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Research article

Cardiac arrhythmia detection using artificial neural network

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ABSTRACT

This paper outlines the development of the 'Cardiac Abnormality Monitoring' wearable medical device, aimed at creating a compact safety monitor integrating advanced Artificial Neural Network (ANN) algorithms. Given power consumption constraints and cost-effectiveness, a strategy combining sophisticated instruments with neural network algorithms is proposed to enhance performance. This approach aims to compete with high-end wearable devices, utilizing innovative manufacturing techniques. The paper evaluates the feasibility of employing the Levenberg-Marquardt (LM) ANN algorithm in power-conscious wearable devices, considering its potential for offline embedded systems or IoT gadgets capable of cloud-based data uploading. The Levenberg-Marquardt ANN is chosen primarily for its practicality in prototype development, with other neural network algorithms also explored to identify potential alternatives. We have compared the six neural network models and determined the model that has the potential to replace the primary neural network model. We found that the 'Kernelized SVC with PCA' can test accuracy. To be specific, in this paper, we will evaluate the performance of the ANN model and also check its feasibility and practicality by integrating it with a constructed prototypical working model.

1. Introduction

The heart's rhythmic sequence dictates its typical beating pattern, facilitating efficient blood circulation in a healthy body. Heart attacks indicate weaknesses and failures within the heart and its myocardium, including conditions like coronary diseases and localized necrotic areas within the myocardium. Such failures often lead to irregular heart rhythms, termed arrhythmias, which can cause discomfort associated with these conditions [1].

Usually, the heartbeat begins when the electrical stimulus from the heart's Sinus Node moves through the heart's muscle tissue. The normal cardiac rhythm is shown in Fig. 1a. In Ventricular Fibrillation, electrical impulses fire abnormally as illustrated in Fig. 1b. While such abnormalities may occur temporarily due to intense physical activities, repeated occurrences indicate an underlying problem and need immediate medical attention.

According to estimates from the World Health Organisation, complications from Coronary Heart Disease (CHD) cause approximately 12 million deaths worldwide annually. Various factors, including diabetes, levels of HDL and LDL cholesterol, smoking habits, obesity, and genetic predisposition, increase an individual's risk of developing coronary heart diseases (CHDs). Recently, var-

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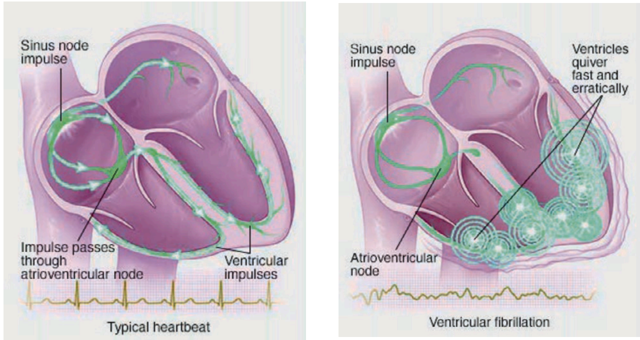


(a) (b)

Fig. 1. (a) Normal cardiac rhythm ; (b) The flow of electrical impulses in the case of Ventricular Fibrillation.

ious studies have shown the impact of Coronavirus 2019 (COVID-19) on the cardiac health of people. Patients who have contracted COVID-19 are at a high risk of developing complex cardiac problems, including arrhythmia. In such cases, it is essential to accurately predict and diagnose these cardiac abnormalities in a timely manner, especially for those individuals who are at particularly high risk of developing these conditions.

In India, in the city of Nagpur, Maharashtra [2], authors conducted the study on Atrial Fibrillation (AF) observed during medical checkup camps. They gathered crucial information, such as blood pressure, height, weight, diabetes screening results, and ECG readings from the residents. Despite atrial fibrillation (AF) being a significant global public health concern [3], the study [4] in a secluded Himalayan village revealed that its inhabitants represent the highest prevalence of AF. In this study, the authors' motivation was to evaluate the ubiquity of AF among the metropolitan population. The pilot study indicated a low prevalence in this region and concluded that AF and arrhythmia can impact people irrespective of their geo, age, or gender. With a wearable arrhythmia detection device, people at risk can be continuously monitored for abnormalities in their cardiac rhythm. A timely diagnosis can be done to control and manage their health, thus avoiding further health complications. A device with an Artificial Neural Network (ANN) capability built into it can provide valuable information to the doctor to diagnose correctly and provide accurate and timely medical attention. Throughout this paper, we aim to develop a mobile, compact, and wearable 'Cardiac Abnormality Monitoring' device trained with ANN capabilities.

The Cardiac Abnormality Monitoring device's importance lies in its lightweight design, which ensures patient comfort while being worn. Equipped with pre-trained Artificial Neural Network algorithms, the device can predict abnormalities. A database securely stores readings, enabling comprehensive pattern analysis and predictions. The cloud-based system ensures easy and secure access to medical data for patients, caretakers, and doctors, anytime and anywhere. Future improvements may involve integrating the device with other medical or monitoring devices (IoT), allowing for automatic alert triggers and proactive care engagement.

