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Chapter 10
PPG-Based Cardiovascular Disease Predictor Using Artificial Intelligence

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ABSTRACT

Heart disease is estimated to be the major cause of death among the middle-aged population worldwide. Researchers assess huge volumes of medical data using a variety of statistical, machine learning, and deep learning methods, supporting healthcare practitioners in predicting heart illness. This work aims to predict the likelihood of people developing heart disease using a wearable wristband that can record photoplethysmography (PPG) signals. Cardiovascular features extracted from the PPG signal are used to train the prediction algorithm. It enables the patient to self-monitor their health and take precautionary measures and treatment at the onset of symptoms of the disease. Random forest, convolutional neural network, long short-term memory networks are trained using publicly available databases comprising both affected and standard parameters and thereby used for comparison with the acquired sensor data for predictive analysis.

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1 INTRODUCTION

Cardiovascular Disease (CVD) is a term that refers to a range of conditions that have an impact on the heart (Afilalo et al., 2009). They include lack of fitness, high cholesterol, hypertension, etc. An improper diet, harmful alcohol consumption, and excessive sugar levels are all factors that contribute to heart disease (Amin et al., 2013). Identifying and treating the people who are at risk of CVD is highly essential in order to reduce early deaths. Hence to prevent early death, an early and accurate medical diagnosis of heart disease must be made (https://appa.who.int/iris/handle/10665/43685). Lack of adequate medical datasets, lack of flexibility in selecting features, and lack of implementation of proper predictive algorithms are all obstacles that delay effective heart disease prediction (Sharma et al., 2020).

Males are more likely than females to get a CVD. It is twice as likely for males to develop heart disease during their lifetime as for females. The increased risk continued even when traditional heart disease risk factors such as lipid disorders, hypertension, insulin disorders, body mass index (BMI), and fitness activity were taken into account (Ebrahim et al., 1999). The factors that contribute to these differences in cardiac illness and mortality rates are numerous. Differential access and poor quality of health care, environmental or neighborhood impacts, persisting racial prejudice, health actions including nutrition, smoking, socioeconomic position, and genetic variation have all been proposed as factors contributing to congestive heart failure (Anderson et al., 1991).

ML and DL are examples of artificial intelligence approaches that can help with early screening and diagnosis of CVD at an early stage, in addition to prognosis evaluation and outcome prediction. With the proliferation of electronic health records (EHR), enormous amounts of quantitative, qualitative, and transactional data have been collected. With the use of clinically relevant information revealed in huge amounts of data, AI approaches can also assist clinicians in making the best clinical resolution, enabling prior diagnosis of subclinical organ dysfunction and therefore improving the quality and efficiency of cardiac healthcare (Faizal et al., 2021). A system based on such risk factors would not only assist medical experts and doctors but also alert patients to the possibility of CVD before they visit a medical center or undergo expensive medical examinations (Ebrahim et al., 1999). As a result, employing suitable classifier algorithms, this research proposes a technique for predicting heart disease using major risk variables. LSTM, CNN, and RF methods are among the major classification algorithms applied in this technique for analyzing whether patients have CVD or not.

In healthcare, machine learning and deep learning have shown effective assistance in assisting with decision-making and predicting from large datasets (Mohan et al., 2019). The machine learning disease prediction system uses information provided by users to identify diseases. Information entered into the web system predicts a patient's disease or the user's symptoms and gives results based on the information given. With its combination of ML and artificial intelligence, DL can be thought of as a means of simulating how humans acquire different types of knowledge. With the computer-aided diagnosis, this field relies on its own ability to learn and improve (Swathy & Saruladha, 2022).

ML is a data analytics approach that automates the building of analytical models. In this branch of artificial intelligence, systems learn from data, recognize the design, and make a conclusion without human interference (Sardar et al., 2019). Supervised machine learning is the type of machine learning where the model is trained based on previous data to make future predictions (Kotsiantis et al., 2007). A deep learning approach can be used to predict a disease based on collected data (Ali et al., 2020). Finding hidden information in a dataset, followed by the ability to apply that knowledge to others, is what it is all about (Kotu & Deshpande, 2o14). Many ways exist within the deep learning methodologies for transforming a large dataset into meaningful information (Vaswani et al., 2017). This method can be used for knowledge discovery, application, and prediction based on knowledge. The forecast is primarily reliant on the data that has been trained. The dataset can be trained using the back-propagation method by using an Artificial Neural Network (ANN). It is made with a multilayer perceptron, which is a fundamental processing unit that can handle non-linear problems while a single perceptron can only tackle linear ones (Suvkens et al., 1995).

It is crucial to complete the diagnosis as soon as possible. Usually, this is done with the assistance of a doctor. Patients will typically receive disappointing results with high medical costs (Ponikowski et al., 2014). As a result, an automated medical diagnosis and prediction system would be tremendously beneficial. To compare prediction models, public datasets on heart diseases are accessible (Abukhousa & Campbell, 2012). The development of machine learning and deep learning allows academicians to create the best prediction models possible by utilizing enormous databases (Bharti et al., 2021). A system-based risk factor would benefit medical professionals as well as patients because it would alert them about potential CVD symptoms even before they visit the hospital or undergo costly medical testing (Larroza et al., 2017). Table 1 showcases the summary of research work pertaining to CVD prediction with the focus on signals and signals source used, features extracted and various classifiers used.

2 SUMMARIES OF PREVIOUS RESEARCH

Globally, CVD has been the leading cause of death in the last decade. In India, the incidence of CVD is expected to increase from 2.27 million in 1995 to 4.8 million in 2022 Over the past several decades, CVD occurrence rates in India have increased from 1.6% to 7.4% among rural populations and from 1.5% to 13.7% among metropolitan populations (Mozaffarian et al., 2016).

