A Model for Real-Time Heart Condition Prediction Based on Frequency Pattern Mining and Deep Neural Networks

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ABSTRACT

Data acquired by sensor-based Internet of Things devices has recently reached huge proportions, including bioinformation. Different kinds of health big data are crated using different methods, and the gathered data is categorized accordingly. The design is possible to evaluate potential dangers associated with one's own concerns with the heart in real time. This paper's goal is to provide a model for individualized heart condition categorization that processes collected biosensor input data in real-time using a deep neural network and a quick and efficient preprocessing approach, incorporating pattern mining techniques. Learning input data and developing an approximation function are two potential uses for the model, and it may also assist users in identifying danger scenarios. In the preliminary processing, a quick Fourier transform is used for the purpose of analyzing the pulse frequency. Data reduction strategies include using the recovered power spectrum's frequency-by-frequency ratio information. Preprocessed data is analyzed using a neural network approach. Among its many applications is the analysis and evaluation of linear data by means of a deep neural network. A network of deep neural networks can employ gradient descent to build multiple layers, each of which represents a node's process. There is a standard, oversight, and noisy category in the trained model that makes use of the pre-collected ECG data. Subsequently, both peaceful and chaotic electrocardiogram (ECG) data were fed into the newly implemented deep neural network system in real time. This research assessed the suggested method by calculating F-measure ratios and knowledge operation cost reductions.This led to a reduction in ECG size to 1:32 with the use of cumulative frequency % and rapidly Fourier transform. An evaluation of the deep neural network's F-measure revealed an accuracy of 83.83% for the model. Results show that the modified deep neural network method, with the integration of pattern mining, can effectively decrease operating time and minimize the amount of massive data in terms of computing labor.

Keywords: Real-time control; Big Data; Pattern Mining; Deep Neural Network; Healthcare; Data Mining; Heart Rate.

1. Introduction

Wearable technology for biodata collection has gone mainstream thanks to the expansion of the IoT sector. By combining with other communication devices, such as smartphones and tablet PCs, the infrastructure of wearable technology has grown, allowing it to surpass technological limitations in areas such as performance, weight, and battery life [1]. Smart home technology and other advancements in intelligent health care systems have facilitated easier access to individual biodata.In addition, huge amounts of biomedical and

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health-related data are generated and stored due to the development of health information systems (HIS) at big hospitals [2]. So, the amount of health data being produced is exponentially growing, eventually approaching the level of big data. But the way things are, healthcare today uses.

When it comes to the responsibilities and preventative actions of patients with chronic illnesses, integrated treatment and care, and tailored service, health big data is mostly useful for treating acute diseases and those affecting hospitalized patients [3]. In order to empower individuals with chronic diseases to take charge of their own healthcare, the healthcare system must be upgraded to a smart health service that utilizes live big data mining [4]. Consequently, it aspires to enhance healthcare in a way that prevents the return of chronic diseases including diabetes, hypertension, dyslipidemia, cardiovascular disease, and stroke, and that promptly detects and treats symptoms of stress and depression [5,6]. For intelligent analysis of data and tailored information supply, it is vital to include individually created IoT-based bio logs big data containing a variety of medical records into a context-sensitive recognition system [7]. Recent years have seen much research into the current health paradigm that is based on neural networks. By learning recurrent connections of sequences, this model is able to extract causal relationships, recognize sequential context information, and identify successful identifications [8]. By utilizing the health platform over the quantitative assessment of hidden extent, this study can monitor a group of diseases that pose a high risk, as well as their long-term complications, negative outcomes, potential risks, and interest in managing latent diseases in assisted living facilities. In the long run, this would help the healthcare service business cater to the elderly better [9].

Using deep neural networks and frequency pattern mining, this study demonstrates a technique for real-time heart condition classification. The proposed method cleans and analyses biodata collected from IoT-based biosensor devices, sorts the input data into three groups (normal persons, patients, and noisy conditions), and then uses this information to build a personalized model in the prevention of cardiovascular illnesses [10]. It consists of a deep neural network architecture that is efficiently integrated and preprocesses power spectrum frequencies using quick Fourier transform [11]. In order to enhance an ML model and generate an ideal model having a high forecast rate for preventing heart conditions, the suggested strategy recommends using a combination of algorithms and algorithms.

