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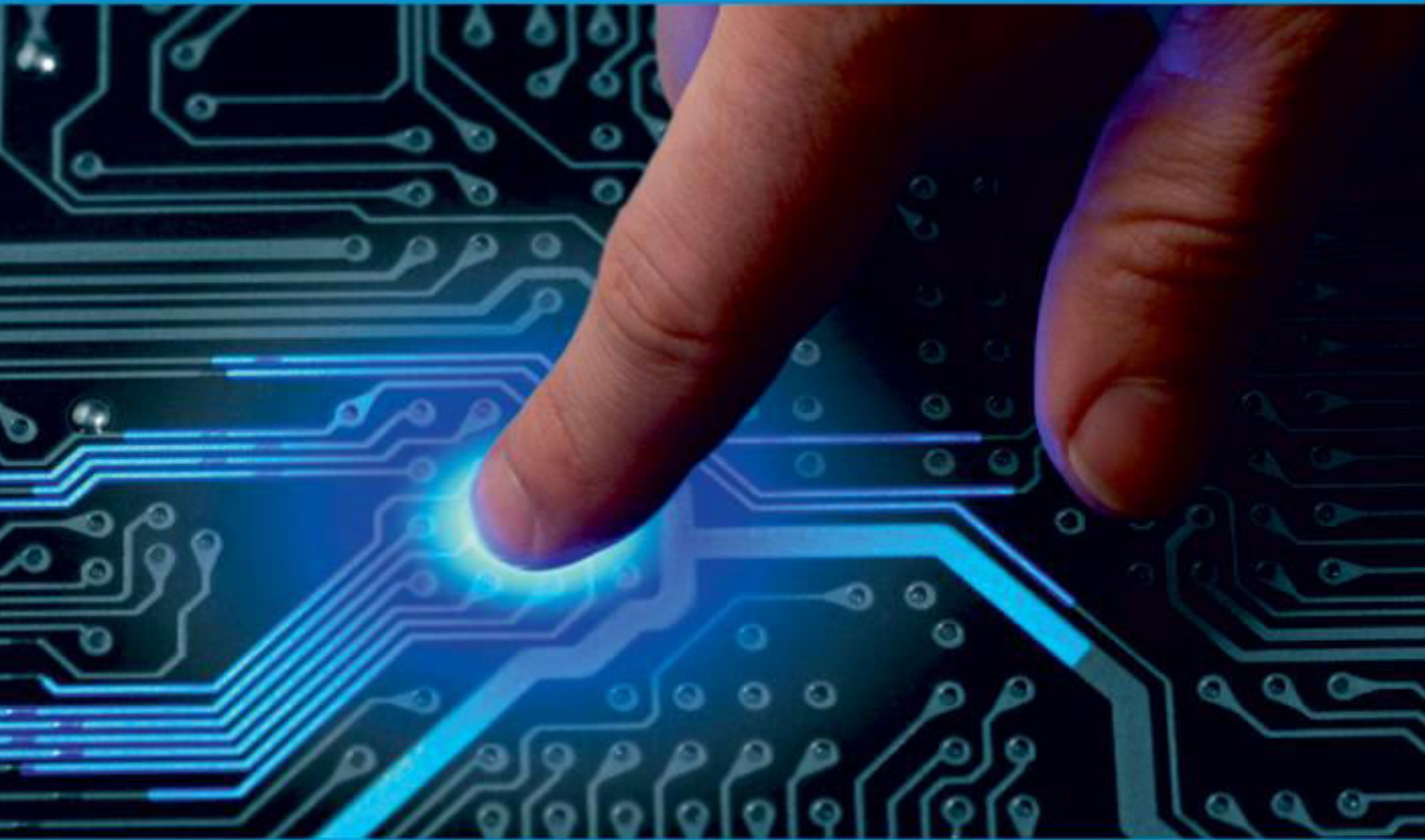

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A Technique Leveraging Deep Learning for the Identification of Coronary Artery Disease

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ABSTRACT: Coronary artery disease (CAD) is a disease in which any deterioration of coronary arteries occurs because of plaque buildup, but the arteries remain narrowed or blocked, which results in inadequate blood flow to the heart. The most common symptom is angina, the chest pain or discomfort that feels worst when you're active, but can also occur when you're sitting down, with pain that may spread to the arms or shoulders. CAD can also lead to very serious complications, including arrhythmias and heart failure. Early detection is complicated by an asymptomatic phase in many patients. About 31 percent of non-communicable diseases are caused by CAD. To address this, this study created a deep learning-based system using a Radial Basis Function Neural Network (RBNN) to detect severe CAD from electrocardiograms (ECGs). A high sensitivity and specificity was achieved with the system, with an AUC-ROC of 0.911. This technology could help improve patient care by identifying patients who need invasive procedures, optimize resources, and improve outcomes for at risk patients.