Artificial Neural Networks (ANNs) are widely recognized and essential tools for evaluation and prediction. In the medical industry, ANN-based consumer solutions are crucial for enhancing the effectiveness and reliability of medical management for the public at large. Artificial neural networks can detect various conditions requiring urgent attention, such as coronary heart diseases and arrhythmias. The availability of digital data for relevant conditions enables the utilization of artificial neural network models, which can significantly reduce both the production time and time-to-market for the model.

A clinical-level interpretation helped establish a fully autonomous plan of action, boosted by ANNs. Although many studies that implement high-performance custom neural network models exist, our study focuses on choosing and testing a neural network model that offers better performance and has a lighter resource footprint to work on a low-power, low-cost device. A strong ANN model powering up a stable device can deliver significant performance over conventional models such as the above-stated Apple Watch.

The format of this paper is presented as follows. The second section lists out some of the literature surveys of considerable importance. The third section briefly describes the Levenberg-Marquardt ANN model. The fourth section gives a detailed insight into the implementation methodology. The fifth section assesses the final results and the overall effectiveness of the ANN model in terms of feasibility and accuracy (implemented in both MATLAB & JupyterLab IPython IDEs). Finally, our paper is concluded at the sixth section.

2. Literature survey

In this study [8], about five hundred pregnant women's echocardiography documentations were congregated by those researchers. The cardiologists contrasted the FECG reference diagnostic with the diagnosis based on NI-FECG after analyzing the obtained NI-FECG. This study concludes that while the NI-FECG approach may be used to detect arrhythmias in infants during the development phase, it is crucial to emphasize advancements in the models used to remodel the P-wave.

The study in [9] discusses the prevalence and differential management of Arrhythmia in unborn fetuses. The study revealed that arrhythmias are more common during the first 18 weeks of pregnancy. They also signify that around 10% of pregnancies get complicated as a result of such cardiac issues.

Table 1
Comparison of our work with other similar articles.

Articles(s)	Approach in the literature	Our Approach
[5]	This study focuses on obtaining the minimum possible data pre-processing using certain deep learning techniques. The authors obtained their results using high-end technology such as Tensor and NVIDIA GPUs.	Our paper focuses on determining the best neural network model that precisely fits and works as expected on a minimalistic, yet capable embedded hardware.
[6]	The authors' groundbreaking study showcases the power of deep neural networks, which were trained on over 10,000 ECG records to detect arrhythmia and thereby achieving over 92% accuracy in their rhythm classes, paving the way for more accurate and efficient diagnosis.	In contrast, our study focuses on exploring a generic yet capable neural network model utilizing a single dataset for use in practical devices. Throughout our experimental progress, we intend to achieve the balance between 'performance' and 'affordability'.
[7]	In this study, based on ECG morphology, the authors developed and trained an elaborate convolutional neural network with a depth of nine layers to classify the type of heartbeat with an incredible accuracy of about 93.47% from the given noise free ECGs.	We focus on choosing the best model that requires minimal hardware resources while providing unparalleled accuracy. The literature studies often use high-end computing resources to train and test the models.

According to this study [10] from Europe PMC, Ventricular Fibrillation has been detected and diagnosed in virtually almost 70% of the participated cardiac arrest inpatients.

In the relevant study in [11], the authors have offered the essential understanding regarding the importance of employing an Apple® wristwatch to monitor and potentially analyze the heartbeat sequence. In this work, the authors have concluded that the device barely performed up to the mark.

Yet in another paper [12], the authors discuss the Intrapartum cardiac arrhythmias in unborn fetuses. With the aid of the direct fetal ECG, the authors of this study collected and compiled 15 diverse incidences of cardiac arrhythmia occurring in fetuses. According to the perspective of this study, there are approximately 12.4 diagnosed cases of arrhythmia for every thousand newborns observed. The report also notes that any ventricular fibrillation (VF) was linked to various forms of health declination.

In [13], the authors have tested the potential and materializing aspects of electronic wearable technologies dedicated solely to detecting VF. This paper also assesses the efficacy of photoplethysmography (PPG) based wearable devices, both with and without the integration of machine-learning algorithms. It finally concludes that the latter provided even more dependable and confident performance statistics.

Improved understanding of the Levenberg-Marquardt ANN model's performance in predicting CHDs is presented in a relevant study [14] by the authors who proposed a novel approach.

In [15], authors classify the VF using only a few selected features from the IBPLN and LM, which were tested on the UCI database. Their experimental results prove to be 87.71% accurate using around 100 simulations on average. For revising the essentials of the mathematical part of the Levenberg-Marquardt neural network algorithm and the concerned corresponding theoretical models, the study in [16] discusses the backpropagation algorithms, neural network computing, and Newton's methods proved to be handy and as a prominent reference for this paper.