Table 1. Summary of related research work

S. No	Author & Year	Signal used & Signal Source	Features Extracted	Classifier Used
1.	**Apurb et al., 2020**	PPG, ECG	Fingertip PPG and Electrocardiogram (ECG) signals are processed based on the phase and amplitude for monitoring continuous systolic and diastolic blood pressure.	Aggregation network-based deep learning
2.	**Alaa et al., 2019**	PPG	Peak-to-Peak Time, Crest Time, and Maximum Slope were found to be vital features for accurate classification	Kernel
3.	**Zaibunnisa et al., 2021**	ECG	Framingham Risk Score.	K neighbor classifier, Support Vector Machine classifier (SVM), Decision Tree classifier
4.	**Galla et al., 2020**	Statistical data Different geographical areas (Hospital)	The fuzzy-based model was used to retrieve real-time patient data.	ANN, Decision Tree, SVM, and Naïve Bayes
5.	**Bharti et.al., 2021**	Public Health Dataset	Peak and thali distribution were found to be featured for accurate classification	K Neighbors classifiers, Random Forest, SVM, Decision Tree
6.	**Abdel et al., 2020**	PCG	Using the spectral density plots, phonocardiogram signals can be generated.	Radial Basis Function (RBF) network and Back-Propagation Network (BPN) techniques
7.	**Fu et al., 2020**	ECG	Long ECG recordings (QRS complexes), Short ECG recordings (P and T wave)	AI algorithms such as CNN and Recurrent Neural Network (RNN).
8.	**Shah et al., 2020**	ECG	A classification analysis of ECG using QRS complexes.	Continuous Wavelet Transform (CWT) and SVM.
9.	**Devansh et al., 2020**	Cleveland database	The UCI repository of the heart patient was conducted through the WEKA tool.	K neighbor classifier, Naive Bayes, Decision tree, and RF algorithm
10.	**Krittanawong et al., 2017**	ECG	To investigate novel genotypes and phenotypes in known diseases, AI approaches are used.	Algorithms include ANN, SVM, Decision Tree, Random Forest, Naive Bayes, and KNN.
11.	**Josep et al., 2012**	Echo-cardiography	Heart rate, respiratory rate, SPO_2, blood pressure.	Kaplan Meier event-free survival analysis.
12.	**Mohammed et al., 2011**	PPG	Maximum Slope, Heart rate, SPO_2.	Artificial Neural Network approaches that classify a PPG signal into two distinct classes i.e., Network-based on Multi-Layer Perceptron (MLP) with back-propagation strategy and Gaussian Mixture Model (GMM).

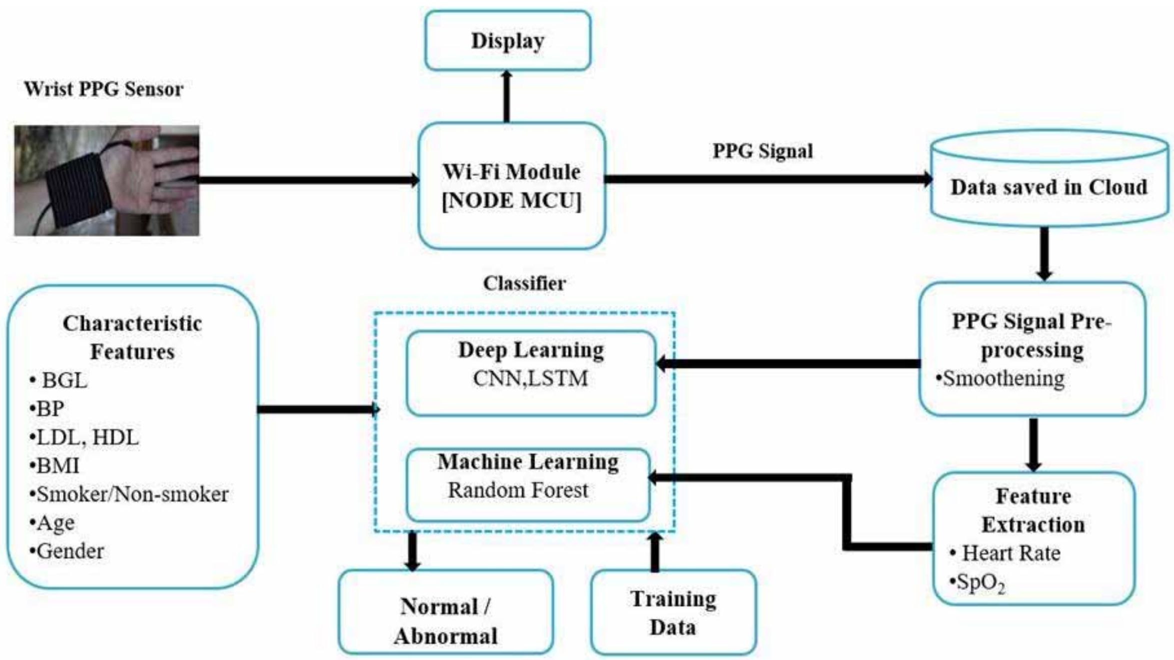
3 METHODOLOGY

In the proposed model, a wearable wristband is designed to acquire PPG signals from individuals, and the signal is saved in the cloud through a Wi-Fi module. The signal can be imported from the cloud, after which preprocessing steps are performed using a smoothing filter. Few feature extraction algorithms are utilized to extract the features relevant to the CVD, and the extracted features are also given to the classifier. The block diagram of the proposed work is depicted in figure 1. The developed wearable wristband with an automated screening system that can predict CVD using PPG signals is shown in figure 2. Appropriate signal processing algorithms have been implemented to extract relevant features that support the prediction of cardiovascular disease. The following classifiers are used for classification and their performance has been analyzed.

- Random Forest
- Convolution Neural Network
- Long-Short Term Memory Network

The non-invasive approach makes use of a simple light source and a photodetector with which the model monitors the volumetric fluctuations of blood circulation to acquire the PPG signal. As a result, small overall solution size is achieved without compromising optical or electrical performance. The external hardware components are integrated into the wearable wristband. File Input File Output (FIFO) allows the sensor to connect to a microcontroller on a shared bus that does not continuously read data from registers. The acquired signals are given to the cloud using a Wi-Fi module. The microcontroller unit has been designed for wearable electronics to achieve the lowest power consumption possible with several proprietary techniques. The Espressif System Smart Connectivity Platform (ESCP) is often designed for minimal space requirements. It has an embedded Wi-Fi capability that can be added to any microcontroller-based system with simple connectivity through the Universal Asynchronous Receiver-Transmitter interface. It operates at a 2.4 GHz frequency, corresponding to 0.125 meters of wavelength. It employs a 32-bit RISC (Reduced Instruction Set Computer) Central Processing Unit. The Arduino AT mega is an advanced virtual RISC microcontroller. The Arduino ATmega-328 is an 8-bit microcontroller and it operates in the range of 3.3V to 5.5V. It can execute many instructions in a single clock cycle and provide almost 20 MIPS (million instructions per second) at 20MHz. It has a high performance and low power design. It covers 32kb of programmable Flash, 1kb of EEPROM, and 2kb of SRAM (Static Random Access Memory). It can perform all the general-purpose tasks on a single machine, like a computer. The devices in the series are precision temperature devices for integrated circuits. Its output voltage is directly proportional to the temperature in degrees Celsius. Therefore, the sensor is calibrated directly to Celsius. No external calibration or trimming is required to achieve normal accuracy. It features low output impedance, a linear output, and precise and unique calibration that facilitates interface with the reader or control circuitry. It requires a power of 60µA and operates at temperatures between -55^0 C and 150^0 C. Organic Light-Emitting Diode (OLED) is a relatively new technology that uses light-emitting diodes where light is produced by organic molecules and could replace today's LCDs and LEDs. The display format is about 128×64 dots. OLED displays emit visible light because they work without a backlight. It can be embedded in textiles and clothing and offers a higher contrast ratio and wider viewing angle than LCDs. It also has much faster response times than LCDs. The Thing Speak server is an open data platform for the Internet of Things that can collect store, analyze, visualize, and manipulate data from sensors.