The main objectives of this paper are:

- To develop a FPM-DNN, a deep neural network frequency pattern mining model for the detection of heart issues in real-time
- To preprocess biosignal data using Fast Fourier Transform and other techniques to enable effective analysis and classification.
- To provide a system that can classify input data into categories such as normal conditions, patient conditions, and noise conditions, thus aiding in the early detection and prevention of cardiovascular disorders.

A summary of the research is provided below. In Section 2, the current literature and study techniques are thoroughly examined. The research strategy, methodology and processing procedures are detailed in Section 3. The results analysis is covered in Section 4. Part 5 explores the main conclusion and Future work.

2. Research Methodology

Zhang et al. [12] Presented in the study is a two-way multiplex convolutional neural network (CNN) that can use electrocardiogram (ECG) data to distinguish between seven different types of cardiac arrhythmias and normal heart rhythm. The convolutional neural networks (CNNs) made use of a layers of one-dimensional model with an layers of auxiliary-two-dimensional architecture. The system is able to handle ECGs of different durations using the frequency-domain model; it achieves a classification accuracy of 96.3% and an average accuracy of 99.1% for ventricular premature contraction (APC).

Kumar et al. [13] produced streptococcal throat infection, which in turn causes heart failure, organ damage, and valve damage; this condition is known as Rheumatic Heart Disease (RHD). One of the symptoms that precedes RHD is Acute Rheumatic Fever (ARF). The accuracy, prediction, and symptom categorization of current RHD detection methods are inadequate. To enhance the accuracy of RHD detection, a novel method called Multi-Layerered Acoustic Neural Networks (MLAN) employs techniques, including the Acoustic Support Vector Machine, Heart Sound Sampling,Recurrent Convolutional Network of RHD and Electrocardiogram Data Sampling.

Pradhan[14] displayed the One of the leading causes of mortality globally, heart disease, can only be diagnosed with the use of cardiac imaging. The authors of this research suggest utilizing a deep neural network to automatically diagnose heart illness based on images of the heart. Pre-processing, extraction of features, choice of features, and classification are the four different processes that are required for the system to function properly. A median filter is used to pre-process the pictures, features are retrieved from the gray scale level co-occurrence matrix's, and the lion particle swarm optimization (LPSO) technique is used to choose key features. A classifier based on deep neural networks uses the characteristics that were chosen to determine whether the picture is normal or if heart failure is present.

Suvanov et al. [15] displayed the Technologies such as Deep Learning and Artificial Neural Networks (ANN) use several layers to make predictions, mimicking the way the human brain functions. They have applications in healthcare, especially cardiology, and are utilized in retail, marketing, and finance. Using scalable datasets, this work seeks to investigate machine learning's role in the prediction of cardiac disease. Social and demographic variables, medical and family history, environmental risk factors, and modifiable and non-modifiable food and lifestyle factors all have a role in the development of cardiovascular disease.

Guo et al. [16] displayed the Healthcare has the ability to go from being an art based on expertise to a data-driven science, because to the large quantity of digitized clinical data produced by the widespread use of electronic medical records (EMRs). In order to accomplish the "5R" objective of rational medication usage and clinical pathways, this chapter explores the difficulties of data-driven diagnosis-treatment pattern mining, suggests a data-driven technique for identifying and predicting unified diagnoses, and mines three types of common treatment patterns.

Onyema et al. [17] displayed the An Internet of Things (IoT) hybrid paradigm for healthcare 4.0 genomic sequence analysis is presented in the study. It takes pattern-matching concepts from Hadoop and applies them to OpenCL and API. When looking for information about biological sequences, the main approach is BLAST. The model makes advantage of many types of parallelism, including those between and within nodes, as well as fine-grained parallelism. For some datasets, the standard BLAST algorithm outperforms its predecessors thanks to the Mapper and Reducer process, which speeds up the procedure.

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Shakeel et al. [18] displayed the Improved accuracy and precision in detecting lung tumours achieved by the use of a K-means clustering approach called BOAKMC, which is based on the butterfly optimization process. For pixel classification, the approach use noise-reduced computed tomography images. To achieve optimum edge classification, it detects overlapping features. While decreasing classification time and failures by 11.19% and 11.12%, respectively, the BOAKMC technique increases accuracy and precision by 10.2% and 13.39%.