From the aforementioned studies, the literature addresses the existence of ventricular fibrillation (VF) in the general population and the importance of utilizing generic algorithms or devices for such purposes. This paper chose the Levenberg-Marquardt NN for the possibility of implementation in MATLAB® and the ease in pairing the above with a hardware (specifically a semiconductor-based) device. The algorithm has been a popular choice of neural network implementation in various other hardware-specific designs. No particular study uses the Levenberg-Marquardt ANN algorithm specifically for detecting ventricular fibrillation, along with the test for building a practical model. Thus, we begin our novel approach to further explore this area by utilizing the evident research gap. We've also compared our results with similar articles, as shown in Table 1.

To summarize the following table, the following studies explore and train various neural network algorithms with pronounced accuracy, but the cost of extensive computational power required to train the neural network model ultimately proves to be the greatest challenge to be dealt with. In the literature, many computationally intensive solutions have been proposed to achieve high accuracy. They consider large data sets, high-end processing tools, and high power demands. We propose a hardware-based solution with high accuracy and minimal power consumption. We aim to determine a minimal yet powerful neural network model capable of giving the best possible results on our prototype.

Major contribution and novelty

As a first step in our study, we follow a 'conventional' approach by building a prototype using Levenberg-Marquardt ANN. This model is one of the most used neural network models for hardware implementation. However, this approach performs well in simulation but doesn't give a good performance practically. Our work attempts to explore other alternative neural network models further and determine the best alternative model for use in such cases. We trained six generic neural network models such as 'Random Forest' and 'Kernelized SVM', to achieve the maximum possible test accuracies. We found that the 'Kernelized SVC (with PCA)' has the highest test accuracy (about 81.2%) for the given database. Furthermore, the overall footprint size of the trained neural network model is suitable to be deployed on embedded hardware.

This paper demonstrates originality by combining wearable technology with artificial intelligence (AI) techniques for cardiac abnormality monitoring. While the individual components (wearable devices, neural networks) have been studied before, integrating these technologies in the specific context of cardiac arrhythmia detection represents a novel contribution to the field. The use of the Levenberg-Marquardt ANN model for this purpose adds a unique dimension to the research, potentially offering advantages over other methods.

3. LM ANN model

As of right now, [17], the Levenberg-Marquardt (LM) method is the most sophisticated non-linear optimisation technique and among the most efficient for MLPs (customised hidden networks). The Levenberg-Marquardt algorithm is primarily used for fitting least squares curves and minimizing the sum of square error functions. The LM algorithm perfectly fine-tunes the parameters of the curve associated with the specified model $f(x,\beta)$ using a practical dataset comprising the variables (x_i, y_i). Where (x_i) and (y_i) are the attributes. In this context, one can efficiently iterate the multiplication of squared variable rates of deviations, ultimately becoming the variable $S(\beta)$ as given in (1).

$$S(\beta) = \sum_{i=1}^{a} [y_i - f(x_i, \beta)]^2 \tag{1}$$

The parameter vector, β, is changed in each weight change step by a fresh approximation, $(\delta + \beta)$. The linear equivalent of the functions $f(x_i, \delta + \beta)$ is used to determine δ [18] as given in (2).

$$f(x_i, \delta + \beta) \approx J_i \delta + f(x_i, \beta) \tag{2}$$

Wherein the variables: $J_i = \frac{f(x_i,\beta)\delta}{\beta\delta}$ is the descent of the function f with respect to the parameter vector β.

Regarding this, we select the derivative of S. To obtain the smallest values of the squares added together, $S(\beta)$, use this δ value and set it to zero. The resulting equation is given in (3):

$$(\lambda I + J^T J)\delta = J^T [y - f(\beta)] \tag{3}$$

$$J = \begin{bmatrix} \frac{\delta y_1}{\delta x_1} & \cdots & \frac{\delta y_1}{\delta x_b} \\ \vdots & \vdots & \vdots \\ \frac{\delta y_a}{\delta x_1} & \cdots & \frac{\delta y_a}{\delta x_b} \end{bmatrix}$$

J is the Matrix of Jacobean, I is the Matrix of Identity, δ is the incrementing factor added to β and λ is the damping factor.

A smaller rate can be used if the alternation of S is quicker, settling the process closer to the Gauss-Newton technique. One step nearer to the descending gradient approach can be attained for fair changes in S by increasing λ [19]. The diagonal matrix of the JJ^T diagonal elements restores the identity matrix (I) in the LM method. Using the said approach, the gradient components can be amended about the curvature to allow for bigger oscillations towards the direction of those minor gradients and intercept the steady convergences in these directions.

