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Detection of Cardiac Abnormalities and Heart Disease Using Machine Learning Techniques

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Abstract: The prediction of heart disease is a very challenging task in medical science, and it is essential to predict accurately for deciding future treatment. Almost 30 million peoples have died due to heart failure and different heart diseases worldwide. Internet of Things (IoT) and machine learning are the techniques that help to understand the heart's current condition. Various researchers have developed a system for predicting heart disease using several methodologies, but still, it remains a challenge to predict the accurate state of heart disease. The cardiac index and vascular age of the heart are the two significant vitals that indicate the precise condition of the heart. In this paper, we proposed heart disease prediction using IoT and machine learning techniques. Initially, we collected data from numerous sensors such as sunroom BP for heart rate, max30100 for blood oxygen saturation, EEG for PT and QR intervals, etc. The hybrid feature extraction and selection techniques and numerous machine learning algorithms have been used for strong training model building. With extensive experimental analysis, few machine learning (ML) and deep learning techniques have been evaluated with the existing implementation. The Recurrent Neural Network (RNN) obtains better detection and classification accuracy than conventional machine learning (ML) techniques such as SVM (Support Vector Machine), Naive Bayes (NB), Random Forest (RF), etc.

Keyword: *Detection System, Internet of Things, Vascular age of heart, Cardiac index, Monitoring System, Machine Learning, Deep learning*

1. Introduction

In recent decades, the global mortality rate from cardiovascular (CVD) illnesses has increased. Every minute, a CVD arrest kills one American. Many researchers have sought to use machine learning to identify CVDs to assist doctors in improving global health care. The WHO estimates that CVDs cause 30% of worldwide fatalities, with 75% occurring in low- and middle-income countries. In India, 25% of the population aged 25-69 died from CVDs [1]. The Internet of Things (IoT) is a term used to describe physical devices with limited storage and computational power. It still has performance, interoperability, security, and privacy concerns that need to be addressed in the near future [2], [3], [4]. Smart objects continually monitor patients for certain disorders [2]. Smart objects have biological sensors that collect health data and send it to a doctor through the cloud/edge for analysis. Thus, IoT helps bridge the gap between patients and physicians situated everywhere [5], [6]. Data mining is an intelligent technology that extracts new information from extensive voluminous databases [7]. Various machine learning algorithms may produce judgments, estimations, and predictions. Currently, most medical data is captured electronically but not analyzed globally. It sits in a database like old handwritten documents, unused. [2], [8] this data may be used to forecast illnesses like cancer [2, 8]. Thus, a unique Information Technology (IT) paradigm is presented, combining IoT, machine learning, and cloud computing to solve existing and future global healthcare system difficulties. Medical aided technology and healthcare services are closely connected and beneficial to the public's health. The use of cloud computing and IoT for medical applications helps forecast chronic illnesses. The development of public cloud (cloud computing) in hospitals may encourage resource sharing, cost savings, medical monitoring, management, and administration systems with high efficiency and accuracy.

1. This system classifies with the collaboration of machine learning and deep learning classification algorithms that provides accurate results for real time data.
2. It predicts the heart disease as well as chronic disease according to current body parameters for synthetic and real-world data.
3. It is a non-invasive system which provides accurate results that collects a data from numerous IoT sensors and predict based on machine learning classifiers. It reduces the error rate and hybrid feature selection eliminates the over fitting problem.

The entire paper is fragmented into the sections as follows: Section II discusses different current strategies for

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detecting and predicting cardiac disease using machine learning algorithms that has been developed by earlier researchers. The research design employed in the development of the proposed system is demonstrated in Section III, while the technique specification for the suggested development is represented in Section IV. In section V, we have described the experimental setup in detail for evaluating the developed work and result obtained with our approach, as well as a comparative analysis with numerous state-of-the-art techniques. Section VI discusses the finding and its future implications.

2. Literature Survey

In this unit, we describe the several state of art systems related to heart disease prediction using machine and deep learning methods. The numerous researchers have already implemented a comparable system with the IoT (Internet of Things) and the well-known synthetic dataset.