Figure 1. Block diagram of CVD predictor



3.1 Pre-Processing

Signal preprocessing focuses on analyzing, altering, and synthesizing signals such as sounds, images, and scientific measurements. This technique can be used to upgrade the transmission, storage viability, and subjective quality and to also detect the components of interest in a measured signal. Preprocessing is a stage that includes artifact removal, denoising, and resampling the signal to comply with detector input specifications. The preprocessing module can be divided into three components:

i. **Extraction** involves the process of extracting important data from multiple homogeneous or heterogeneous data sources.
ii. **Conversion** refers to the cleaning and manipulation of data to convert it to the proper format.
iii. **A load** is the insertion of the transformed data into the memory of the processing unit that processes the training data.

Applying an appropriate filter to the signal is necessary in order to remove the artifacts and spurious noise added to the signal. Smoothing the data removes random variation, and they show a typical trend and cyclic components. Smoothening is achieved using the moving average filter in this method. Machine Learning and Deep Learning algorithms work well when the data is introduced in a format that emphasizes the relevant aspects needed to solve the problem. Feature extraction practices, including, data transformation, data reduction, data wrangling, feature selection, and feature scaling, help reconstruct raw data into a format suitable for a particular type of algorithm. This can significantly decrease the processing power and time required for training and guessing new machine learning and AI algorithms.

3.1.1 *Moving Average Filter*

As its name suggests, it is a low-pass FIR (Finite Impulse Response) filter that is frequently used to smooth out data or signal arrays. It takes n number of samples at a time and works by summing those samples to produce a single output point. Cycles of long-term trends can be identified through moving averages, which can resolve short-term fluctuations. Based on the application, there may be a difference between short-term and long-term moving averages, which will be reflected in the moving average variable. A moving average is a statistical technique that filters out higher frequency elements of non-time series data without relating them to time in any particular way. But it usually does imply a certain order. In this case, the structure of the Low Pass Filter is very transparent to filter out undesirable noise from the intended data. The smoothness of the output increases with magnitude (the parameter L), while as the data becomes increasingly blunt, sharp transitions become less apparent. Moving average filters possess the following characteristics: an excellent time-domain response but, an insufficient frequency response. There are three main functions of the moving average filter:

i. Using L input points, an average is calculated for those points by the filter, which produces an output value.
ii. As a result of complex computations, the filter introduces a significant delay.
iii. Low-pass filtering (with excellent response in the time domain but a weak response in the frequency domain). For an L-point discrete-time moving average filter, the difference equation is given in Equation 1, where x is the input vector, and y is the average output vector.

$$y[n] = \frac{1}{L}\sum_{k=0}^{L-1} x[n-k] \tag{1}$$

As shown by the frequency response, the roll-off is extremely slow, and the attenuation in the stopband is not adequate. Considering the attenuation, the stopband is very weak. The moving average filter is unable to split one frequency band from another. When good performance is measured in the time domain, it is weakly measured in the frequency domain. Despite their excellent smoothing capabilities (effects appear in the time domain), moving averages are very destitute low-pass filters (effects are seen in the frequency domain). Noise reduction can be achieved by adding a few adders and delay elements. With low-pass filtering, the capacity to suppress the stopband sidelobes and to achieve an excellent frequency domain response is less important than basic filtering ability, which is where moving average filters are most useful. The main assumption of regression models utilizing moving averages is that the independent error terms are undetectable and the parameters are estimated by the weight.

3.2 Feature Extraction

The technique involves computing preselected characteristics of a PPG signal, which are then fed to a final processing scheme such as a classifier, to aid in CVD prediction using PPG-based systems. In the following step, vital feature points are extracted from the PPG signal by using differential thresholds. Three steps are involved in this method: interpolation, differentiation, and determination of extreme points.

Our goal is to create new features from existing ones in the dataset, which will reduce the number of features in the dataset. It also helps to reduce the amount of redundant data in the data set. Characteristic features extracted from the individuals are listed in table 2.

Table 2. Characteristics and details of cardiovascular disease

S. No	Characteristic	Details
1.	Age	Age of patient in years
2.	Gender	0 =Male; 1=Female
3.	Smoking condition	0 = Non-Smoker; 1 = Smoker
4.	Height	Height of the patient in Centimeter (cm)
5.	Weight	Weight of the patient in Kilogram (kg)
6.	Hypertension	Diastolic and systolic blood pressure at rest (in mm/Hg)
7.	Blood Glucose Level	Fasting blood sugar levels are above 120 mg/dL. Less than 100 mg/dL (5.6 mmol/L) is normal and 100-125 mg/dL (5.6-6.9 mmol/L) is considered prediabetes.
8.	Cholesterol	Serum cholesterol (0 = Normal range, 1 = High cholesterol level)
9.	Cardiac arrest	There are four types of cardiac arrest: angina pectoris, atypical angina, non-anginal pain, and asymptomatic.
10.	Temperature	Temperature is acquired through the sensor (varies according to the patient)
11.	Heart Rate	Maximum heart rate achieved
12.	SPO_2	Maximum oxygen saturation is achieved through the PPG signal.
13.	Target	Predicted Outcomes = Normal, Disease_ Risk

3.3 Database

Data that is needed for forecasting is obtained from open sources. Collecting data is an important step because the quality and quantity of the data directly determine the success of the proposed model. A common approach is to get data from open sources such as Kaggle (https://www.kaggle.com/datasets). Kaggle is a data science community with tools and resources, including externally sourced artificial intelligence. This is a technique for assessing and sharing the performance of ML and DL algorithms. It can be used for regression problems and supervised learning algorithms. This step takes one record and divides it into two subsets.