An alternate representation of this algorithm can also be depicted using quasi-Newton methods. The LM algorithm was developed to get close to the second sequence training streak instead of the absolute need to compute the Hessian matrix (4). The Hessian matrix can be approximated by training the feed-forward network, and the evaluation function takes the figure of adding squares.

$$H = JJ^T \tag{4}$$

while its corresponding slope (5) can be worked out as:

$$g = eJ^T \tag{5}$$

For Newton-like recondition, the LM algorithm uses the following conjecture to the matrix of Hessian as given in (6):

$$x_m - 1 = x_m - \frac{eJ^T}{[\mu I + J^T J]} \tag{6}$$

When the scalar variable μ approaches zero, it transitions into gradient descent with a smaller step size as it increases in magnitude. Newton's method is faster and more precise. This method decreases the performance function with each accomplished step and only increases it when a corresponding approximate step increases it. At every algorithm's iteration, the rendering function is diminished in this manner.

Focusing on the implementation in MATLAB®, the above-discussed Levenberg-Marquardt backpropagation algorithm can be employed to train and create an NN file using the inbuilt training function '***trainlm***.' It is a priming function that renovates bias & weight values according to the said LM enhancement. Though this chosen ANN model consumes more power and RAM, the results are considerably faster. They are of higher quality when compared to the other equivalent backpropagation algorithms. Specifically, in this paper, we evaluate the performance of this model and also check its feasibility and practicality by integrating it with a constructed prototypical working model.

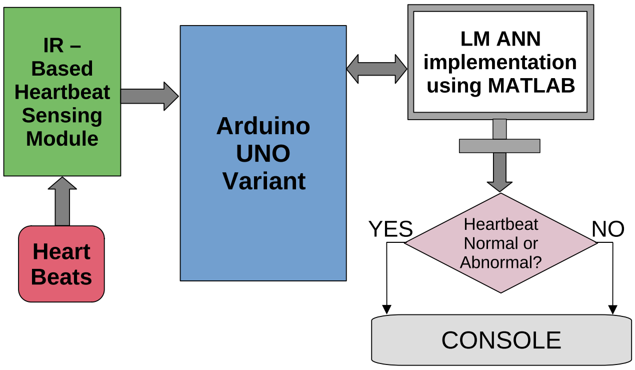
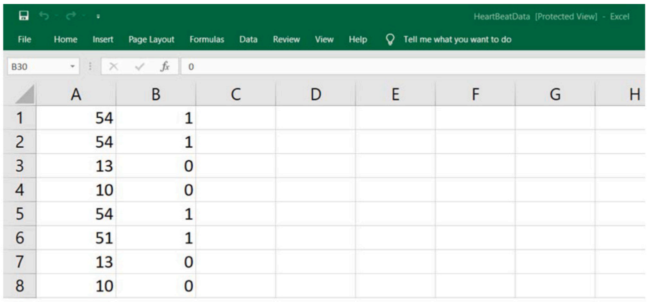


Fig. 2. Block Diagram (using MATLAB®).



	A	B	C	D	E	F	G	H
1	54	1						
2	54	1						
3	13	0						
4	10	0						
5	54	1						
6	51	1						
7	13	0						
8	10	0						

Fig. 3. Contents of the created 'HeartBeatData.xlsx' database.

4. Implementation methodologies

4.1. Primary implementation using MATLAB® 2023a tool:

This paper discusses an instantaneous embedded working model with the necessary aid of MATLAB® 2023a academic version software and LM ANN. The working model comprises a basic variant of the popular prototyping board Arduino UNO (with ATMEL ATmega328P, an 8-bit microcontroller), an IR (Infra-Red) based pulse reading sensor - for monitoring the cardiac rhythms in real-time. The observed readings shall be stored in a spreadsheet program database file, and that particular file will be further utilized to train the Levenberg-Marquardt model. The trained ANN then decides whether the input cardiac rhythm is normal. The primitive block diagram for the device is shown in Fig. 2.

Simulating and training from scratch, the following three MATLAB® files are created:

- **HeartbeatCode.m** initializes and establishes the connection between the Arduino UNO and the MATLAB® software. It also creates an Excel database, 'HeartBeatData.xlsx.' It then writes the cardiac rhythm values (monitored on a real-time basis) into the file, checks whether they are higher or lower than the specified limit, and writes the corresponding result in the next column.
- **Main.m** uses the "HeartbeatCode.m" file and its Excel database to create and train a neural network file using Levenberg-Marquardt ANN, save the trained network as 'net. mat' and display the data, performance, and regression graphs.
- **TestValue.m** uses the trained 'net. mat' neural network file to predict the condition of the cardiac rhythm from a sample input value.

It is to be noted that the three MATLAB® files needed to be executed in the exact order specified above. Training the ANN model repeatedly leads to inconsistencies in their respective regression test results. After the **HeartbeatCode.m** file is executed, and the contents of the 'HeartBeatData.xlsx' Excel database are as shown in Fig. 3.