KEYWORDS: Coronary Artery Disease, Deep Learning, Radial Basis Function, Neural Network

I. INTRODUCTION

Obstructive coronary artery disease (CAD) is the most common form of cardiovascular disease and is a major public health problem in the UK and worldwide. CAD is one of the top leading causes of mortality. A coronary disease occurs when atheromatous plaques (fatty deposits composed of cholesterol, cellular waste and other substances) accumulate within the coronary arteries. These plaques can augment until they restrict the passage of blood in a way that significantly restricts the lumen, or the inner opening, of an artery. This narrowing is important; if blood flow to the cardiac muscle is obstructed by the tightening of the coronary artery, the heart muscle may not receive enough oxygen. If this oxygen deprivation persists it can lead to ischemia, and show as angina (chest pain) or a heart attack. When a vulnerable plaque ruptures, a blood clot forms and blocks the artery causing heart muscle tissue to die from lack of oxygen due to a heart attack. The risk of a heart attack can be reduced by timely identification of atheromatous plaques and the degree of vascular stenosis. Clinicians have gained much greater ability to visualize the structure of the coronary arteries and assess the extent of stenosis non-invasively through advances in medical imaging technology. Stress echocardiography (SE), cardiac magnetic resonance imaging (MRI), and computed tomography coronary angiography (CTCA) are among the most effective of the currently available imaging modalities. And each of these techniques bring with them unique advantages in the evaluation of coronary artery health, allowing for earlier intervention that can have a dramatic effect on patient outcomes and potentially save people's lives. Use of these advanced diagnostic tools helps healthcare providers to better manage CAD and prevent it's impacts on both individuals and the healthcare system as a whole [5].

An efficient screening methodology based on Radial Basis Function Neural Networks (RBFN) is developed through a deep learning approach. RBFN is a three-layer architecture machine learning algorithm that is rapid and effective, and can be used for regression as well as classification tasks. The simplest design is employing radial basis functions as activation functions and thereby the algorithm employs a supervised learning approach that simplifies design and enhances the function approximation capability. RBF networks are becoming increasingly popular in the scientific fields, because of their faster training than traditional back propagation networks, which makes them suitable for time sensitive applications. In areas of computer vision, speech recognition, and signal processing, as well as in healthcare for tasks such as diabetic retinopathy detection, cardiac arrest identification, left ventricular systolic dysfunction diagnosis, and atrial fibrillation prediction from electrocardiogram, they have shown effectiveness. This shows the

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tremendous potential of RBF networks as a diagnostic aid that could greatly improve diagnostic accuracy and improve patient's outcomes in medicine.

II. RELATED WORK

In this research, Shokouhmand et al. (2021) propose a novel reference less framework for aortic stenosis identification using SCG and GCG morphological characteristics and HRV metrics, filter architecture optimization, subject and chunk level datasets creation. We employ robust machine learning techniques, such as XGBoost, which outperform previous methods and demonstrate superior predictive capability, resulting in a cheap and reliable solution for wearable cardiac monitoring [1].

Zreik et al. (2019) describe in this study a method for automatic and non-invasive identification of coronary arteries that need further invasive testing, based on the invasively measured fractional flow reserve (FFR). Because coronary blood flow can be blocked by multiple stenoses and plaques, it is necessary to assess the functional significance of stenosis by a comprehensive evaluation of the whole artery, not a localized analysis. The methodology encodes the complex three-dimensional multiplanar reformatted (MPR) volumes of coronary arteries using two convolutional autoencoders (CAEs) and a support vector machine (SVM) based on the presence of significant stenosis. The proposed approach showed the ability to identify arteries that require invasive evaluation by achieving an area under the receiver operating characteristic curve of 0.81 ± 0.02 at the artery level and 0.87 ± 0.02 at the patient level [2].

Machine learning (ML) has been used to advantage in the healthcare domain for decision making and predictive analytics based on large data resources. Recent advancements of Mohan et al. (2019) study in the IoT sectors has further illustrated the study by utilising ML methodologies, and culminated in a hybrid random forest linear model (HRFLM) with an accuracy of 88.7% in heart disease prediction. The heart rate time series and various clinical records are used in this model and a radial basis function network (RBFN) is used for classification with a training dataset of 70% of the total data with an accuracy of about 0.8147 [3].

