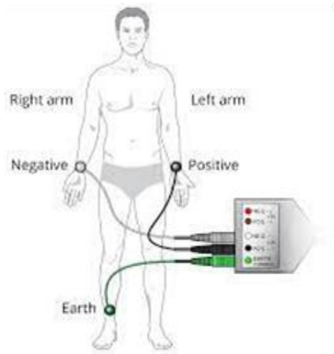

Figure 2: ECG Acquisition Technique

b) AF Detection

CNNs have been utilized for AF detection With greater accuracy than earlier techniques, Yao et al[87] extraction of the immediate heart rate sequence and feeding of it to an end-to-end multi-scale CNN that outputs the AF detection result produced improved results. Two CNNs with three and two layers that were fed spectrograms of signals from AFDB using the short-term Fourier transform and stationary WT, respectively, were compared by Xia et al. [88]. According to their research, using stationary WT results in a somewhat higher accuracy for this task.

Other architectures besides CNNs have been applied to AF detection. To categorize ECG data from AFDB for AF detection, Andersen et al. [60] transformed them into RR intervals. The RR intervals were then divided into 30 segments.

B. Phonocardiogram

Phonocardiogram Classification of normal and pathological cardiac sound recordings was the focus of the 2016 Physio net/Computing in Cardiology (Cinc) Challenge (PHY16). Five databases (A through E) totaling 3126 PCGs with durations ranging from 5 seconds to 120 seconds make up the training set.

The majority of the strategies use spectrogram techniques to transform PCGs to pictures. To segment the beginning of each pulse, Rubin et al. [69] employed a logistic regression hidden semi-Markov model. These segmented heartbeats were then converted into spectrograms using Mel-Frequency Cepstral Coefficients (MFCCs). Using a two-layer CNN with a modified loss function that maximizes sensitivity and specificity as well as a regularization parameter, each spectrogram was classed as normal or abnormal. The average likelihood served as the signal's final classification.

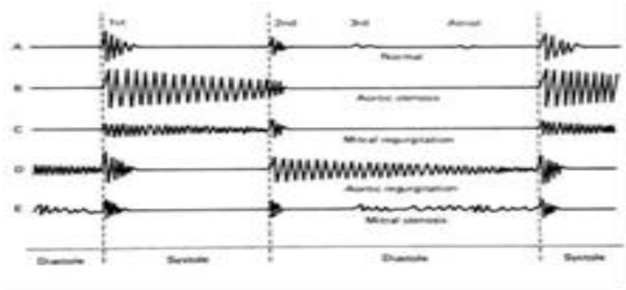

Figure 3: Phonocardiogram

C. Other signals

a) Oscillometric Data:

Oscillometric data are used for estimating SBP and DBP which are the haemodynamic pressures exerted within the arterial system during systole and diastole respectively [66].

b) Data from wearable devices:

Wearable devices, which impose restrictions on size, power and memory consumption for models, have also been used to collect cardiology data for training deep learning models for AF detection. Shashikumar et al. [65] captured ECG, Pulsatile

D. Photoplethysmography

(PPG) and accelerometry data from 98 subjects using a wrist-worn device and derived the spectrogram. using continuous WT.

E. Deep Learning Using Imaging Modalities

Magnetic Resonance Imaging (MRI), Fundus Photography, Computerized Tomography (CT), Echocardiography, Optical Coherence Tomography (OCT), Intravascular Ultrasound (IVUS), and other imaging modalities have all been used in cardiology. The majority of deep learning's achievements in this field have been made possible by designs that make prediction easier.

a) Magnetic Resonance Imaging

MRI is based on the interaction between a system of atomic nuclei and an external magnetic field providing a picture of the interior of a physical object [67]. The main uses of MRI include Left Ventricle (LV), Right Ventricle (RV) and whole heart segmentation.

i). Left ventricle segmentation

CNNs were used to segment the LV using MRI. Tan et al. [68] trained and evaluated two CNNs using STA11 and SUN09, one of which was utilized to localize the LV endocardium and the other to determine the endocardial radius. They are able to perform on par with earlier state-of-the-art methods by utilizing deformable models without filtering out apical slices. The authors of [69] trained a five-layer CNN using MRI from the SUN09 competition. SGD produced a superior Dice of 92% when they used it to train their model instead of RMSprop. In addition, CNNs and RNNs were used. In [70], the authors created a recurrent u-net that can benefit from spatial correlations between slices by learning image representations from a stack of 2D images.