The values in the first column represent the rate of the cardiac rhythm, while the values in the second column denote whether there is a prevalence of cardiac abnormality (1 for Yes and 0 for No). Fig. 4 (a-d) illustrates the circuit diagram for the working model, along with the mentioned module.

Due to the resolution limitations in using a readily available cardiac rhythm detection module (such as MAX30100), we have opted to design a custom made Infra-Red based detection module that ideally suits the constant need for modification and troubleshooting while also exploiting the robustness of the improvised module.

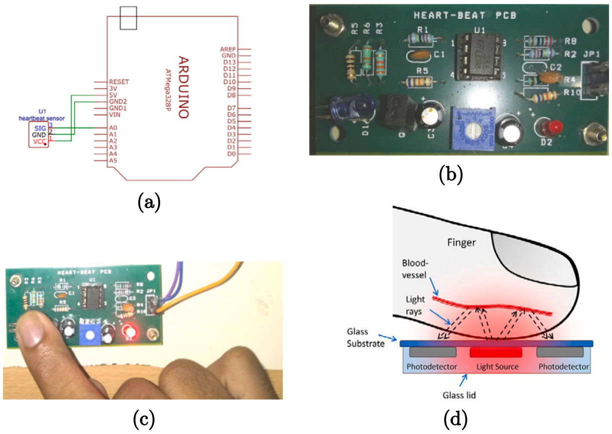


Fig. 4. (a) The circuit diagram of the working model (b) The custom-made cardiac rhythm detection module (c) the readings taken by keeping the index finger between the IR diode and the photo-transistor (d) A generic illustration of how the device detects the cardiac rhythms.

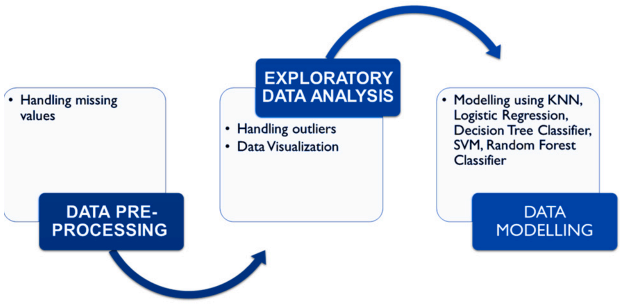


Fig. 5. Block Diagram (using JupyterLab IPython IDE).

4.2. *Additional implementation using JupyterLab IPython IDE*

Furthermore, this paper also tests the feasibility and performance of various other algorithms (such as Random Forest and KNN, to name a few) using JupyterLab IPython online IDE. The general block diagram for data pre-processing and data modeling is shown in Fig. 5.

4.2.1. *Data pre-processing*

The following procedures are taken to pre-process the taken database:

- Clean the data.
- We observed that 5 out of 279 attributes contained missing values.
- Further analysis revealed that almost 350 missing values were found in an attribute, which we eventually dropped.
- We replaced the columns containing such empty values with their mean values.
- Added names for all the attributes (columns) in the dataset for clarity.
- Finally, we separated the target attributes from the original dataset and then used them for neural network modeling.

4.2.2. *Data modeling*

Some of the algorithms that we chose to evaluate (against the LM ANN) are

- K Nearest Neighbors (KNN)
- Logistical Regression
- Decision Trees
- Random Decision Forest
- Support Vector Machine (SVM)

The dataset file containing hundreds of patients' clinical histories is used to experiment with the mentioned models. To ease the readability and clear understanding, we have chosen only 5 accounts and displayed them (along with reduced columns) in Table 2.

Table 2
Sample data set of patient's clinical history used in the experiment.

Age	Anaemia	Diabetes	High BP	Platelets
75	0	0	1	265000
55	0	0	0	263358.03
65	0	0	0	162000
50	1	0	0	210000
65	1	1	0	327000

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	5	1000
Elapsed Time	-	00:00:49	-
Performance	1.22	8.37E-26	0
Gradient	2.55	5.18E-14	1.00E-07
Mu	0.001	1.00E-08	1.00E+10
Validation Checks	0	2	6

Fig. 6. Training Progress Values of the LM ANN as reported by MATLAB®.

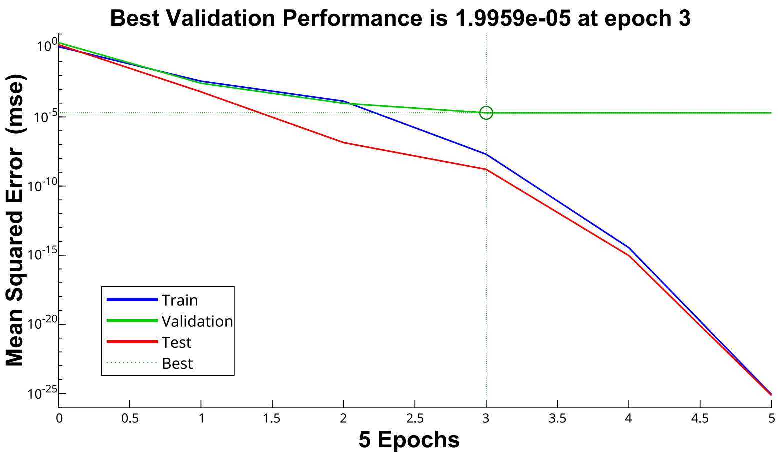


Fig. 7. Graphical plots depicting the quality of the Training Performance.