Humayun et al. [1] presented a technique for detecting problems using the PPG signal's auscultation of heart sounds. Intending to emulate Finite Impulse Response (FIR) filters, the authors developed a CNN model consisting of recurrent time units. The active filters take an input vector and use a mathematical equation to turn the continuous and discrete signal into a filtered approximation. Chowdhury et al. [2] presented a transportable method for detecting heart illness early using noises emitted by the heart. In MatLab, the model was used to train the dataset PhysioNet2016 using machine learning methods. The system is the framework of a virtual stethoscope that is incorporated which monitors and diagnoses any abnormalities in the patient's heart signals instantaneously. Transmission is accomplished via reduced wireless technologies between the instrument and a home computer. The impulses formed by the mechanical force of the heart during the cardiac cycle are represented by PCG as per Tiwari et al. [3]. The authors were interested in generating work with PCG because of the inexpensive cost and the fact that it is not an intrusive technology, and the ease with which it could be adapted for remote usage through smartphone signal recording. As a result, they suggested heart rate categorization architecture based on CNN and Q transforms. As per Ukil et al. [4] remote and computerized hospital administrator offers a lot of promise in healthcare. IoT and deep learning may help with diagnostic implications screening and save time for patient care. The researchers propose a model which is based on PCG data for the presence of cardiac problems; however they raise concerns regarding the usage of IoT and the confidentiality of patient medical records. Marchet al. [5] highlighted physiological responses of the nervous system to external stimuli that tend to interact with heart rates, such as psychological symptoms and health exercises. Observing these changes in physiological data using a wearable device and then assessing the person's situation with machine learning algorithms may serve as a tool for cardiovascular fitness prison.

Ren et al. [6] employed deep neural networks to identify Phonocardiogram (PCG) scale pictures to distinguish between normal and pathological noises of the heart. Datasets from the various real-time signals were used to generate PCG signal reconstructions. The Matlab 2017 toolbox wavelet generates scalogram pictures in cardiac sounds. Sinharay et al. [7] made a similar proposal. Still, they changed a sensor with a cost to a mobile phone so that the equipment could function similarly to auscultation, working with patients with manoeuvring challenges, the elderly, and newly controlled patients, and starting to think of countries with relatively low public transportation fluidity. Gradl et al. [8] used virtual reality to create a model. The investigation included immersing 14 individuals in circumstances that might elicit behavioural changes and allowing them to see their heart activity in real-time using sensor modules and cellophane. Doshi et al. [9] advocated using videoconferencing to diagnose cardiac disease remotely, a new discipline that has emerged due to developments in mobile computing. The researchers analysed at present remote diagnostics systems and developed a prototype device to help with heart disease identification. The prototype is produced at a low cost. It was designed primarily for remote diagnostic testing in rural or inaccessible places and installations of military personnel that have been isolated or accident scenes where expert care and management are tough to come by. Shuvo et al. [10] introduced CardioXNet. This model included identifying five characteristics in the categorization of patients, including standard, arterial snoozes, mitral synopsis, valve disease, and mitral valve protrusion. The categorization was done utilizing Network architectures, Un-supervised networks that have been pre-trained, recurrent and reflexive NN (neural networks), and the DL approach.

Through health records, Du et al. [11] showed the utilization of machine learning (ML) methods, huge data, and statistical methods. The researchers has built a CVD developing risk score and tried machine learning (ML) techniques like various supervised learning classification algorithms since health data exhibit nonlinear properties. With severe gradient boosting nonlinear algorithms, they improved accuracy indexes. As per Amiri et al. [12], doing PCG cardiac evaluations in new-borns is one of the most difficult jobs. The complexity in distinguishing physiological aspects of the signal collected from infants justifies this assertion. The technique of categorization between healthy and pathological heart sounds was utilized in the investigation. It used SVM techniques to achieve 92.2 per cent accuracy, using equipment consisting of a digital stethoscope coupled to a smartphone and a public cloud with process automation. Electromagnetic radiation is another way of heartbeat observation that is becoming more popular as smart watches become more popular. Photoplethysmography (PPG) is most widely employed in pulse oximeter in medical situations to monitor saturation of oxygen and monitor increased rate of heart, according to Elgendi et al. [13]. Liu et al. [14] built a database of heart sounds with free/open access for academics to utilize as a dataset in machine learning methods. It illustrates that cardiac auscultation had been extensively researched owing to its significant potential for reliably detecting disease in clinical applications. The shortage of quality open datasets thoroughly vetted and standardized with cardiac sound recordings, however, limited comparison assessments of methods are available in the literature. Thyagaraja et al. [15] described smartphone-based mechanical equipment that can collect, analyse, and detect 16 different heart sounds in detail. The suggested system is transportable, low price, and does not need a professional, experienced user to perform. Machine learning techniques are used in the model [15].