In this proposed model, the data is separated into the training data being 80% and the test data being 20%. First, there is the training data, which is used to fit the model and is referred to as the training dataset. We don't use the second subset to train the model, but instead provide the input element from the dataset to the model, which makes a prediction and compares it to the expected value. Using the model file, the second dataset is referred to as the test dataset. Here using the model file, certain types of patterns can be recognized. Training data is sent to the classification algorithm. After training, the classification algorithm will produce the expected outcomes. When it comes to predicting or classifying a problem, the distribution of the data is crucial. We can observe that heart illness is identified 54.46 times in the dataset, while no heart disease occurred 45.54 times. As a result, we must balance the dataset to avoid overfitting.

Figure 2. Designed wearable wristband

3.4 Random Forest

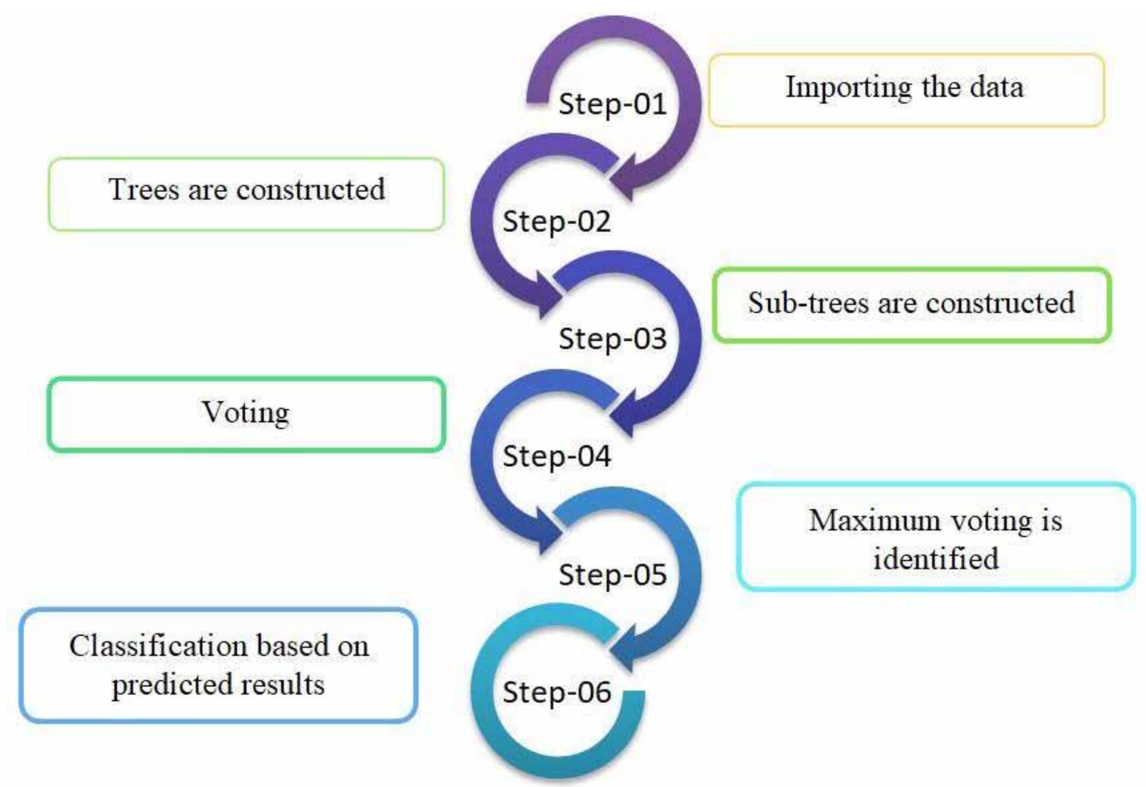
An RF is a classifier that consists of multiple decision trees for different subsets of a given data set that uses the mean to better predict the accuracy of that data set. The building blocks of RF algorithms are decision trees. RF is a popular machine learning algorithm related to direct learning techniques. The more trees there are in the forest, the greater the accuracy and the avoidance of overfitting problems. It can also maintain accuracy even when most of the data is missing. This algorithm can be used to determine disease propensity and disease risk. As a result, doctors can judge a patient's reaction to a particular drug. An RF algorithm consists of a series of decision trees, where each tree in the ensemble consists of data samples taken from training samples with replacements called initial samples, as shown in figure 3.

A method for predicting heart disease has been proposed by using this classifier that results in 84% accuracy. Cardiovascular disease is predicted using ensemble learning approaches. The proposed methodology entailed combining the different deep learning algorithms with the RF, a machine learning technique that is used to evaluate the CVD. Artery blockage denotes the existence of cardiac risk. Many researchers are working in this field to develop software that can assist doctors in making decisions regarding the prediction and diagnosis of heart disease (Romiti et al., 2020). In this proposed model, data mining techniques can be used to predict cardiovascular disease in advance, allowing patients to receive appropriate treatment. Here, the different algorithms are used for comparative analysis, but the prediction accuracy of the RF algorithm is the lowest. Based on the algorithm, sensitivity is 85.67%, specificity is 52.38%, and accuracy is 84.76%.

The classification in RF uses an aggregate method to achieve the results. After training, averaging the predictions from all the separate regression trees can be used to make predictions for unseen samples. Seventy-eight regression trees were formed approximately. By default, for every 500 datasets, 10 regression trees are formed. Then the sub-categories or subtrees are formed. It can be of two types in this proposed model. Our decision tree uses continuous variables. A continuous variable decision tree has a continuous target variable and is known as a continuous variable decision tree. There is a linear relationship between the predictor variables and the target variables, so the basic learner is just as accurate as the ensemble learner. This classifier is used to diagnose patients by assessing their previous medical history. In comparison to the decision tree algorithm, it is more accurate in predicting the outcomes of thousands of input variables that can be processed without deleting them. This works in four steps.

i. Choose a random sample from a particular dataset.
ii. Create a decision tree for each sample data set and get the prediction output from each decision tree.
iii. Vote for each expected result.
iv. As the final prediction, select the output result with the most votes.