Coronary artery disease (CAD) is a common manifestation of cardiovascular disease (CVD) and a major global cause of death. The primary pathological mechanism causing CAD is atherosclerosis and accurate diagnosis of CAD by angiography depends on accurate lesion identification by the clinician, who uses visual evaluation for lesion identification. Freitas et al. (2022) propose the DeepCADD architecture to improve this process, using an angiography dataset to perform automatic lesion detection, instance segmentation, and performance optimization using a ResNet-50 backbone. DeepCADD has high sensitivity (approx. 0.89) and reduced false negatives, and validation studies show that it may be an effective screening tool for detecting narrower lesions and automating angiographic assessments [4].
To evaluate the relevance of the dataset, a comprehensive dataset of relevant clinical information and 5 minute single lead ECG recordings from 107 healthy individuals and 93 patients with coronary artery disease (CAD) was first established and investigated by Yao et al. (2020). This dataset was then evaluated concurrently with five different scenarios, using different ML algorithms to distinguish the two cohorts using different features from RR and QT interval time series as well as ST-T segment waveforms. Attributes from the QT interval time series were notably better for classification performance than attributes from the RR interval time series. The results were further optimized by integrating additional features from ST-T segment waveforms with the features extracted from RR and QT interval time series, resulting in the best performance metrics of 96.16% accuracy, 95.75% sensitivity, and 96.40% specificity. An automated system for CAD detection was developed based on these optimal results, by building on these optimal results using extreme gradient boosting (an ensemble machine learning framework) and a residual neural network. The results of this investigation support the use of data from ST-T segment waveforms and QT interval time series for automated CAD identification using ECG analysis [5].

In this work, Cong et al. (2019) present a process based on deep learning for the classification and localization of stenosis on coronary angiography images from a cohort of 194 patients who participated in a multi center investigation. Furthermore, stenosis activation maps were used in a weakly supervised approach for stenoses positioning. Evaluative tests for detecting 3-CAT stenosis in the RCA and LCA and 2-CAT stenosis in the RCA and LCA were successfully detected with AUC values of 0.91/0.85 and 0.91/0.87, respectively. The sensitivity for the RCA and LCA for stenosis identification at the most critical sites was 0.72 and 0.60, respectively, and the mean squared error between the detected

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and actual center points was 69.6 and 79.5 pixels in a 512 x 512 image. In these results, the approach is shown to be highly effective in classifying stenosis severity and satisfactory in localizing stenosis [6].

In this study, Ramprakash et al. (2020) developed a framework to understand the key principles of assessing patient risk profiles from clinical data factors. The suggested model is constructed using a statistical model in conjunction with a Deep Neural Network. The problem of fitting or overfitting has been solved. Both on training and testing datasets, this model performs better. The efficacy of the model to accurately forecast the presence of heart disease in individuals was tested using DNN and ANN methodologies. Training was done 242 times and validation was done 61 times. The same variables were in the training and testing datasets. The optimal configuration was identified using a grid search methodology. The weights were refined using an 80-20 holdout validation. Convergence threshold of 0.00001 is used and IBFGS algorithm is applied [7].

Vayadande et al. (2022) have taken Cleveland heart disease dataset in this study because heart and circulatory diseases are major global health problems and have caused major upheavals to medical field in recent years.s. Predicting or continuously monitoring patients with cardiac issues is complex and resource intensive in developing nations. Various data mining and machine learning techniques on the databases can accurately forecast the features of the cardiac condition. In this study, the Cleveland heart disease dataset is used, with 303 instances and 14 attributes, to apply multiple algorithms like Logistic Regression, SVM and Neural Networks. The aim is ultimately to build a good predictive model of cardiovascular disease that will be optimized by volume of diverse algorithms and the effectiveness will be tested with precision and sensitivity [8].

III. PROPOSED METHODOLOGY

A. Dataset

The Cleveland Heart Disease Dataset which we used is from the UCI Machine Learning Repository and has 303 instances with 14 attributes. One of these is a target variable indicating the presence of heart disease, and the remaining 13 independent variables serve as support for predictive modeling. The dataset consists of 8 categorical and 5 numerical variables, allowing for many different analytical approaches, summarized in Table 1. The patient records range in age from 29 to 79, thus allowing a detailed look at heart disease by demographics, including gender representation (coded as 1 for males and 0 for females). In addition, four types of angina are identified and critical numerical attributes like resting blood pressure and cholesterol levels are identified. Taken as a whole, this dataset offers a reasonably solid foundation of how to study the intricacies of disorders of the heart and their causes.