According to Gómez-Quintana et al. [16], congenital cardiac disorders (CCDs) which are caused by a heart abnormality impact around 1% of all new-borns and account for 3% of all child mortality. An ultrasound examination may identify CVD between the 12th week and 16th weeks of pregnancy. The researchers' objective was to use machine learning (ML) and the XGBoost technique to construct a tool that would improve clinical decision-making. After analysing the model, they compared the model's degree of accuracy to that of an experienced paediatric urologist with the same cohort. Due to the heterogeneity in medical professionals' interpretive research capability to detect pathological qualities during cardiovascular auscultation, Chorba et al. [17] proposed a numerical technique as an exciting candidate to aid in diagnosing afflictions in the medical field through auscultation. The authors suggested that combining DL techniques with the Convolution layer and applying a softmax function with the final layer to normalize the probability distribution identifies murmurs and valvulopathy. In the remediation program public dataset was used for the training. As per Balakrishnan et al. [18], heart rate surveillance may help anticipate illnesses with the world's greatest fatality rate. The researchers advocated monitoring by utilizing low price wearable technology, Cloud Computing, and integration with machine learning techniques and statistical linear regression methods.

MLP offers several distinguishing properties in classification, including speed, ease of implementation, and the need for minimal training sets [19]. The input, hidden and output layers are the three primary layers of MLP. After treatment, hidden layers are intermediary layers that link the input layer to the output layer. J is the total input values after multiplying with their weight vectors in MLP hidden units. The sum of the input w_{ij} and output y_i is calculated. Gradient descent is a helpful approach for training neural networks [20]. After computing the error function's derivatives, it updates chosen at random weights to a negative gradient. After attaining the maximum number of iterations, the algorithm's training is terminated. The regression model is reduced using the gradient descent approach. CNN is a powerful neural network model that uses convolution, nonlinear activity, dropout, plus pooling layers to learn complicated features [21]. It was created to help with image-related tasks, including picture segmentation and classification. CNN conducts training in an end-to-end manner by providing efficiency. Fully linked layers are used towards the model's conclusion to encode semantic information. It's a feed-forward network that maps features by applying filters to the output of the preceding layer. Convolutional layers, pooling and sub-sampling layer upon layer, flatten layer, transfer functions, drop out, and fully connected layer are the essential components of the CNN model. Convolutional layers automatically extract, and the output of something like the convolutional is sent to fully – connected layer. The convolution layer decreases the characteristics mapped by convolutional layers to prevent overfitting. Pooling may be either maximum or average, with the maximum pooling layer favouring sharp features over the average hidden state. The data is converted into an array by the flattened layer so that it may be sent to the fully linked layer. In a convolution operation, we used the ReLU in CNN.

Saikat Bose et. al. [22] advocates for the use of a novel data security protocol to verify the appointment of candidates for service. The process began with the private information being obfuscated in the e-initial mail's section for each area on the server run by the commission. Circular orientation of private share pieces and their hosted matrix intervals are determined by hash operations. The same hash operations and public sharing are used to verify any digitally signed letters that are downloaded from the designated location. On-the-spot fingerprints are hidden using identical concealment techniques in two sections for each section of the electronic letter. Each region's fourth segment is encrypted using a hash function to protect the copyright signature of the posting location. The commission's server verifies the legitimacy of the appointment and the validity of the candidate's signatures to ensure that the certified electronic letter is sent in its whole to the designated location. The effectiveness of the suggested procedure is established above the previous ways by the improved test findings from broader angles.