Sridhar et al. [19] provided the Injuries, cancers, and genetic mutations may cause brain abnormalities, which can raise death rates by as much as 86%. To avoid these illnesses, detection is essential. In this study, we present a multi-objective neural network that can detect brain abnormalities automatically. We use particle bee and ISO map spectral approaches to gather brain signals, filter out noise, and extract features. Metrics and tools from MATLAB, such as accuracy, sensitivity, specificity, F-measure, and error rate, are used to assess the system's efficiency.

Kavitha et al. [20] demonstrated a web service-oriented healthcare application for cancer illness prediction and medical treatment using the Pattern Matching with SVM Classifier in combination with the MVC framework. The data is generated by an application named SQL YOG, and the pre-condition patterns linked to cancer are built using MY SQL API scheduler. People fill out surveys using their web browsers, while the pattern-matching method matches their input pattern to the pre-condition pattern. Cancer-related patterns are categorized using SVM. The approach's performance is quantitatively and qualitatively tested using sensitivity, accuracy, and specificity parameters.

3. A Model for Real-Time Heart Condition Classification Based on Deep Neural Network Frequency Pattern Mining

a. *Using the Fast Fourier Transform for Preprocessing*

Through the development of a bioinformation processing system, the research intends to assess real-time risk variables using healthcare IoT technologies. Bioinformation gathers numerical and time-series biosignal data, such as a person's height, weight, temperature, and blood sugar levels. The two main ways to get biosignals from the heart are by using ultrasonography or electrocardiography (ECG). The techniques used by mobile devices are diverse and include approaches based on infrared and optic sensors, parts of the body that are easier to measure, and sensors connected to clothes. The personal measuring instrument utilized determines the sort of biometric information that is gathered.

Issues like as poor resolution, missing, and noise may be effectively addressed using a range of resolutions and strong preprocessing methods. The research compared data processing methods, conducted qualitative and quantitative evaluations, and made use of easily accessible, wearable electrocardiogram (ECG) sensors as well as pulse sensor input devices. This is possible to format data from pulse sensors as a frequency, and methods for identifying typical heartbeats make use of frequency features. Among the many transform methods used in signal processing, communications, speech, and images is the Fourier transform. Features may be extracted, noise can be filtered out, and frequency bandwidth can be studied. Nevertheless, To investigate the correlation between frequency and time, the rapid Fourier transform is used since the slower Fourier transform cannot do so. The fast Fourier transform is used in this study. It eliminates repetitive operations to increase its transform speed and effectively conveys the impact as a function of time.

$$Ft(u) = \sum_{n=0}^{N-1} G(x) e^{i\frac{2\pi ux}{N}} \tag{1}$$

The equation 1 of the rapid Fourier transform is stated, under the constraint that the input function of a discrete signal is denoted by the symbol G(x). Regarding the equation (1), the letter N stands for the entire amount of data, and the letter i stands for an imaginary number .

In the equation, if the variable e is defined as WN and the variable N is denoted as $2K$, then the equation 2 , with the terms even number and odd number being separated out.

$$Ft(u) = Ft\_even(u) + Ft\_odd(u)W_{2K}^{u} \tag{2}$$

The Equation 3 describes the computation of the Fourier Transform at index $(u + k)$ by combining the Fourier Transforms of even and odd-indexed elements at index u with the twiddle factor W_{2K}^{u}.

$$Ft(u + k) = Ft\_even(u) - Ft\_odd(u)W_{2K}^{u} \tag{3}$$

In Equation 3, The efficient calculation of the DFT and the reduction of computational complexity from $O(N\text{^}2)$ to $O(N \log N)$ are both made possible by this formula, which is fundamental to the FFT algorithm. In order to analyze frequencies, electrocardiogram (ECG) sensors employ the rapid Fourier transform, which produces 100 samples per second. Before you can apply the transform, you need to establish the endpoint and normalize the frequency of pulse data in real-time. Normally, R-peak is detected using the Pan-Tompkins method. Adding a hidden layer and learning different power spectra are both capabilities of a neural network system. To account for outliers, the sample size need to exceed the maximum size of the R-R wave. Taking the user's reaction time into account, the analysis time need to be a minimum of one second. The rapid Fourier transform uses 356 discrete data sampling cycles and has a base time of 2.56 seconds. The initial output is bi-symmetrical data, which, after being squared, is transformed into the power spectrum. With the use of a band-pass filter in the power spectrum, noise filtering may eliminate inaccurate electrocardiogram data caused by sensor startup or failure. By combining the three-section separation approach with the classification of frequency data into eight parts, this study enhances the ECG frequency analysis method. Depending on the sensor and the location of the wearable, the total input frequency of the derived data may vary.