Apart from the basic factors some key categorical attributes for diagnosing heart disease are included in the dataset. Binary sex means 1 for male and 0 for female. Chest pain type has four categories: (1) typical angina, (2) atypical angina, (3) non-anginal pain, (4) asymptomatic. The fasting blood sugar is binary, so 1 means a level >120 mg/dl (true) and 0 means otherwise (false). Estes' criteria categorize resting electrocardiogram results as normal (0), ST-T wave abnormality (1), or left ventricular hypertrophy (2). Angina induced by exercise is binary (1 for presence, 0 for absence). The slope of the peak exercise ST segment has three categories: (1) upsloping, (2) flat, and (3) downsloping. The target class is binary, 1 for heart disease and 0 for normal condition. The attributes also help to understand patient conditions for cardiovascular analysis. The same is summarised in Table 2.

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Table 1. Data Description in detail

S. No.	Attribute	Code given	Unit	Data type
1	age	Age	in years	Numeric
2	sex	Sex	1, 0	Binary
3	chest pain type (CPT)	chest pain type	1,2,3,4	Nominal
4	resting blood pressure (RBP)	resting bp S	in mm Hg	Numeric
5	serum cholesterol (SC)	cholesterol	in mg/dl	Numeric
6	fasting blood sugar (FBS)	fasting blood sugar	1,0 > 120 mg/dl	Binary
7	resting electrocardiogram results (RER)	resting ecg	0,1,2	Nominal
8	maximum heart rate achieved (MHR)	max heart rate	71-202	Numeric
9	exercise induced angina (EIA)	exercise angina	0,1	Binary
10	oldpeak =ST	oldpeak	depression	Numeric
11	the slope of the peak exercise ST segment (STS)	ST slope	0,1,2	Nominal
12	Class	target	0,1	Binary

Table 2. Nominal Data Description

Attribute	Description
Sex (M or F – Binary)	1 = male, 0= female;
Chest Pain - Type	Value 1: typical angina Value 2: atypical angina Value 3: non-anginal pain Value 4: asymptomatic
Fasting Blood sugar (FBS)	(fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
Resting electrocardiogram results (RER)	Value 0: normal Value 1: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV) Value 2: showing probable or definite left ventricular hypertrophy by Estes' criteria
Exercise induced angina (EIA)	1 = yes; 0 = no
the slope of the peak exercise ST segment (STS)	Value 1: upsloping Value 2: flat -- Value 3: downsloping
Class (Binary)	1 = heart disease, 0 = Normal

Feature Extraction

Cleveland heart disease dataset has 14 columns, containing both categorical and numerical variables, and no null entries. First, the dataset is subject to exploratory data analysis, and then categorical variables are encoded into a single hot vector. Single hot encoding is a process in which categorical variables are converted to multiple binary attributes, equal to the number of categories in the original variable. Newly created attributes use binary values, in which the value is 1 if the attribute is present in the original column for that particular row. For instance, the chest pain variable can have the values of 1, 2, 3 or 4. After this, the dataset is extracted to obtain the target variable, which is the presence or absence of heart disease in a patient, based on the attributes given in each row, and the categorical data is encoded to a single hot vector. Then, we partition the dataset into the training and testing set. The training set has dimensions

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(181,24) and the testing set dimensions (122,24) giving a train test split ratio of 0.40. Furthermore, the training set is further separated from the validation set. We will optimize model parameters using the training set, and use validator set to compute the loss function through it.
The entire process flow is shown in figure 1.