3. Proposed System

Heart disease is the main cause of mortality for both men and women, and both stand an equal chance of passing away from the condition. According to the data that is currently available, cardiovascular illness is responsible for about one third of all fatalities that take place anywhere in the whole globe. The diagnosis of cardiac conditions has been the subject of a significant amount of study in recent years, with the goal of making the process more reliable. The people who work in the healthcare profession have a tough time correctly identifying illnesses when there is a significant number of data available. Both data mining and machine learning involve the process of transforming vast volumes of raw data into information that can be utilized to form reliable forecasts and choose the best course of action. The bulk of the time, accurate prediction of heart disease requires a great deal of specific information due to the complexity that are involved. As a consequence of this, there is a greater degree of optimism among the researchers on the prognosis of illnesses, in particular ailments that are associated with the heart. Wearable and implantable Internet of Things devices make it feasible to collect patient data from individuals who are dispersed across a number of different places. At this initial step of the process, the data is obtained via the use of IoT devices that are implanted into the human body, data that is gathered from benchmark datasets, and health records.

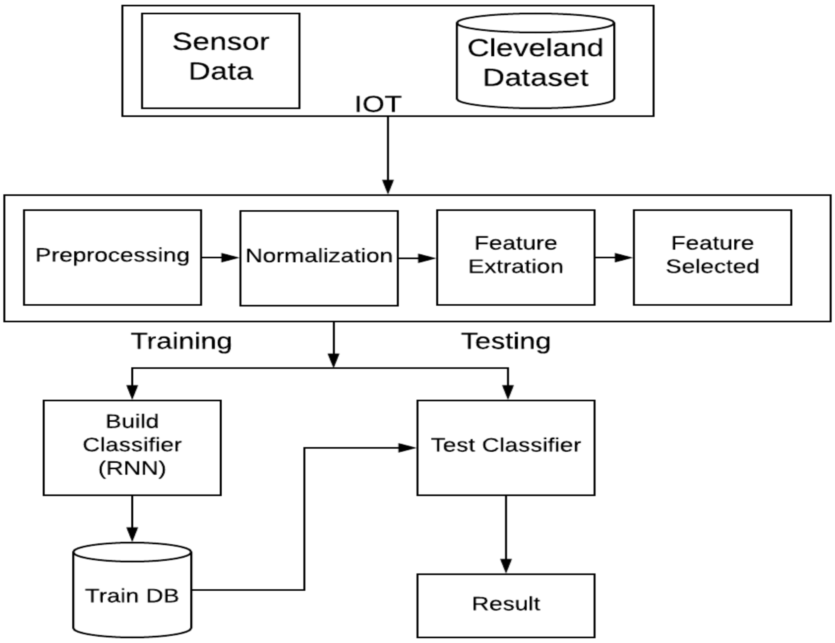

Fig. 1: Proposed System Architecture

The above Figure 1 demonstrates propose system architecture for synthetic and real time IoT data processing environment. The patient's age and gender, which are two of the total 25 attributes that make up the data set, are the ones that are utilized to determine their personal information. This is because these two features are the only ones that have anything to do with the patient's age and gender. The 12 attributes are vital as a result of the essential medical record that they include. Clinical records are an imperative need for both the process of diagnosing heart illness and evaluating the severity of the condition. The RNN is used as current classifiers and which is evaluated with some conventional machine learning classifiers. For the purposes of this study, a broad range of categorization models that are the product of machine learning were used. After computing each model's accuracy using the given dataset, the results are compared to the RNN to determine which one is more accurate. The three different activation function are used such as Relu, Sigmoid and Tanh for evaluation of multiple results with various cross validation techniques.

Recurrent Neural Network (RNN)

In RNN, we define the input, hidden, and feedback layers sections during feature extraction and feature selection. After selecting all features, the SoftMax function is applied to select the final feature vector for classification. The SoftMax function is described as below;

$$\hat{y}(n) = \text{softmax\_}(W(n)\, h(n) + b(n))$$

Here, y(n) represents extrapolation options for task process n, W(n) represents the weight that must be known, and b(n) represents a bias time. The linear layout of cost utility for all intersections is our complete cost function.

$$\varnothing = \sum_{n=1}^{N} .\, \lambda_n \, L(\hat{y}(n), y(n))$$

Now, λ_n is the respective weight for specific (n) task.