b. Power spectrum extraction and real-time acquisition of frequency patterns

In order to assess heartbeats, the research employs an electrocardiogram (ECG) biosensor to capture pulse data. A pulse sensor that measures heartbeats and extracts, amplifies, and filters biopotential signals in noisy environments is the AD8232 chip. It may be made compact or modularized with an external battery and operates on 170 µA ultra-low power. The acquired data is processed using the 32 KB RAM and 16 MHz speed of the Arduino Uno (R3) microcontroller board. The HC-05 Bluetooth module may send and receive data using the IEEE 802.15.1 protocol. When compared to XBee, Bluetooth allows for a low-power system to be implemented since it permits data reception and transmission without requiring a separate module in this section of reception.

In Figure 1, The Healthcare 2020 device is a bioinformation measuring device specifically engineered to monitor activity and fitness signals within the healthcare field. It is capable of signal extraction, amplification, and filtering under conditions of noise using an ultra-low power of 170 A and is small-form or modularizable via an external battery. The device is characterized by a 100-fold amplification factor and a common-mode reject ratio of 80 dB. At a rate of 9600 bits per second, the internally transformed digital value is sent. In order to process the raw data, we used an Arduino Uno (R3) microprocessor board.

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One such low-power system implementation is the HC-05 Bluetooth module, which can receive and transmit data. A terminal server received the collected electrocardiogram samples and executed a fast Fourier transform on them. The lefthand side of the modified spectrum of power is yielded 254 discrete values. The total value was organized into eight parts, and the collected data was divided into eight sections as well. To model subjective context recognition via a neural network and to build semantic links between heart conditions and human actions, the bioinformation data is used. According to the model, each device has to send a total of around 15 KB of data. The module of the terminal transmits 11 pulse data points, and a total of 254 points are accumulated and delivered at 2.6-second intervals.A deep neural network model allocates 360,000 data points per hour for processing per individual. However, in the context of a simulation scenario, the required data processing rate is 3,600,000 per hour.