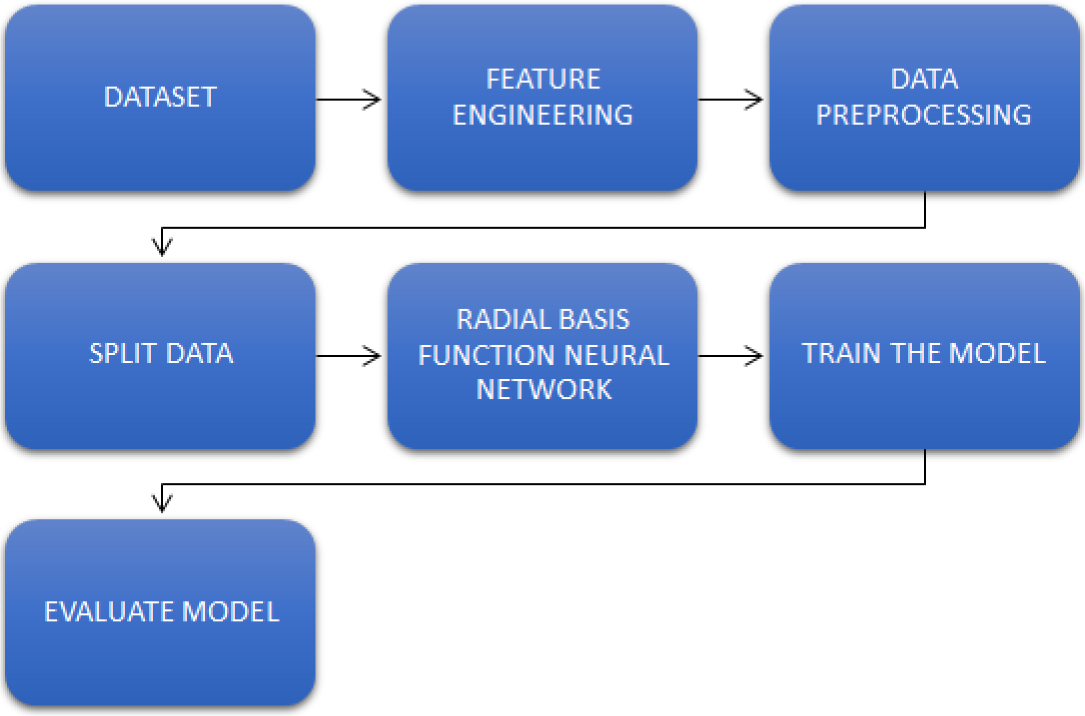

Fig 1. Process Flow Diagram

Radial Basis Functions and Classification

A Radial Basis Function (RBF) is a special type of mathematical function that, fundamentally, is based on distance in its calculations. RBFs have a unique characteristic in that they depend on the distance from a central point, and so can have a wide range of behaviors based on the parameters and criteria they use. By virtue of its inherent flexibility, RBFs can be adapted to be useful across many different applications in different fields, including machine learning and data analysis. RBFs find one very important application, that of constructing artificial neural networks, in particular for classification. In this context, RBFs are used to define boundaries over data samples with the same label. The diagram of this classification technique is visually represented as distinct regions, each region having characteristics of the data points and corresponding to a specific label. Defining these boundaries is an essential process because they permit the categorization of new, unseen data points according to their closeness to the already known regions. A simple classification mechanism can be used by assigning each closed region a label which reflects the majority of its constituent data samples. Yet, it should be noted that task of accurately defining these borders can be highly complex. A classification performed with RBF networks exhibits varying effectiveness under different circumstances: depending on the sample distribution, choosing the RBF parameters, and the number of dimensions in the feature space. This results in practitioners often finding it difficult to achieve optimal boundary definitions, which requires careful thought and possibly more advanced techniques to improve the classification process.

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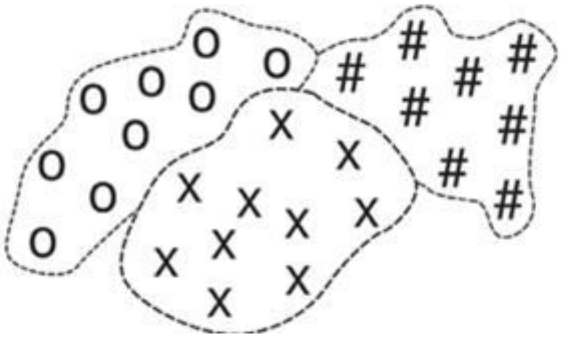

Fig 2. Border between Classes

A more effective approach is to use a range of clearly defined boundaries and combine them well to create a complex border. But this method is more creative and precise in design. Radical shapes, in particular, are nicely suited to this endeavor since their symmetrical nature and dynamic forms will contribute to the visual appeal of the border without losing structural coherence and balance. With the utilization of these geometric elements one can achieve a beautiful balance between simplicity and complexity to produce a strangely cool, sophisticated yet striking design that simply beckons you to really look and see what is actually there.

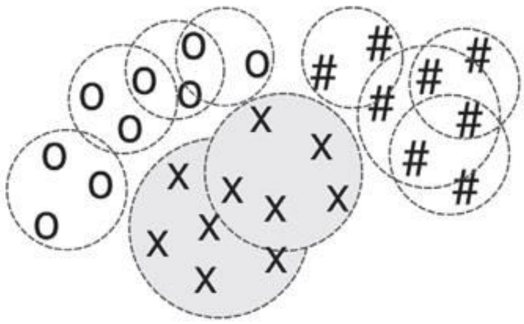

Fig 3. Border defined with RBF's

In the context of Radial Basis Functions (RBFs), it is important to note that data samples belonging to the same class can be covered by multiple circles (as shown in the accompanying figure). This characteristic permits a large increase in the coverage area, since each circle corresponds to a different RBF. In so far, more nuances and more flexibility of modeling data distribution are possible with utilizing plural RBFs, and therefore it would be possible to model complicated patterns and relationships between the data elements. Using this approach allows us to gain a more thorough insight into the underlying structure of the data, and as a result more effective classification and regression tasks.