Figure 3. Data flow in random forest



3.5 Convolutional Neural Network

The Artificial Neural Network (ANN) is made up of interrelated nodes that function similarly to real neurons in that they receive, process, and output data. Nodes in any artificial neural network can be classified in three ways: input nodes, hidden nodes, and output nodes. As with sensory neurons in the central nervous system, input nodes function similarly, bringing a data set to processing. The details from the data set are processed by hidden nodes, and the last elucidation of the data is represented by output nodes. Convolutional neural networks are a type of artificial neural network that "learns". This can happen through a variety of mechanisms, such as backpropagation (Krittanawong et al., 2017). The most commonly used model type in Python programming is the successive type. It is the easiest method to create a CNN model. This allows us to build the model layer by layer. The term "convolution" in CNN refers to the mathematical function of convolution. A linear operation multiplies two functions to produce a third function that shows how one function changes the shape of the other. Convolutional neural networks (CNNs) indicate that networks use a mathematical operation called convolution. A convolutional neural network (CNN) consists of an input layer, a convolution layer, a pooling layer, and an output layer. CNN's biggest advantage over previous models is that it automatically discovers important features without human control (Nasrabadi & Haddadnia, 2016).

The Convolutional Neural Network method uses structured data to determine early heart disease risk. Our model's accuracy is 95.35%, with a sensitivity of 99.18% and a specificity of 31.36%. In the future, the work will be to expand our algorithm to include unstructured data as well. Medical specialists have approved all of the quality and laboratory tests that have been considered so far. Both organized and unstructured data can be utilized with the CNN algorithm. Images can also be used in conjunction with CNN algorithms to forecast certain diseases. The reason for this is that it employed a very good optimization strategy to improve the CNN algorithm's accuracy. CNN is a kind of deep neural network (DNN) with a spectral layer that specifically learns lower and higher-level features. CNN is a useful model for predicting statistics, modeling, and other tasks. Simply put, it outperforms CNNs thanks to three additional concepts: local filters, max-pooling, and weight sharing. Figure 4 shows the architecture of CNN, which is used to predict cardiac disease. To extract important features, the CNN is composed of a few pairs of convolutions and pooling layers. The convolutional layer always comes after the pooling layer. Pooling is commonly used in the frequency domain. For the problem of variability, max-pooling produces good results. The highest filter activation from different points within a particular window is collected by a layer called a max-pooling layer. At this stage, the convolution features are created at a lower resolution. The max-pooling layer allows the architecture to tolerate tiny changes in the placement of the pieces of the object, resulting in faster convergence. On the other hand, fully connected layers aggregate the inputs from all points into a 1-D feature vector. The overall inputs are then classified using the SoftMax activation function layer. The CNN architecture consists of two main parts:

i. A convolution tool that splits and identifies various features of a dataset for scanning in a process called feature extraction,
ii. An integrated layer that uses the convolution process output to predict the class of a dataset using the features extracted previously.

Input Layer: The foremost layer is called the input layer. The input layer of the neural network contains artificial input neurons, which then send the output data to the system for further processing.

This layer transfers data directly to the next layer. The next layer is the first hidden layer, where the data is accumulated by the first hidden layer.

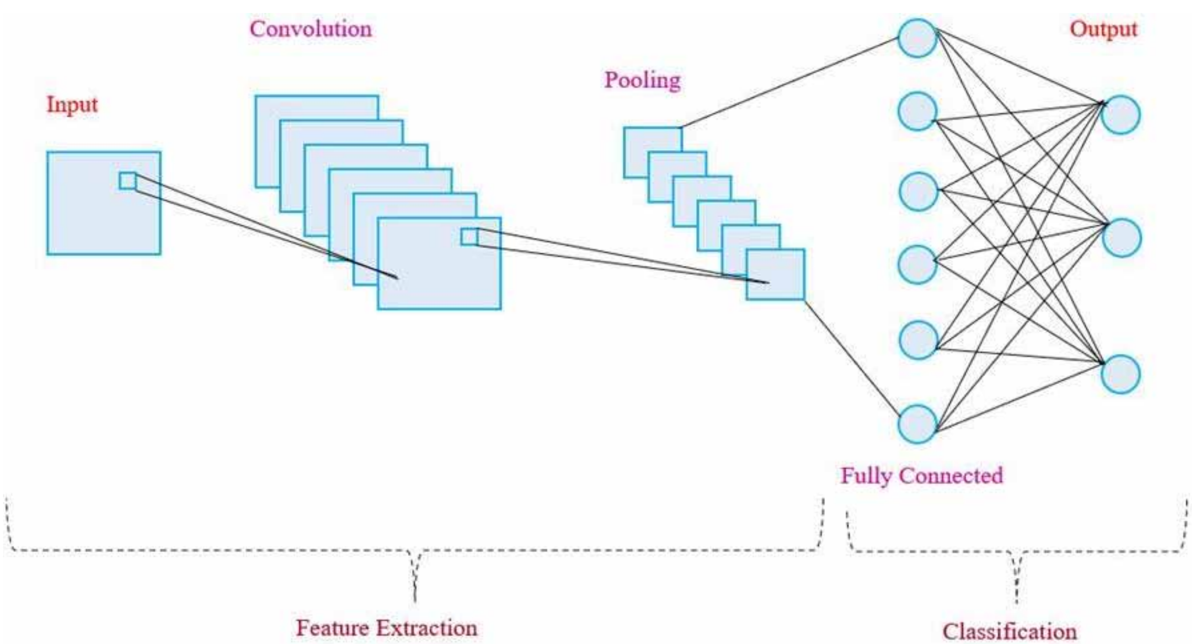
Convolutional Layer: The convolutional layer is the basic structure of a CNN where most of the computations are performed. Convolution is the first layer that extracts features from the input training data, also known as a convolution matrix or convolution mask. It consists of a digital filter that analyses the input data using convolution. The result of the convolution operation is passed to the second layer as the convolution layer proceeds to perform the convolution on the input data. Convolution converts every pixel in the received field to a single value.

Pooling Layer: In addition to their parametric reduction, pooling is the layer added after convolution. Pooling layers are neither necessary nor sufficient for proper deformation stability in CNN algorithms. Pooling layers help control overfitting by gradually reducing the size of the view, reducing the number of parameters, and reducing the amount of memory.

Dense Layer: A densely connected layer consists of multiple layers connected by weight matrices and multiplexed input data by each layer's weight matrix. Also known as the "line layer" this layer connects each input neuron to each output neuron. The output of the convolutional layer represents the high-level features of the data.

The architecture of the CNN model is represented in figure 4.