5. Simulation & evaluation of results

5.1. *Output results (using MATLAB® 2023a academic version):*

On executing the **Main.m** file, the following values are obtained upon successfully completing the training, in addition to the creation of '*net. mat*', which is a fully trained neural network file:

Fig. 6 shows that the neural network was trained in 49 seconds, with 2 out of 6 validation checks performed for 5 consecutive epochs. Fig. 7 illustrates the performance of the training, validation, and testing phases for up to 5 epochs. The best validation performance value of 19959e-05 was achieved during epoch 3. However, the training and testing performances are significantly lower. The training states (gradient, mu & validation checks) are all plotted accordingly in Fig. 8 (a), Fig. 8 (b) and Fig. 8 (c) respectively. The Error Histogram plot in Fig. 9 shows that the results are obtained with near zero errors and relatively higher precision. The linearity observed in the regression plots indicates that the training was proper and successful.

Graphical plots in Fig. 10 (a-d) depict the training performance, validations, and test regressions. The linear plot indicates that the training was successful. Although the results shown in Fig. 10 (a-d) show theoretically that the training was successful, the practical performance was not comparable. Small datasets of average quality impact our prototype's predictive accuracy for cardiac issues.

5.2. *Output results (using JupyterLab IPython online IDE)*

This part of our study aims to identify the optimal Neural Network model using a different dataset containing a variety of factors, including Age, Sex, Height, Weight, and many pertinent cardiac measurements. In the first step to clean the raw dataset, certain

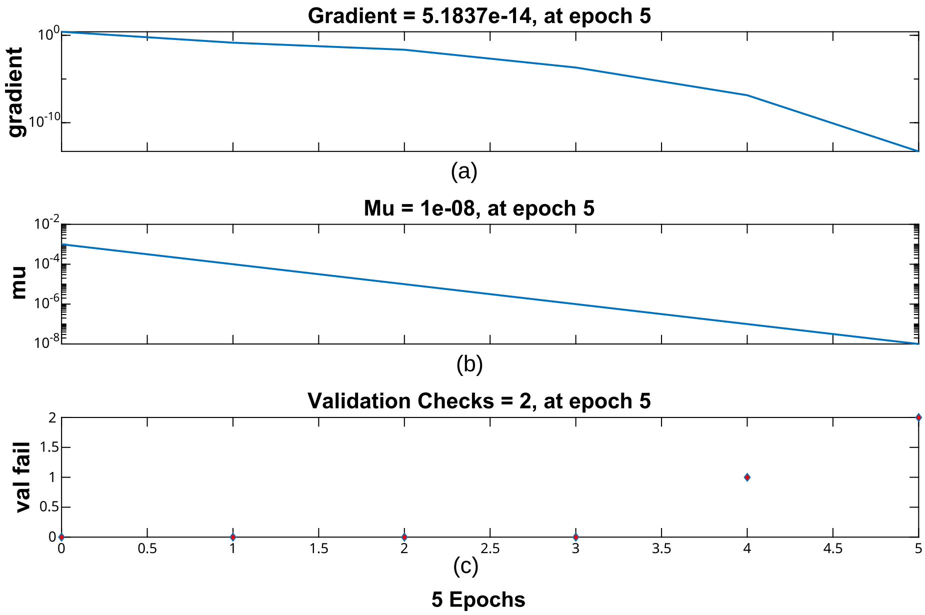


Fig. 8. Gradient and MU plots of the Training States (a) Gradient (b) Mu (c) validation check.

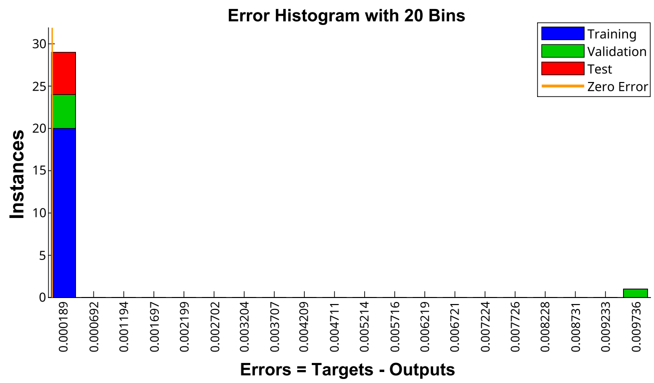


Fig. 9. Graphical representation of Error Histograms depicting the near zero prediction errors in training, validation, and test cases.

attributes containing mostly null values are dropped, and others are credited with mean values. After this step, the outliers in the dataset, mostly present in the 'Height' and 'Weight' attributes, are manually corrected. After the data cleaning procedure, the dataset is utilized for running tests using various NN algorithms to achieve the best Training and Test accuracy. A few of the following arrhythmias are originally present in our chosen dataset and the same has been depicted as a graphical plot shown in Fig. 11.