Gaussian Functions

Kernel function is defined as any extra function that is related to some specific topic or mathematical framework, specifically in the context of machine learning and statistical modeling. Radial Basis Function Networks (RBFN) are one of the many kernel functions within the realm of RBFN, and one such kernel function is the Gaussian function that is a fundamental building block for many applications. The Gaussian function is characterized by its distinctive bell-shaped curve and is mathematically expressed in equation 1.

$$g(k) = ae^{\frac{-\|k-b\|^2}{2c^2}} + d \quad (1)$$

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This formula is based on a single input parameter, called k; and four internal parameters: a, b, c and d. While the initial form of the equation is the source of a certain flexibility in defining various Gaussian functions, this framework provides a lot of flexibility allowing for the way those functions are defined. Figure 3 shows a visual representation of the output of a Gaussian function as it changes with a one-dimensional distance, and explains the role that each parameter plays in the function. It is important to realize that the parameter k is the variable parameter, which is an outer point in the function. On the contrary, the parameter 'b' gives the centre of Gaussian function, which is fundamental in defining peak of function. In particular, when using Gaussian functions across different dimensional spaces, the "k" and "b" parameters are mostly changed. As an example, if we have a three-dimensional space the parameters will be (x, y, z) expanding the functionality of the function beyond a single dimension. In addition, the Radial Basis Function Network (RBFN) is composed of n different numeric input nodes, one for each distinct point in an n dimensional space. That is, parameter "b" can be positioned to include all input nodes, while keeping the minimum radius by varying parameter "k." Much work was done on analyzing different values of a and c that could define the RBF parameters including defining a and c and their effect on the RBF mean. Combined, these parameters constitute a complete set of tools to manipulate Gaussian functions in a multidimensional context, to be used in a variety of applications in data analysis and modeling. The RBFN graph is given in Figure 4.

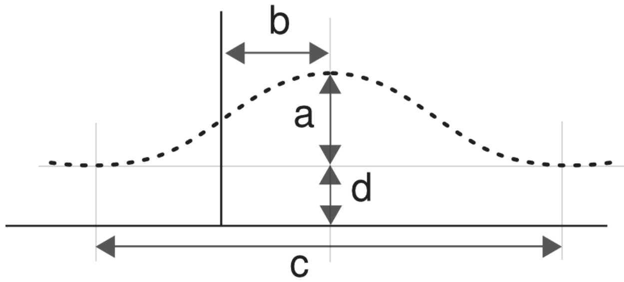

Fig 4. RBFN Graph

An RBFN has an unusual architecture in that output neurons have connection weights to the radial basis functions (RBFs). The setup of this is so distinctive that it can be used to simplify the Gaussian function used in RBFs. In particular, we can eliminate consideration of the 'a' parameter, which is usually related to the width of the Gaussian, simplifying the application of the function within the network. Additionally, the coefficient of $(2c^2)^{-1}$, which is obtained from the standard form of the Gaussian function, can be efficiently substituted with a parameter called beta (ß). This substitution not only improves the flexibility of the model but also makes it easier to define the RBF for use in RBFNs. Therefore, the revised RBF given in equation 2 can be written in such a way that they are optimally aligned with the operational dynamics of the network for better performance and adaptability in different applications.

$$g(k) = e^{-\beta \|} \parallel k - b \parallel^2 \quad (2)$$

RBFN for classification

Radial Basis Function Networks (RBFNs) are a novel way to classify data by defining regions for different classes in an n dimensional space. RBFNs are different from Multi-Layer Perceptron Neural Networks (MLPNNs) that depend on building linear separation boundaries, but they use multiple Radial Basis Functions to separate these classes effectively. Several advantages over traditional MLPNNs are afforded by this methodology. The inherent flexibility of RBFNs in handling the complexity of the classification task is one of the most important benefits of RBFNs. RBFNs accommodate the dynamic addition or removal of RBFs to the network as the required separation boundaries become more intricate and specific. This allows the network to tune its performance according to data nature. In practice, the collective decisions of each RBF for the respective classes are aggregated in the RBFNs. The evaluation of the output from each RBF contributes to a comprehensive decision-making framework for the entire network. The robustness of classification can be improved by being able to contemplate the decision of multiple RBFs. Moreover, the number of RBFs in the network can improve greatly in classification accuracy. The most recent classification outcome is determined based on a linked class, and each RBF's decision is a foundational input. By taking a cumulative decision-making approach, the network is able to refine its predictions over time, based on the new patient records or data points added to the system. As a result, the RBFN not only learns from new information, but also becomes more predictive.