Figure 4. Data flow in Convolutional Neural Network



3.6 LSTM

In the discipline of DL, LSTMs are artificial recurrent neural networks (RNNs) that can learn sequence dependencies in sequence prediction problems and are designed to overcome the problem of backflow of errors. LSTMs are designed to work differently from CNNs because LSTMs are typically used to process and predict a given sequence of data (Jasmin et al., 2016). It is widely used for sequence prediction problems and has proven to be very effective. An LSTM network was used to accurately classify auricular fibrillation (A-Fib) in a variety of electrocardiography, echocardiography, or plethysmography data. It achieved 99 percent accuracy. Using LSTM models, structural heart distortion threats were also automatically identified from digital phonocardiogram (PCG) signals for use in congenital heart disease screening applications. Additionally, it has been demonstrated that a bi-directional neural network architecture built by utilizing the Bi-LSTM-Attention method increases the accuracy of cardiovascular disease applications (accuracy of 98.49 percent) above the literature review. Deep learning applications have also been reported for medical imaging, where futuristic results have been achieved, and neural networks have worked well for many challenging situations in biomedicine.

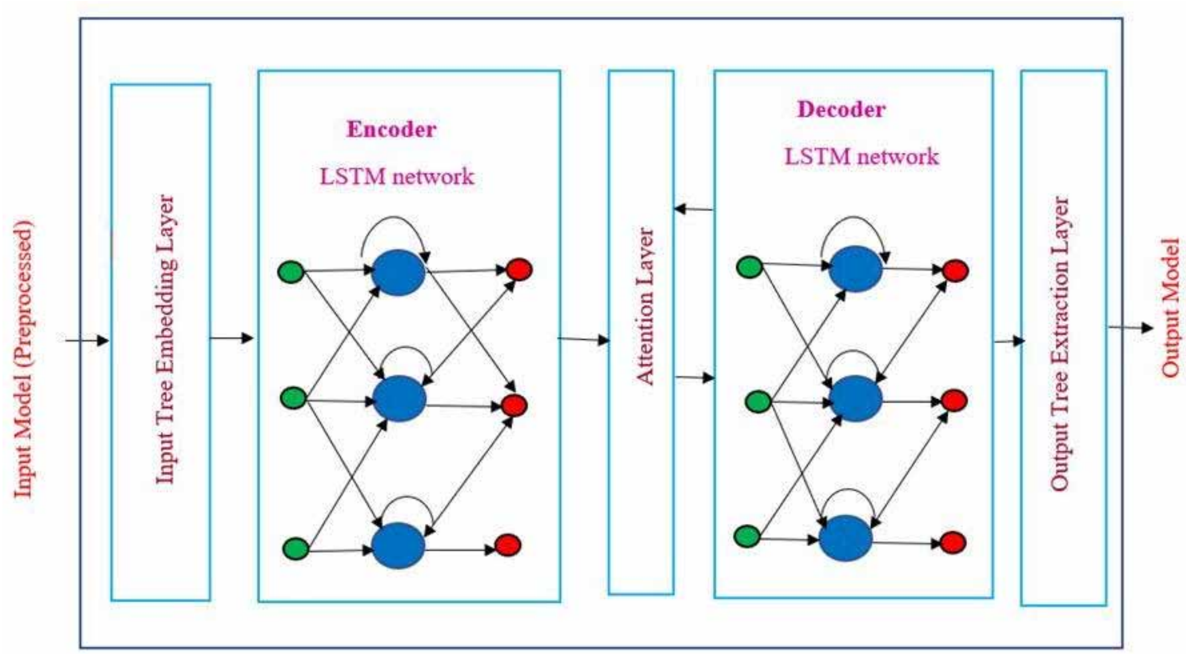
Prior strong prediction models struggled to deal with data spanning multiple periods with different intervals, and handling large volumes of patient hospital records was ineffective in improving forecast accuracy. The goal of this research is to use enhanced LSTM models to predict cardiovascular disease. To predict cardiovascular disease, in an attempt to improve the standard LSTM, a new model and architecture were suggested as shown in figure 5. To overcome the prediction time limit vector obtained by smoothing an irregular period imposed by an irregular time interval, which is then fed into the forgetting gate of the LSTM, we can keep important information from the past and forget about unnecessary information. Information is stored in cells, and memory manipulation is performed by three gates:

Forget Gate: The conditional determination of which information should be discarded from a block.
Input Gate: The memory state is updated conditionally based on which input value was provided.
Output Gate: Input and block memory are taken into consideration when deciding what to output.

It is used for processing, forecasting, and classification based on time series data. It provides a wide range of learning rates, input, and output bias parameters. The main advantage is that the complexity of each weight update is reduced to 0(1) by LSTM, similar to backpropagation in time (BPTT). LSTMs have recently gained popularity because they can solve the problem of dissipating gradients (Krittanawong et al., 2020).

The architectural structure of the LSTM network is represented in Figure 5.

Figure 5. Dataflow in Long Short-Term Memory Network



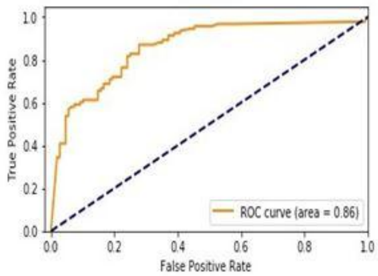
4 RESULTS AND DISCUSSION

The PPG optical mechanism enables clinicians to expand the scope of the screening devices and their applicability. New advancements in medicine have made it possible to incorporate PPG into wearable devices for real-time monitoring and prediction of cardiovascular disease. The quality of PPG measurements is also an advantage, as the device measures several variables to quantify cardiac activity and normal blood volume. The PPG typically uses a series of pulse and peak detections to measure oxygen saturation and heart rate. Cardiovascular disease with a focus on arterial disease is one of the few targets for photoplethysmography. The research was conducted on super-intending ML and deep learning classification methods by combining RF, CNN, and LSTM. This research aims to forecast whether the subject will develop cardiovascular disease or not.

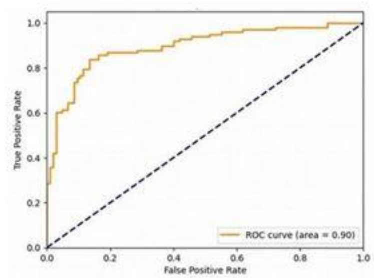
4.1 The Evaluation Process Used

There are five components in the evaluation process: the confusion matrix, precision rate, precision, recall, sensitivity, and F1 score. The confusion matrix is a table. With both true and predicted values, these can be canalized into the true positive and the true negative. The evaluation process is composed of four models: the first one is a True Positive (TP), where the values are recognized as true. The second model is False Positive (FP), which is identified as being true despite being false. In the third case, the value is true, but a False Negative (FN). The fourth model is defined as the True Negative (TN). Then the value is negative and is recognized as such.