- Normal
- Old-anterior Myocardial Infraction
- Old-inferior Myocardial Infraction
- Left-bundle branch block
- Right-bundle branch block
- Ischemic changes (CAD)
- Sinus tachycardia
- Sinus bradycardia
- Atrial Fibrillation or Flutter
- Ventricular Premature Contraction (PVC)
- Other types

From the dataset, about 70% of the base information is split for the purpose of training and the rest for the purpose of testing. At first, 70% of the dataset is used as a feed for training and testing the 6 chosen NN models. In the first step of our basic training, we obtain the results shown in Fig. 12.

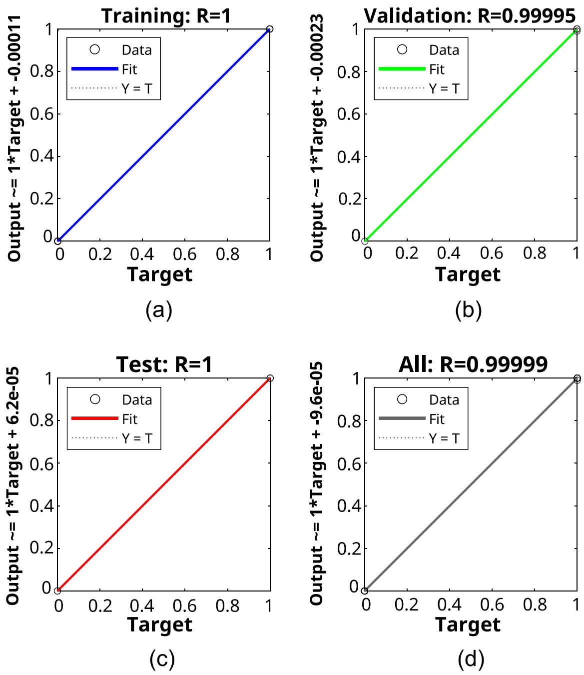


Fig. 10. Graphical plots depicting the (a) training performance, (b) validations, and (c) and (d) test regressions.

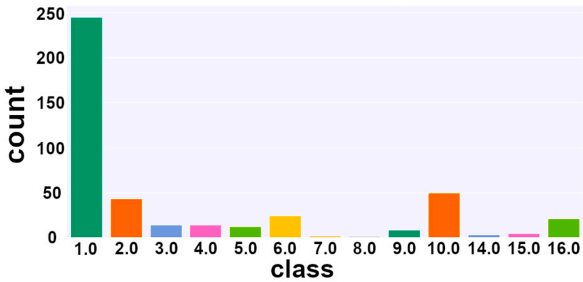


Fig. 11. Visual representation of 13 (out of total 16) types of arrhythmias present in the dataset.

	Model	Train Accuracy	Test Accuracy
0	KNN Classifier	0.648199	0.648352
1	Logestic Regression	0.939058	0.780220
2	Decision Tree Classifier	0.789474	0.681319
3	Linear SVC	0.880886	0.780220
4	Kernelized SVC	0.850416	0.791209
5	Random Forest Classifier	0.883657	0.747253

Fig. 12. Initial testing and training results for all six NN models.

The Principal Component Analysis has been carried out to enhance the training and testing accuracy even more. This analysis essentially 'concentrates' the diverse attributes (technically known as dimensions here) from the dataset that show maximum differences. After training and testing all the models, this time with the inclusion of PCA, the results obtained are shown in Fig. 13.

In addition, the obtained values have been graphically represented in Fig. 14 & Fig. 15 for better clarity and readability.

From the above-obtained results, the 'Random Forest Classifier Model with PCA' boasts high training accuracy but couldn't achieve better test accuracy, reducing the practicality of using this model. On the other hand, however, Linear and Kernelized SVCs (with PCA) prove to be more practical in terms of (real-time) testing accuracy with an obtained value of 0.802198.

	Model	Train Accuracy	Test Accuracy
0	KNN Classifier with PCA	0.645429	0.648352
1	Logestic Regression with PCA	0.783934	0.791209
2	Linear SVC with PCA	0.808864	0.802198
3	Kernelized SVC with PCA	0.839335	0.802198
4	DecisionTree Classifier with PCA	0.753463	0.604396
5	Random Forest Classifier with PCA	1.000000	0.736264

Fig. 13. Testing and training results for all six NN models after the inclusion of PCA.