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B. Implementation

Radial Basis Function (RBF) networks have almost uniform methodology concerning the training and testing. The training consists of generating a new RBF using multiple database records, potentially leading to areas of potential misclassification. As the training progresses, further RBFs are added, which can lead to the network behaving inconsistently with its training categories, and therefore, a special strategy is applied. RBF networks consist of two training layers: The RBFs are in the hidden layer and the weights in the output layer are linear and with sigmoid functions, so the training is in two parts. Feedback based supervised classification systems use a mechanism to refine their internal parameters with known input and known expected output. If the output layer does not work out, then node parameters must be adjusted. The RBFN structure is defined, but the algorithms can be modified for different outcomes depending on the application.

Output Layer Training

These nodes are characterized in this layer with specific weights (wi) for each of Radial Basis Function (RBF) nodes and specific values of the corresponding threshold values all together which lead to a desired result. A Radial Basis Function Network (RBFN) is a network that seeks to determine whether an input matches one or more pre-defined classes. Therefore, nodes of this layer must be considered as having a binary output mechanism. This is a Binary output meaning that it indicates whether a class membership is present or not, so that the network can classify inputs on the basis of how near they are to the center of the RBF nodes. A nuanced decision-making process is thus enabled such that each node assesses the input against its weight and threshold to produce a refined class, making the network more able to classify correctly and is given in equation 3.

$$\text{Output} = \sum w_i \text{RBF}_i > \text{Threshold} \tag{3}$$

Hidden layer training

This layer is where nodes can be configured to the smallest degree possible with a specified array of parameters that are intricately tied to different kernel functions, with the Gaussian function being the focus of this study. In particular, the research uses the condensed Gaussian function, which exhibits its own unique properties and flexibility. This function incorporates two essential internal parameters that play a pivotal role in the training process: so the area of coverage (β) referring to the spread of width of the distribution, and the center position (b), the focal point of the Gaussian distribution. Together, these parameters enable us to refine the adjustment of the nodes in order to improve their ability to model complex data patterns.

This initial determination of the positions of the Radial Basis Function (RBF) within the model is done using the foundational k-means algorithm. The training process unfolds through a series of methodical steps designed to optimize the performance of the RBF network. The steps are as follows:

1. **Data Aggregation**: The organizing of the training dataset in the first place was to group together all instances with the same label. This step is important, since many more subtle distinctions are impossible to disentangle by the model from data that are not homogenous.

2. **Center Position Calculation**: After grouping the data, we compute the next position, called “b,” which represents the centroid (or center of training data points) within a particular label category. To facilitate the RBF centreing, this centroid is computed by averaging the coordinates of all points in the group, i.e. finding a reference point around which the RBFs will be located.

3. **Average Distance Computation**: After setting the center position, the algorithm will find out how far every training data point, or “a,” is from the centroid ‘b’, and sums them up in average distance, what we can refer to as “c”. It is this distance measurement that is important as it is the spread of the data around the centroid, and therefore provides a more nuanced understanding of the data distribution.

4. **Beta Parameter Setting**: The second step is to choose the parameter β from the average distance “c.” In particular, we calculate β as $\beta = (2c^2)^{-1}$. This parameter greatly determines the width of the RBF, determining how the function responds to input as a function of their distance from the centroid.

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5. **Weight Assignment**: Finally, the algorithm gives the weights of the outputs a value corresponding to the classification. If the model gives a correct prediction, then the weight is 1, i.e. a high confidence on the model's prediction. On the other hand, a weight of 0 is assigned for those outputs that don't match the expected classification. The binary weighting system serves to reinforce the learning process by concentrating on the improvements in accuracy of the variable with the most errors.

These systematic steps provide a powerful way for the k-means algorithm to initialize the RBFs in such a way that a robust training process opens the door for a strong improvement in the model's predictive capacity.

Testing RBFN

Each of the cardiac condition is represented by a particular neuron in the output layer of the neural network. The output neurons are given the values of a weighted input and Radial Basis Function (RBF) values. Each RBF value is computed by measuring the distance of each RBF to a reference point that is specified by the input neurons. This is important because it lets the network judge how close the input data is to the characteristics of known cardiac ills.