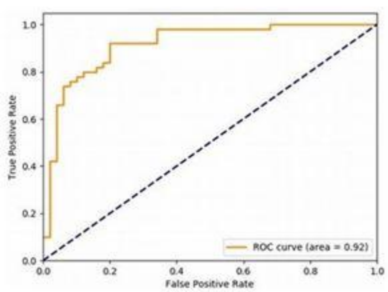
Figure 6. ROC curve and Confusion matrix of RF, CNN, LSTM



640	107
10	11



604	123
0	5



579	72
102	15

4.2 ROC Curve

Receiving Operating Characteristics (ROC) curves are used in machine learning to assess models, in particular when data is skewed, by visualizing their performance. The ROC curve is a graph that represents how well a classification algorithm performs at all classification thresholds. A ROC curve plots the following two variables:

i. Rate of true positives
ii. Rate of false positives

The True Positive Rate (TPR), is known as the probability of the observations that are predicted to be positive and are positive, given in eqn.2.

$$TPR = \frac{TP}{TP + FN} \quad (2)$$

In contrast, the False-Positive Rate (FPR) is the probability of the perception that its prognosis is positive but ends up being negative. The False Positive Rate (FPR) is described as in eqn.3.

$$FPR = \frac{FP}{FP + TN} \tag{3}$$

Consider heart data, which has 13 features: age, gender, smoking status, blood glucose level, height, weight, blood pressure, and cholesterol. The goal is to determine whether a particular individual has cardiovascular disease based on the above features. An example of this kind of problem is a binary classification problem. Alternatively, it could be dividing the population into two categories. For example, suppose there are 100 samples (each sample corresponds to one patient's information) out of which 90 samples are positive (they have heart disease). Therefore, the classification is correct because all 100 samples (100 patients) have heart disease. The accuracy of 90% was achieved without ever building the model. The dataset appears to be skewed, which means there are a greater number of positive samples (patients with cardiovascular disease) than negative samples (patients who do not have cardiovascular disease). Therefore, it is not advisable to decide on the best model by focusing solely on accuracy. This does not represent the data completely. Sometimes may get high accuracy, but the model will probably not perform so well on real-world samples. Therefore, ROC becomes more important as an evaluation metric.

Visual interpretation of data is easier with a simple graphical approach by using this ROC curve. It computes accuracy as a composite measure of the whole range of the test without taking prevalence into account, simplifying sampling. The threshold can be determined using any cut-off value. It is possible to calculate useful summary measures (e.g., the area under the curve). It is possible to compare two or more curves (e.g., comparing a new test with a previous one). Instead of predicting classes directly, it can be more flexible to predict the probability of an observation belonging to each class. A key reason for the flexibility is that probabilities can be interpreted differently based on different thresholds, which allows the operator of the model to balance concerns regarding the representation of false positive and false negative constructed by the model. Logistic regression is an analytical technique that is recognized by the approximate regression model when the response variable is binary. To estimate how well the logistic regression model, inserted into the database, can look at two metrics as given in eqn.4 and Eqn. 5.

Precision is followed by specificity, which is a ratio. True Negative cases group as negative: therefore, it measures how adequately the classifier recognizes negative cases, also called a True Negative.

$$\text{Accuracy} = \frac{TP + FN}{TP + FP + TN + FN} \tag{4}$$

Specificity: The chances that a model will predict a negative result for observation if the result is negative. To check the performance of the model, accuracy is applied. This variable is defined as the sum of True Positives and True Negatives divided by the sum of True Positives, True Negatives, False Positives, and False Negatives as given by Eqn 5.

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100 \tag{5}$$

Sensitivity: The probability that the model will predict a positive result for observation if the result is positive as given in Eqn. 6.

$$\text{Sensitivity} = \frac{TP}{TP+FN}\times 100 \tag{6}$$

There is sensitivity to what proportions are in reality. A positive case was predicted to be positive (or TP). The term "sensitivity" refers to recall as well. Further, a healthy person was predicted to have a harmful diet. A comparison of the results obtained by various researchers in terms of their CVD predictive performance is shown in table 3.

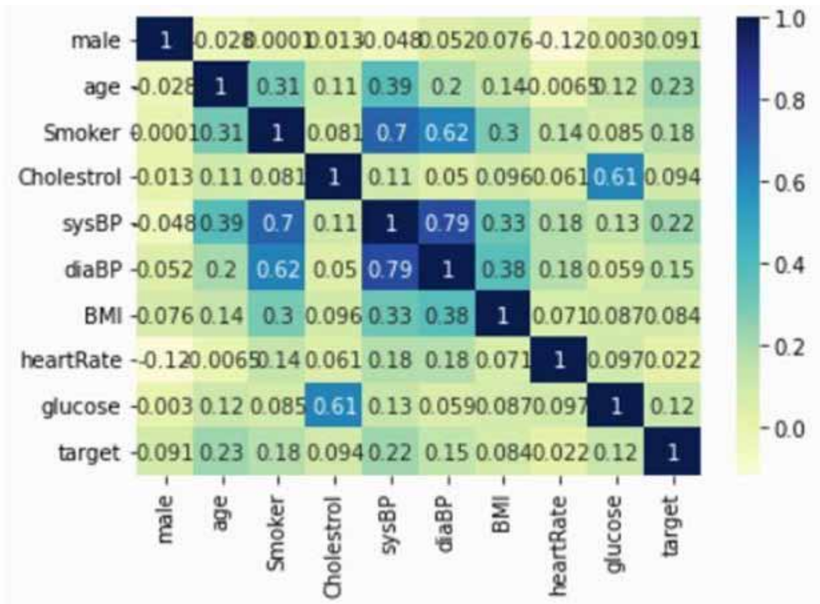
Table 3. Performance metrics of CVD prediction by various approaches

Author	Techniques	Accuracy
Wajid Shah et al.	Naive Bayes Decision Tree K-Nearest Neighbor	90.59% 82.31% 45.67%
Baban Uttamrao Rindhe et al.,	Support Vector Machine Random Forest	84.0% 80.0%
Ibrahim Abdel Motaleb et al.,	Radial Basis Function Back Propagation Network	98.0% 90.8%
Devansh Shah et al.,	Naive Bayes CNN Decision Tree RF	88.15% 90.78% 80.26% 86.84%
Kumar Dwivedi	Naive Bayes Classification Tree Logistic Regression Artificial Neural Network SVM	83.0% 77.0% 85.0% 84.0% 82.0%
The proposed model	LSTM CNN Random Forest	98.82% 95.78% 84.76%

4.3 Correlation Heat Map

A correlation plot is a plot of the covariance matrix or another metric that determines the strength of a linear federation. This matrix represents the magnitude and direction of the continuous relationship between the two parameters, with permit values ranging from -1 to 1. The covariance matrix functions provide information about the correlations between coefficients. This can be used to examine whether particular random variables have a relationship with one another. This is a great way to visualize correlation matrices as heat maps to pick out the correlations between features. The relationship between gender, age, smoking status, cholesterol, hypotension, hypertension, body mass index, pulse rate, and blood dextrose levels are expressed as a graph as shown in figure 7.