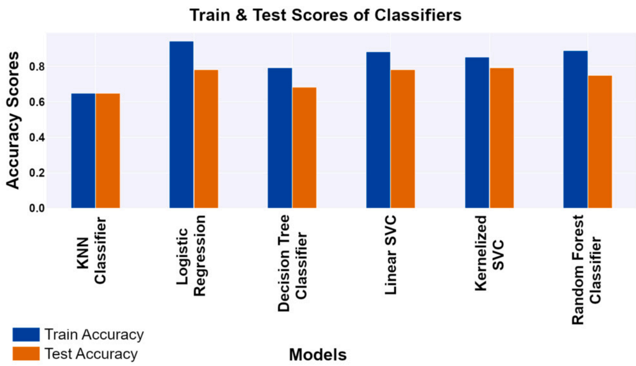


Fig. 14. Visual representation of all the six Neural Network Models (without PCA).

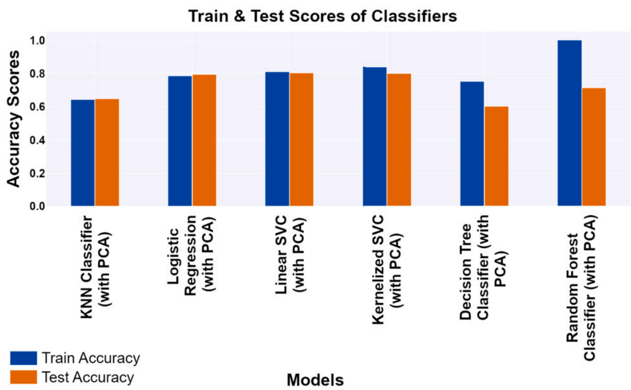


Fig. 15. Visual representation of all the six Neural Network Models (with PCA).

6. Conclusion & future work

6.1. Conclusions

Based on the created Excel database values, we have verified the accuracy checks for the trained and created (using Levenberg-Marquardt ANN) neural network. In addition, with the aid of the constructed hardware working model, we achieved the real-time monitoring of the cardiac rhythm through a customized MATLAB code. The evaluated precision of the test data is obtained to be

1 (high). However, the scope of the LM ANN used here is limited, which proved to be a major motivation in testing and finding a capable alternative neural network model and a strong and reliable dataset.

Judging from the results of the alternative implementation (using JupyterLab), it is inferred that the Kernelized SVM model outperforms the other classifiers (test accuracy). This particular model has the highest training and testing accuracy with a pronounced accuracy of 80.21% shown in Fig. 13 and Fig. 15. These results suggest that the Kernelized SVM model can be carried out (as an alternative to the LM algorithm) to predict and diagnose various cardiovascular diseases and abnormalities. Through our results, we have successfully evaluated the feasibility and efficiency of a cardiac rhythm monitoring and predicting wearable device powered by the potential capabilities of the LM and Kernelized SVM algorithms respectively.

The LM ANN requires larger datasets to give the expected performance. The computational power required for computing the Hessian Matrix for this algorithm is also significantly greater [20] and may not be suitable for our requirements - a low-cost, low-power wearable device. Therefore, we continue to explore alternate neural network models that could perform well with limited, yet higher-quality datasets and have a lighter footprint on the target device on which it is designed to work.

6.2. Future work

Furthermore, the said potential capabilities of the Kernelized SVM NN model can be incorporated into a prototype model and evaluated for hardware feasibility and performance. If the results are positive, then the prototype can be upgraded into a full-fledged commercial-grade consumer product.

6.2.1. Using advanced microcontrollers

With rapid advancements in the wearable and flexible electronics domain field, compact devices can exploit the capabilities of the LM neural network by utilizing advanced 32-bit, low-power, low-cost, and ARM® Cortex-M-based microcontrollers. Microcontrollers also have sufficient resources to fit a full-fledged trained neural network model.

6.2.2. Using nanotechnology

Future advancements in Nanotechnology can also exploit the said NN model and develop an ultra-thin wearable device manufactured using various suitable nano-materials. Further exploration into this potential domain is beneficial for improving our prototype into a full-fledged device ready for the consumer market.

6.2.3. Using wireless protocols (IoT)

The presented working model can also be implemented as an IoT-themed working gadget, employing various IEEE wireless protocols such as Zigbee (802.15.4 protocol), Wi-Fi (802.11 b/g/n/ac protocol), Bluetooth Low Energy, etc. This approach can potentially minimize our device's hardware complexity while leaving all the real-time computation and prediction to a cloud-based service.

CRediT authorship contribution statement

Sangeetha R.G.: Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Kishore Anand K:** Software, Investigation, Data curation. **Sreevatsan B:** Visualization, Validation. **Vishal Kumar A:** Validation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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