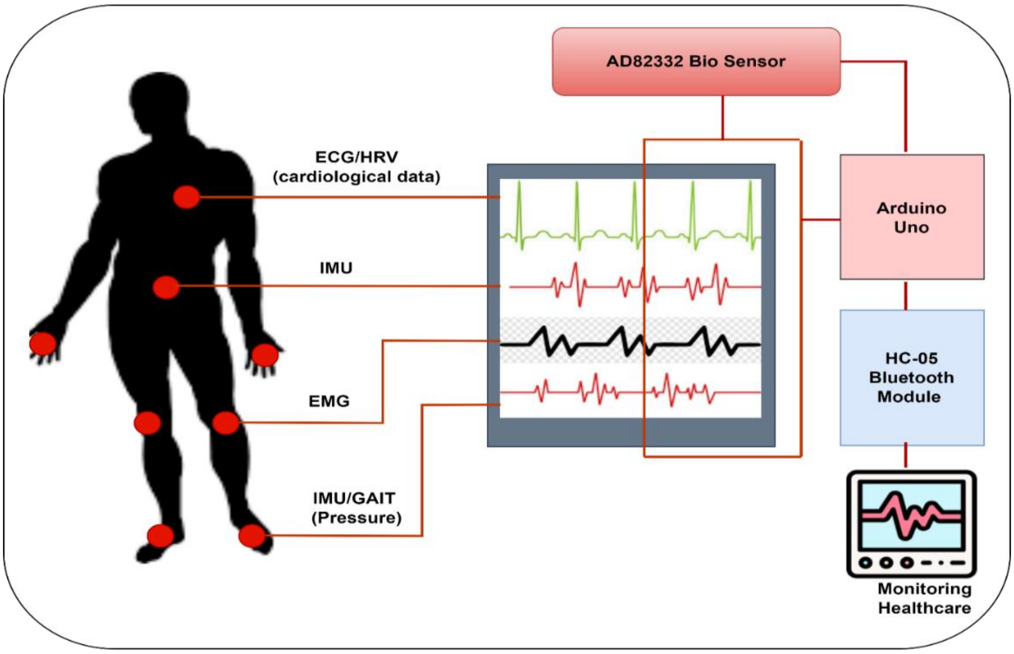

Figure 1: Comprised Pulse measuring Process

c. *Heart Condition Classification using a Deep Neural Network*

Bioinformation processing makes use of machine learning to analyze heartbeats by grouping and classifying data using deep neural network methods. By analyzing electrocardiogram (ECG) data, these algorithms can differentiate between normal heart rate during activity and rest, as well as between emergencies. When building a model using the deep neural network, training as well as inference are the two most important aspects. Pulse frequency risk analysis makes use of supervised learning, which is one branch of the larger learning process. There are eight neurons in the model's input layer, twenty-seven in the model's three-stage hidden layers, and three neurons in the model's output layer, which displays normal, aberrant, and noisy outcomes, respectively.

A simulation scenario requiring 3,600,001 units of data per hour is beyond the capacity of the human data processing capacity, which stands at 360,000. Sorting biodata into normal, aberrant, and noisy categories is the first step in getting it ready to be utilized by a deep neural network model. The fundamental information gathered when the subject is at rest forms the basis of this categorization. The deep learning technique is helpful for data classification and processing, and it is one way to handle massive data sets in bioinformation. It does electrocardiogram (ECG) analysis and can tell in an emergency whether or not the patient's pulse fluctuates while rest, during action, or both. Training and inference are the two main components of a deep neural network model construction process. The initial input layer is the first stop in training a neural network. The next step is to find the weights of every node by use of feedforwarding.

The kind of work at hand dictates whether a supervised or autonomous learning approach is more appropriate. Supervised learning may be used to evaluate the possibility of an abnormal heart rate. The input, output, visible, and layers that remain hidden are the mainstays of deep neural network models. Various data states, such as erratic, normal, abnormal, and steady pulse, may be used for data learning. To keep the discrepancy between the resulting value and the true value of every single node to a minimum, a weight is required. The precision of the output in the error correcting phase dictates how the weight is adjusted; it is calculated and updated using gradient descent. Developing a model of deep neural networks for processing very big data requires modifying the framework to change the layer widths, complexity of the mistake reduction functioning, and the learning rate of every node. As the number of concealed layers increases, the cost of connecting weights also grows exponentially. The system follows a preprocessing-based data classification procedure, which includes sending classified values to a terminal and then training the sent values using operation processing.

d. Processing and Configuration for Classification of Heart Conditions

To consistently store the data, identify the data, and handle the obtained data, the design is required to create an integrated data schema. A terminal processes biometric data in real time, independent of the received data or the request from client. A distinct table is used to store the processing results after the quick Fourier transform. In Figure 2 we can see the schematic of the terminal designs, which incorporates the biodata collection module.