Figure 7. Correlation heat map



The linear relationship of a continuous variable is defined using dataset correlation. A correlation matrix is a square with equal variables in its rows and columns. The line at 1.00, running from top left to bottom right, is the main diagonal, showing that each variable is always perfectly correlated with itself. This matrix is symmetrical, mirroring the matrix below the main diagonal in the same proportions shown above in the heat map. There are three main types of input data for building heat maps: wide format, correlation matrix, and long format. The following steps show how to generate a correlation heat-map:

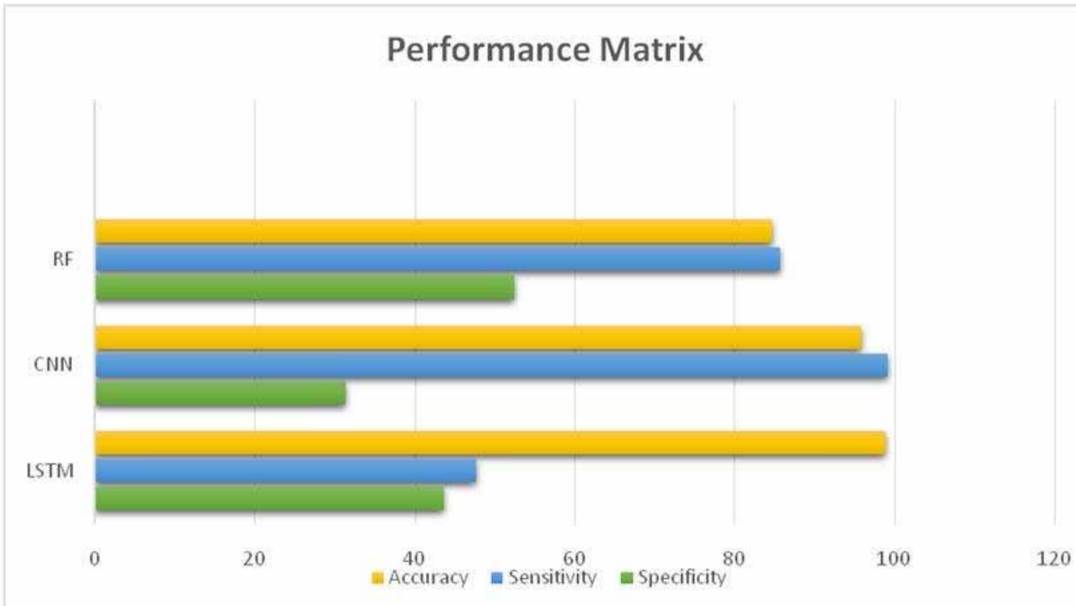
- First import all the modules.
- Second, import a file that stores the data.
- The third plot of the heat map.
- Fourth plot with matplotlib.

The heat map contains values representing different shades of the same color for each displayed value. In general, darker shades of a chart represent higher values than lighter shades. Before determining the correlation, we need to calculate the covariance of the two variables under consideration. The correlation coefficient is resolved by using the formula.

$$\text{Correlation} = \rho = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \tag{7}$$

Correlation between two random variables or two-dimensional data does not necessarily imply causation.

Figure 8. Performance metrics of proposed work



5 CONCLUSION

We can construct intelligent technology that can anticipate disease using susceptibility, reducing money and time for health checkups and tests. It is possible for patients to independently monitor their health and take precautions and remedies in the early stages of the disease. Various ML and DL approaches can be used by apps to accurately acquire and respond to user behaviors based on previous confessions. The development of a tool for predicting CVD successfully and splendidly requires an increasing number of deaths. However, the application's success depends on the precision of the classification program. The purpose of combining multiple algorithms is to improve performance. Unable to identify CVD at that very early stage will have a very slim probability of being cured. Hence, the proposed technique can produce the best possible predictions with high accuracy. The ultimate goal of our research is to enable proper and straightforward communication between medical professionals and patients without the need to visit a medication center and to make a healthcare app to prevent CVD to avoid future discomfort. Users can transmit the examined outcomes as images and upload them into real-time systems using DL. It can also use this method to predict lung diseases in the future.

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Leveraging AI Technologies for Preventing and Detecting Sudden Cardiac Arrest and Death

Machine learning approaches have great potential in increasing the accuracy of cardiovascular risk prediction and avoiding unnecessary treatment. The application of machine learning techniques may improve heart failure outcomes and management, including cost savings by improving existing diagnostic and treatment support systems. Additionally, artificial intelligence technologies can assist physicians in making better clinical decisions, enabling early detection of subclinical organ dysfunction, and improving the quality and efficiency of healthcare delivery. Further study on these innovative technologies is required in order to appropriately utilize the technology in healthcare.

Leveraging AI Technologies for Preventing and Detecting Sudden Cardiac Arrest and Death provides insight into the causes and symptoms of sudden cardiac death and sudden cardiac arrest while evaluating whether artificial intelligence technologies can improve the accuracy of cardiovascular risk prediction. Furthermore, it consolidates the current open issues and future technology-driven solutions for sudden cardiac death and sudden cardiac arrest prevention and detection. Covering a number of crucial topics such as wearable sensors and smart technologies, this reference work is ideal for diagnosticians, IT specialists, data scientists, healthcare workers, researchers, academicians, scholars, practitioners, instructors, and students.

Topics Covered

- Artificial Intelligence
- Cardiac Arrest
- Computer-Assistive Techniques
- Deep Learning
- Heart Diseases
- Machine Learning
- Mobile Health
- Smart Technologies
- Sudden Cardiac Arrest
- Sudden Cardiac Death
- Wearable Sensors

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