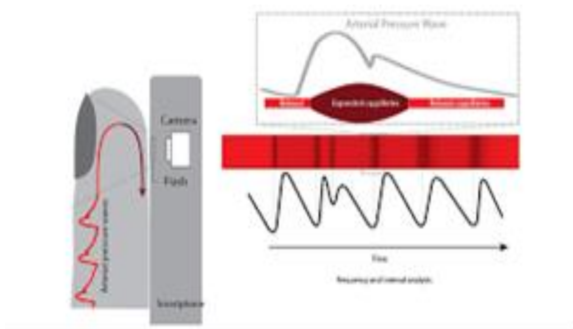

Figure 4: Photoplethysmography

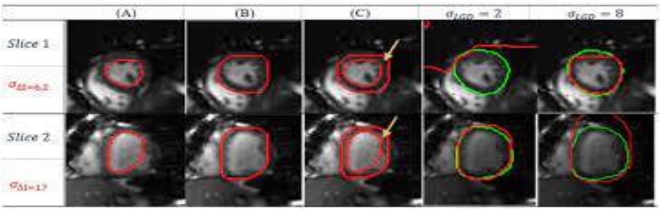

Figure 5: Left Ventricle Segmentation

ii) Overall view on deep learning using MRI

There are several different architectures that have been used in MRI. The majority of the time, CNNs and u-nets are utilized exclusively or in RNN, AE, or ensemble combo. The issue is that most of them don't work end-to-end; instead, they rely on preprocessing, manually created features, active contours, level sets, and other non-differentiable techniques, which makes it difficult for them to scale in response to the arrival of fresh data. End-to-end models should be the primary goal of this field, even if doing so results in short-term accuracy reductions; future advancements in design could close the accuracy difference. In [71], the authors examined the applicability of cutting-edge 2D and 3D CNN designs as well as adaptations of them and made an intriguing discovery regarding entire heart segmentation.

F. Vessel Segmentation

In fundus imaging, CNNs have been utilized to segment vessels. The earliest noise reduction techniques utilized by the authors in [72] were histogram equalization and Gaussian filtering. After that, an RF served as the classifier while a three-layer CNN served as the feature extractor. In contrast to an average, weighted, and median ensemble, a winner-takes-all ensemble reportedly produced the best results in the authors' experiments. To get rid of the sharp edges outside of the field of view and normalize the luminance and contrast inside of it, Zhou et al. [73] used picture preprocessing. The intensity difference between thin and wide vessels was then decreased by using filters to enhance thin vessels after training a CNN to produce features for linear models. Then a thick CRF was adapted.

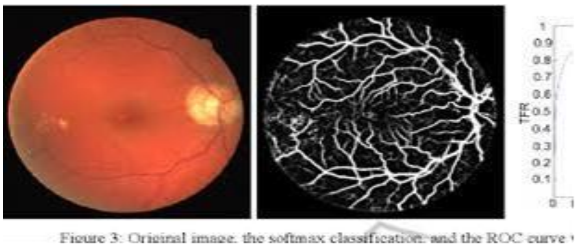

Figure 6: Vessel Segmentation

G. Microaneurysm and Hemorrhage Detection

Haloi [74] MA detection was trained using a three-layer CNN with dropout and maxout activation functions. ROC experimentation and DIA presented cutting-edge research. The authors of [75] developed a model that learns a generic descriptor of the shape of the vasculature using the internal representation of a u-net variant. Then, they evaluated the vasculature embeddings on a task for retrieving images based on the vasculature and on a task for classifying diabetic retinopathy, where they demonstrate how the vasculature embeddings enhance the classification of a method based on MA detection. The authors of [76] merged manually created features with augmented features discovered by a CNN. A RF classifier was then applied to this ensemble vector of descriptors to find candidates for MA and hemorrhage.

H. Computerized Tomography

A non-invasive approach for identifying obstructive arterial disease is computerized tomography (CT). Assessment of the coronary artery calcium score, localization, and segmentation of cardiac regions are a few of the applications of deep learning with CT.

CT was utilized to detect coronary calcium using deep learning. Three independently trained CNNs are used in the Lessman et al. [77] technique for coronary calcium scoring to estimate a bounding box around the heart, in which linked components above a Hounsfield unit threshold are taken into consideration as candidates for CACs. In order to categorize the recovered voxels and distinguish them from other high intensity lesions, three concurrent CNNs were fed two-dimensional patches from three orthogonal planes. Based on the Agatston score, patients were categorized into one of five typical cardiovascular risk groups.