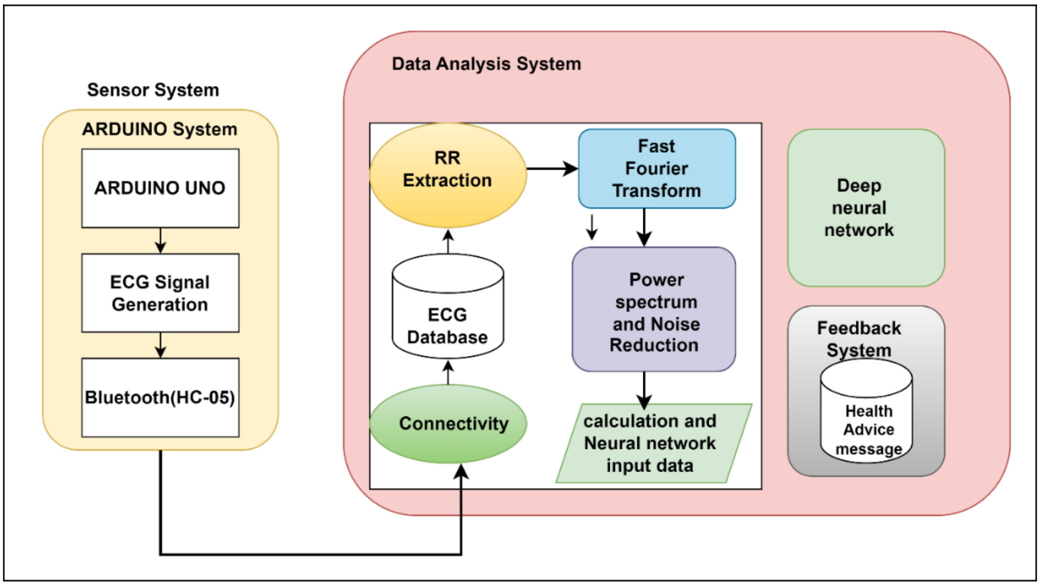

Figure 2: System Configuration and Processing for the Heart Condition Classification System

Figure 2 shows how this study simulates complex nonlinear interactions using a model of deep neural networks that uses feedback evaluation. A configuration consisting of many hidden layers is formed utilizing eight input nodes that are built in line with the frequency input. Customers have easy access to online services thanks to the final output model's use of a web server as the communication medium. The server system has an Intel processor with 8 GB of memory available, while the sensor data collecting and operation terminal device has an Intel Celeron N is the number of2930 1.83 Mhz CPU and four gigabytes of memory.

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Use of a compiler language for software implementation necessitates a number of libraries, including those for serial connections, internet service, and database connection. Versions of Java utilized for development include Java Standard Environment (construction 1.8.0_111-b14), IntelliJ IDEA (Build: 191.670761), MySQL (Version 8.0.15), and MySQL Workbench (Version 8.0.15). A total of 41.46 MB of ECG database space is required for the use of deep neural networks and quick Fft transforms, with approximately 50,000 pulses of basic data making up 82% of that space.If the risk of a cardiovascular disease is high, a button is included for the electrocardiogram, or ECG, information screen. By using this button, you may see graphs showing total harmonics after the rapid Fourier transform, as well as evaluations of the deep neural network's normal, aberrant, or noisy states. Customers may get personally relevant information and calculate their risk index of cardiovascular disease based on fluctuations in their own unique pulse using the online service screen.

4. Results and Discussion

This article presents the results of an assessment of a deep neural network framework for real-time categorization of heart conditions using biosignal data. The model was tested for accuracy, efficiency, and effectiveness. Techniques for data reduction, evaluations of accuracy and recall, learning rate and epoch analysis, real-time classification, and performance measures like as F-measure, accuracy, and recall are among the most important components. The purpose of the research is to achieve the following objectives: minimize the quantity of data that is processed in real-time; evaluate the effect that learning rate and epochs have on the accuracy of the model; and identify the ideal training parameters. The Recall, Precision, and F-Measure are specified in Equation (1), (2), and (3), respectively.

$$Recall = \frac{|X \cap Y|}{X} \tag{1}$$

$$Precision = \frac{|X \cap Y|}{Y} \tag{2}$$

$$F - Measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3}$$

where Y is the set of all the recommended positive picture books, and X is the set of all the positive picture books. Because the significance of the lower number is considered, the F Measure, which is the harmonic mean of Recall and Precision, can indicate the total influence of the advice. Having said that, keep in mind that there are a few variations.

In figure 3, Three approaches are detailed through it: MLAN, LPSO, and FPM-DNN. There are five, ten, fifteen, and twenty-one possible outcomes for each approach. When it comes to 5, 7, 8, 80.9%, and 81% accuracy, MLAN is your best bet. With LPSO, the accuracy drops to 69.3% for5, 80% for10, 89.3% for15, and 83% for 20. Accuracy for 5, 10, 15, and 20 is 87%, 90%, and 91%, respectively, for FPM-DNN. In comparing the methods' performance across many contexts, these figures provide a comprehensive perspective.

In figure 4, separate cases, the accuracy ratings of three distinct approaches—MLAN, LPSO, and FPM-DNN—are shown. The accuracy of a model's positive predictions may be measured by its precision. For 5 situations, MLAN achieves a 68% accuracy rate, LPSO achieves an 80% rate for 15 scenarios, an 89.3% rate for 15 scenarios, and an 83% rate for 20 scenarios. The accuracy of FPM-DNN is 87% for 5 situations, 92% for 10, 93% for 15, and 97% for 20 scenarios. The precise numbers offered here allow for a comparison of the three networks' performance under various experimental settings, namely MLAN, LPSO, and FPM-DNN.