It should be noted that labeled data will come from entirely different repositories for the training of each task. The teaching is then done in a deterministic fashion by looping over the assignments:

Therefore, we should use a calibrating approach to further improve the output with each task after the mutual learning stage. From each stage t, we define the LSTM divisions to be a series of Rd vectors: an input gate, a decoder (ct), a forgetting gate (ft), an offset gate (ot) and a previous hidden (ht). D is the number of models of an LSTM. The entries for the gating dimensions in [0, 1] are it, ft and ot. The foregoing are the transformation coefficients for LSTM:

$$\begin{aligned}
\mathbf{i}_t &= \sigma(\mathbf{W}_i\mathbf{x}_t + \mathbf{U}_i\mathbf{h}_{t-1} + \mathbf{V}_i\mathbf{c}_{t-1}),\\
\mathbf{f}_t &= \sigma(\mathbf{W}_f\mathbf{x}_t + \mathbf{U}_f\mathbf{h}_{t-1} + \mathbf{V}_f\mathbf{c}_{t-1}),\\
\mathbf{o}_t &= \sigma(\mathbf{W}_o\mathbf{x}_t + \mathbf{U}_o\mathbf{h}_{t-1} + \mathbf{V}_o\mathbf{c}_t),\\
\tilde{\mathbf{c}}_t &= \tanh(\mathbf{W}_c\mathbf{x}_t + \mathbf{U}_c\mathbf{h}_{t-1}),\\
\mathbf{c}_t &= \mathbf{f}_t^i \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t,\\
\mathbf{h}_t &= \mathbf{o}_t \odot \tanh(\mathbf{c}_t),
\end{aligned}$$

Here xt is the source at the time - step, it indicates the fractal dimension LG (logistic regression) and indicates the wisdom multiplying of elements. The forgotten gate conceptually determines how much each component of the memory module is removed, the input gate determines how much the other unit is changed, and the activation function controls the internal storage state display. The snippet procedure facilities the learning and is listed below.

Training Procedure

Input: Train dataset TrainingData[], Mulitple activation funct[], Threshold Th

Output: Extracted Features Feat_set[] for finished trained module.

Step 1: Set block of input data d[], activation function, epoch length,

Step 2 : Feat.pkl ← ExtractFeat(d[])

Step 3 : Feat_set[] ← optimized(Feat.pkl)

Step 4 : Return Feat_set[]

System Testing Algorithm

Input: Train dataset TrainingDBLits [], Test dataset TestingDBLits[] and Threshold Th.

Output: Resulset <cls_name, Sim_Weight> all set whose weight is heavier than Th.

Step 1: For every test records as given in the following equation, it works in convolutional layer for both testing and testing.

$$\text{testingFeat(k)} = \sum_{m=1}^{n} (\quad \text{featSet[A[i] ... . A[n]} \leftarrow \text{TestingDBLits)}$$

Step 2 : Create feature vector from testingFeat(m) by using following function.

Extract_FeatSet_x [t…..…n] = $\sum_{x=1}^{n}(t) \leftarrow$ testingFeat (k)

Extract_FeatSet_x[t] Is the outcome of every pooling layer that is extracted from every convolutional layer as well as forwarded to net convolutional layer. Every layer holds the feature extraction of every object for test dataset.

Step 3: For every train objects by using following function,

$$\text{trainingFeat(l)} = \sum_{m=1}^{n} (\quad \text{featSet[A[i] ... . A[n]} \leftarrow \text{TrainingDBList)}$$

Step 4: Create new feature vector from trainingFeat(m) by using following function. Extract_FeatSet_Y[t……n] = $\sum_{x=1}^{n}(t) \leftarrow$ TrainingFeat (l)

Extract_FeatSet_Y[t] is the result of every pooling layer that is extracted from every convolutional layer as well as forwarded to net convolutional layer. Every layer holds the feature extraction of every instance for train dataset.