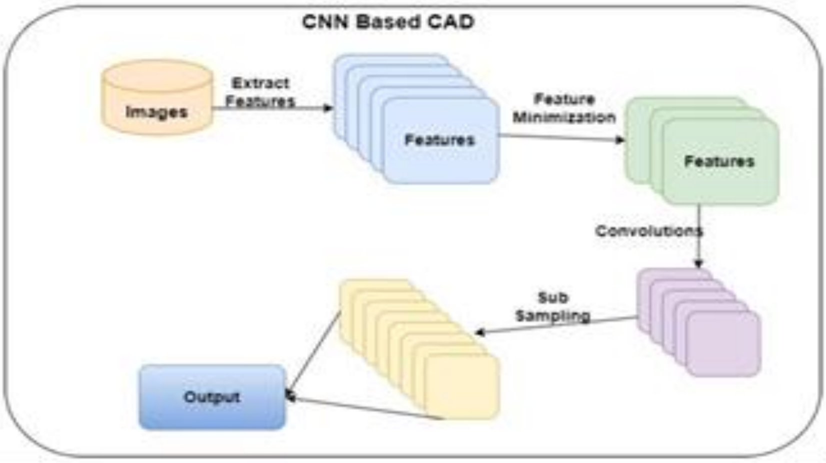

Figure 7: Block Diagram of Computerized Tomography

I. Echocardiography

Ultrasound waves are used in the imaging technique of echocardiography to show the heart region. Deep learning is mostly used in echocardiography for LV segmentation and quality score evaluation, among other things. In echocardiography, DBNs have been utilized to segment the left ventricle. The authors of [78] developed an approach that separates rigid and nonrigid detections using a DBN that simulates the LV's look and shows that it is more reliable than level sets and deformable templates. Nascimento et al. methods of manifold learning, which divides the data into patches and has each patch suggest a segmentation of the LV, was employed by them. A DBN multi-classifier that gives each patch a weight performed the patch fusion.

Table 1: Technology Used In Different Research Work

Year	Technology Used	References
2019	Machine Learning	[5], [13], [27], [40],
		[41], [43], [44]
2018	Machine Learning	[37], [38], [39], [45]
	Data Mining	[6], [36]
	Deep Learning	[35]
	Fuzzy-ANN	[18]
	Machine Learning	[10], [34], [46], [53]
2017	Fuzzy	[22]
	Data Mining	[42]
	Machine Learning	[30], [31], [32], [47]
2016	Data Mining	[28], [33], [52]
	Deep Learning	[29]

	Fuzzy-ANN	[4]
2015	Fuzzy	[16], [17]
2015	Data Mining	[16], [49], [50]
2015	ANN	[51]
2014	Genetic Algorithm	[7]
2014	ANN	[7], [23]
2013	ANN	[12], [25]
2013	Data Mining	[48]
2013	Genetic Algorithm	[2]
2012	ANN	[24]
2012	Fuzzy	[21]
2012	Genetic Algorithm	[3], [1]
2011	ANN	[14]
2009	ANN	[8]
2008	Machine Learning	[11]

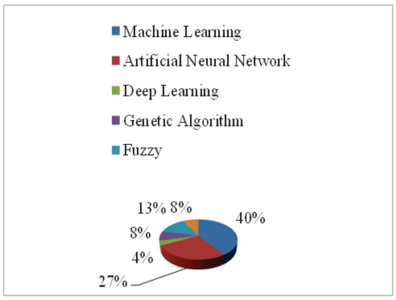

Figure 8: Share of Different Technologies used for Heart Disease Prediction

IV. DISCUSSION AND FUTURE DIRECTIONS

After observation and due review of the different research work in process of heart disease detection noninvasive methods are always proved beneficial and faster for the diagnosis of the cardiac patients. In this era of IoT and Communication Revolution Different Hardware systems along with the Data science and Artificial intelligence will definitely increase the prediction of cardiac diseases fast and accurate. Systems Enabled with AIML (artificial Intelligence and Machine Learning) will be able to reduce the manual pressure and limitations of physicians.

V. CONCLUSION

Heart disease is a significant public health issue in modern culture. Machine learning and neural networks have become increasingly applicable in a variety of sectors, making them potential technologies in the healthcare industry. It is clear from the comparative research that artificial neural networks and machine learning yield the most precise and trustworthy predictions for cardiac disorders. If these models are put into practice, patients will be able to easily, quickly, and accurately diagnose cardiac conditions while also receiving end user assistance and consultant services. Additionally, it will provide patients with a fun self-service experience.

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