Once fine-tuned during that training phase of a network, the internal parameters of the neurons are used to maximize performance and accuracy. The output of the network is generated through a series of systematic steps, which are as follows:

1. **Input Initialization**: First, we have to set each input neuron value for the network to give. That's vital since it lays the groundwork for all other calculations.
2. **RBF Calculation**: And we calculate the values of all the RBFs on the basis of input neurons. This calculation represents how well the input data is in converged with the given RBFs reference points for the RBFs network to distinguish between different cardiac conditions.
3. **Weighted Sum Calculation**: After doing the RBF calculations, the network takes the input, computes the weighted sum for each output neuron. This is accomplished by multiplying the weight of each RBF and RBF value, and summing these results. First, this is necessary to determine which RBFs affect the output neurons.
4. **Threshold Application**: A final step consists in applying a threshold to the sums of each of the neurons. This thresholding process allows us to determine whether or not the output neuron is activated (i.e., to translate the weighted input and RBF values into a definitive classification of the cardiac condition represented by that neuron).

By performing these lengthy activities, this methodology of the neural network can properly evaluate and classify numerous cardiac diseases in accordance to the input data it is given, which is of great assistance to the medical diagnosis and patient care.

IV. RESULTS

A comprehensive evaluation of the model was performed using different performance metrics to gain a robust view of the model being effective. The precision, recall and F1 score key metrics were analyzed in detail as they are a critical basis of how the model's capabilities for predicting are done. Of all the contemporary deep learning techniques, the radial basis function neural network showed an outstanding accuracy of 83%, so impressive that it was particularly noteworthy comparing with the performance of other deep learning techniques. Such accuracy shows the model to be reliable yet competitive over the advanced machine learning frameworks landscape. The precision score was recorded at 0.782 and we delve deeper into the individual metrics. This means that when the model predicts a positive outcome, it is correct 78.2% of the time, which is a reasonable level of reliability in the positive identifications. Additionally, the model was able to recall 93% of the actual positive cases at 0.930. In particular, this high recall rate is helpful in situations where the cost of missing a positive case is high.

The F1 score (F1 score) of 0.850 balanced precision and recall. This is important because it gives us a single score, which combines the model's accuracy in positive predictions with its ability to capture all relevant instances. The strength of the performance is indicated by a score of 0.850 which indicates that the model generally has good trade-off between precision and recall.

In addition, the area under the receiver operating characteristic (ROC) curve was 0.911. It is also this value that indicates how well this model performs as the true positive rate relative to the false positive rate at a variety of thresholds. The radial basis function neural network perform so well in classification that the corresponding AUC stands at 0.911 and suggests that the model is very good at distinguishing positive class and negative class.

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In summary, the radial basis function neural network capabilities are strong in its domain and is a reliable as well as a good approximator of some function. This has been visualized in Figure 5 as ROC Curve.

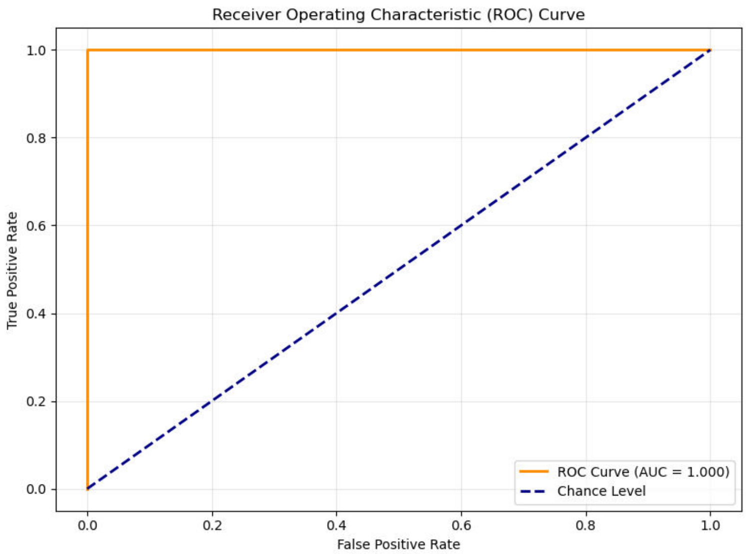

Fig 5. ROC Curve

V. CONCLUSION AND FUTURE WORK

In medicine, identifying and prognosing heart disease is critical. This work introduces Radial Basis Functions (RBFs) and Radial Basis Function Networks (RBFN) and proposes a new method for classifying heart disease in patient records using an automated continuous improvement technique. RBFNs are simpler, more flexible, with only three layers, and thus more efficient than Multi-Layer Perceptron Neural Networks (MLPNN). We are currently implementing the RBFN classifier system and expect it to perform better than MLPNN using a large amount of patient records. The core implementation is complete, and the user interface design is underway for the purpose of demonstrating the system's potential in cardiac disease classification. It is expected that this method will impact other classification methods to increase their accuracy and future studies will explore deep learning techniques such as Deep Belief Networks, Restricted Boltzmann Machines, and Deep Autoencoders to further improve diagnostic accuracy.

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