Step 5 : Now compute every testing records with whole train dataset, in dense layer

$$\text{weight wt} = \text{calculateSim (FeatSetx ||} \sum_{i=1}^{n} \text{FeatSety[y])}$$

Step 6 : Return Weight wt

4. Results and Discussion

In the section under "Results," we conducted an analysis of the data collected by our system using a variety of machine learning (ML) and deep learning classification methods. Six different machine learning models were used in conjunction with the newly developed training library in order to identify patterns of frequent, dubious, and harmful behaviors. The 5, 10, and 15-fold cross-validation model were used, and the behavior categorization training-database served as the basis for the testing and evaluation of the machine learning algorithms. The categorization method that was used to all of the parameters is shown in the following figure, which also indicates how consistent each implementation has done with different classifer.

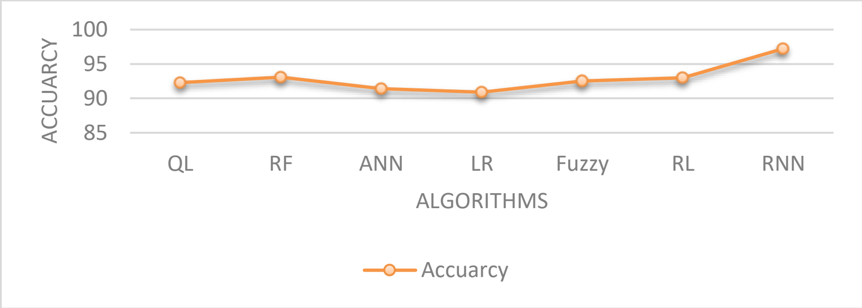

Fig. 2: Evaluation of the efficacy of different ML and RNN classification systems

The total accuracy of all of the methodologies, including our suggested RNN, is shown in Figure 2. The overall accuracy rating for it is 97.23 percent. The Linear Regression (LR) method has a minimum accuracy of 90.90 percent, which is higher than the accuracy achieved by other methods.

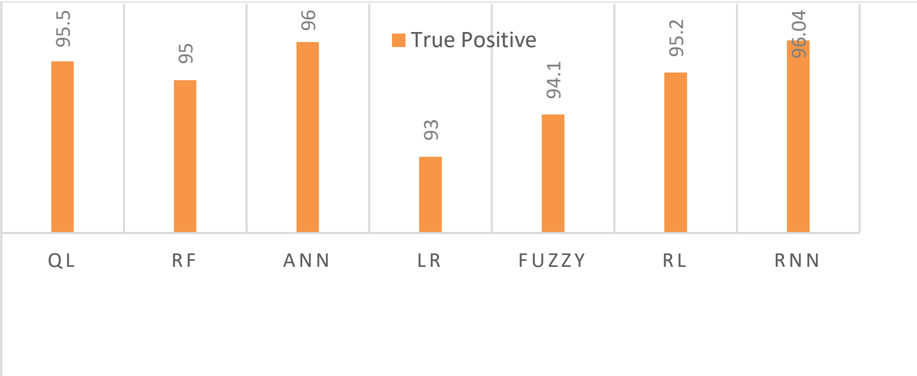

Fig. 3: Evaluation of several ML and RNN classification methods using true positives

Figure 3 shows the True Positive (TP) value for all algorithms, including the one being offered as an improvement. Its TP ratio comes out to around 97.40 percent. As compared to other approaches, the accuracy of the Linear Regression (LR) algorithm is guaranteed to be at least 93.00 percent.

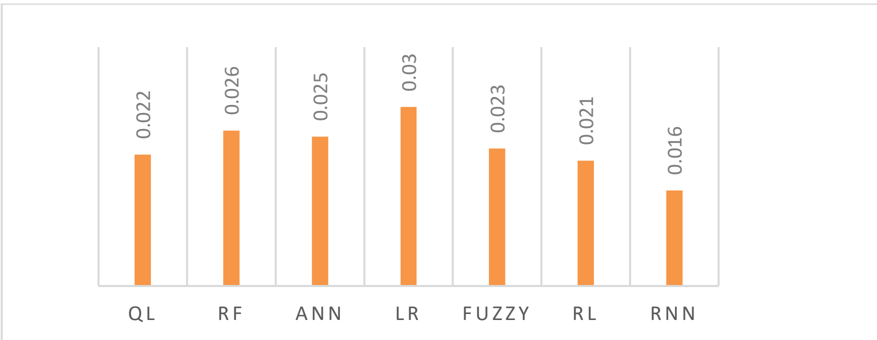

Fig. 4: Evaluation of different ML and RNN classifications with regard to the False Positive

Figure 4 illustrates the overall accuracy of all of the strategies, including the RNN that was just suggested. It is accurate to within 97.23 percent of the time. The Linear Regression (LR) approach has an accuracy rate of at least 90.90 percent, placing it above that of competing techniques.