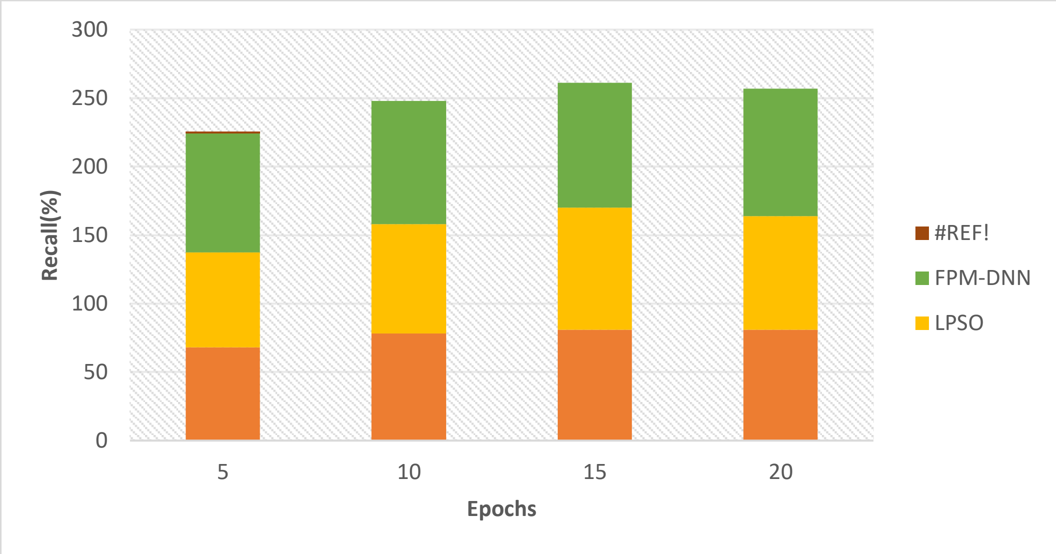

Figure 3: Recall of FPM-DNN

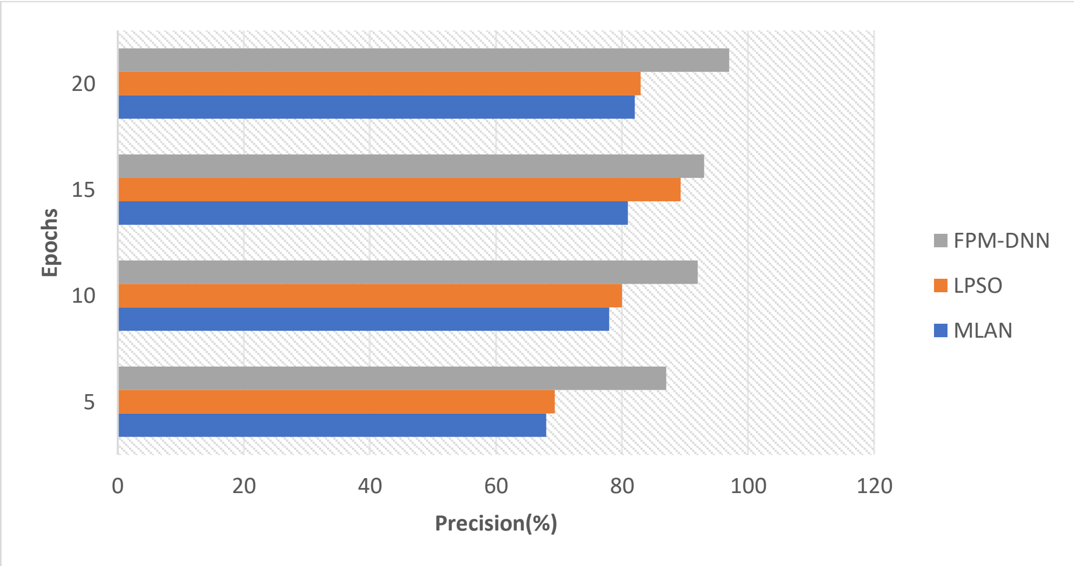

Figure 4: Precision of FPM-DNN

In figure 5,A number of different situations are shown, each of which has the F-measure scores for three distinct methods: MLAN, LPSO, and FPM-DNN. In order to evaluate the effectiveness of a model, the F-measure is a statistic that takes into account both accuracy and recall. The values of LPSO vary from 81% to 68%, whereas MLAN's values are 68%. Indicating the success of each approach in recognizing positive cases and capturing all relevant ones, the F-measure values create a balance between accuracy and recall. This balance determines how well each method performs. The F-measure values that are higher suggest that the overall performance is better. By providing a comparative study under a variety of experimental situations, these values make it possible to conduct a more in-depth evaluation of the performance of a model.

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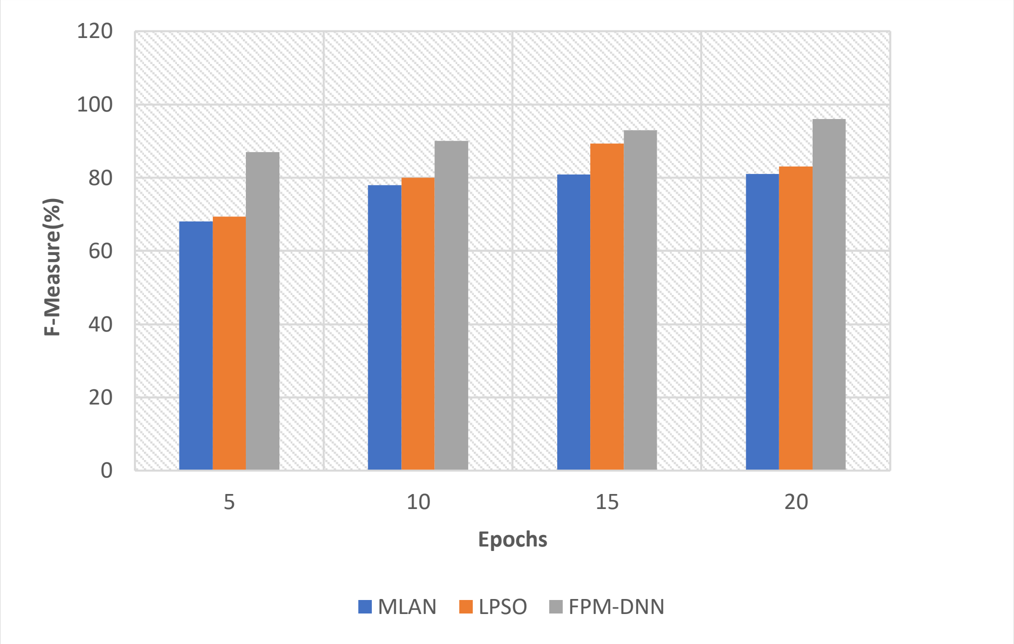

Figure 5: F-Measure of FPM-DNN

5. Conclusion

An improved health data processing model is necessary to increase healthcare's scalability in light of recent economic growth and advances in the internet of things (IoT). There are benefits and drawbacks to using various data processing models. Convergence, in an effort to overcome the drawbacks, might lead to improvements in accuracy or reductions in operational resources. Improving data fitting and reaction speed were the primary goals of this research, which used pulse sensor data to address traditional issues with combining rapid Fourier transform with deep neural network models. This research assessed the suggested model's efficacy by looking at the pace of decrease in data operating costs. This led to a 1:34 reduction in ECG size by the use of cumulative frequency percentage and rapid Fourier transform. Consequently, the suggested approach increased a realistic degree of individualized healthcare service while reducing the cost of large data processing operations and securing accuracy. The implementation and evaluation of learning based on neural network algorithms and rapid Fourier transform were carried out for telemedicine that is based on IoT equipment. With a learning rate of 0.012 and 20 epochs, the model of the deep neural network achieved an F-measure of 83.73%. It demonstrated that a healthcare strategy that is both affordable and widely available is within reach. Based on the outcome, enhancing system performance is achieved by the integration of several algorithms. A variety of users may be satisfied with the highly tailored service by providing information about risk patterns and rates. Users may easily assess their risk index for cardiovascular illnesses using the offered information, and then take measures to prevent or mitigate the environmental variables that increase their risk.

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