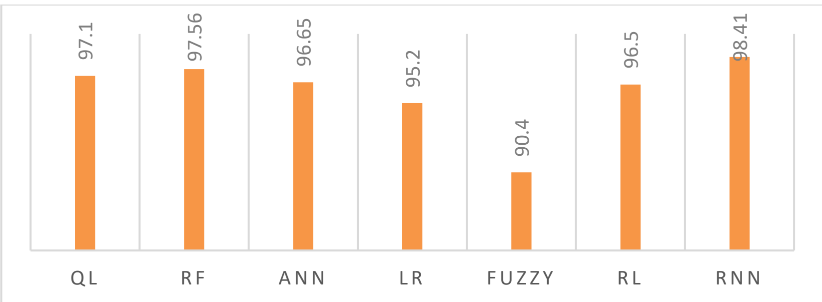

Fig. 5: Evaluation of several ML and RNN classification systems using the True Negative metric

The True Negative of all of the different techniques, including the proposed RNN, is shown in Figure 5. It has a degree of accuracy that is 98.41% of the time. The Fuzzy Logic method has the lowest TN of all the other techniques, coming up at 90.40 percent.

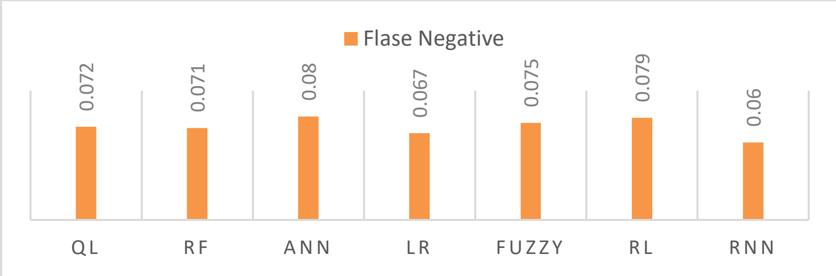

Fig. 6: Evaluation of many ML and RNN classification systems based on a false negative

Figure 6 illustrates the proportion of incorrect predictions made by a system that makes use of numerous algorithms; both LR and RNN consistently make the fewest incorrect predictions overall. Figures 2–6 highlight the significance of a diverse experimental study focused on a variety of statistical tests utilizing seven distinct algorithms: Q-Learning, RF, Fuzzy logic, Nave Bayes, Linear Regression, RL, and Random Forest with Recommended Perceptron Algorithm. These algorithms were chosen because of their ability to produce more accurate results than traditional methods. For the purpose of data management, the RNN classification technique was used while the classifier was in operation. The neural network was shown and spoken about for each of the models. Both of these metrics of uncertainty illustrate how accurate the system is in terms of accurately recognizing, erroneously categorizing, declining, and recalling devices.

5. Conclusion

This research describes heart disease detection and classification using IoT and Machine learning methodology for a real-time environment. The key goal of this research was to create a reliable cardiovascular disease prediction model. This was accomplished with the help of ML (machine learning) techniques and the Internet of Things. Parameters are used to create the prediction model. After speaking with domain experts, the criteria are chosen. This study found that the RNN method worked better without hyper parameter adjustment, however the proposed model proved to be an effective strategy with hyper parameter tuning. The feature extraction techniques such as TF-IDF, bigram features, autoencoder features and relational features are used for collecting the hybrid features. The significant benefit of the extraction of such homogeneous features produces a high detection rate. The proposed RNN classification algorithms achieve the highest classification accuracy, around 98.50% for both synthetic and real-time datasets. As a result, the RNN achieve the highest classification accuracy over the traditional machine learning algorithms. In terms of future developments, we believe that additional study should be done to simulate this suggested system by incorporating new parameters using hybrid approaches such as deep learning architectures and more legitimate datasets. Weather forecasting, election forecasts, sales projections, and other Bioinformatics estimations, for example, may all benefit from these methodologies.

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