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# An intelligent approach for enhancing the quality of service in IoMT based on 5G

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**ABSTRACT**

The concept and growth of superior individualized healthcare technologies are influenced in significant ways by the rising areas of "Artificial Intelligence (AI) and the Internet of Things (IoT)". Most people use wearable devices for mHealth, hence there are many potential applications for the "Internet of Medical Things (IoMT)". Only 5G can provide the necessary support for smart medical devices to perform many different types of demanding computing activities. Today, heart disease was the major mortality on a global scale. For patients who need a greater accurate diagnosis and treatment, the advancement of medical innovation has created new obstacles. Although many studies have focused on diagnosing cardiac disease, the findings are often inaccurate and fail to fulfill patients' expectations of quality of service (QoS). So, this paper introduces a novel "feed-forward Bi-directional long-short term memory (FF-Bi-LSTM) algorithm to predict heart disease more accurately with enhanced QoS in IoMT based on 5G". Linear discriminant analysis (LDA) and min-max normalization are employed, respectively, for preprocessing and feature extraction. Several measures, including precision, recall, accuracy, and f1-score, are used to the assess effectiveness of the suggested strategy. The proposed method also compared to certain existing techniques. These results show that the suggested strategy outperforms existing strategies in terms of improving QoS.

**Keywords**: M-Health ,IoMT , AI, QoS , Heart Disease , FF-Bi-LSTM

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## 1. Introduction

IoT is extensively used in several industries and contributes significantly to the betterment of our daily lives. The provision of e-Health services is one of the most important aspects of the Internet of Things since it enables physicians to monitor their patients remotely and provide advice on how to stay safe without taking time away from their busy schedules. An information technology revolution is essential for healthcare to meet the growing demand for safe, efficient care. An "Internet of Medical Things (IoMT)" is an industry-conceived solution that involves connecting patients' and physicians' medical equipment online in order to share information. Medical sensors that are physically linked to individuals and may communicate readings or data to healthcare providers like hospitals or specific physicians who can act on the information are included in IoMT devices. Big way sensors, wearable medical monitors, and other similar devices send vital information about a patient's health as part of IoMT [1]. Healthcare IoT systems may benefit greatly from the use of Big Data and AI. Artificial intelligence (AI)-based Data processing approaches have the potential to greatly advance global public health. Technologies in the “Internet of Things (IoT)” make it possible to reduce the worldwide cost of preventing chronic diseases. Self-administered treatments may be aided by the real-time health data obtained by these devices. The IoMT is used to connect mobile devices and apps for healthcare and mHealth [2]. Wireless communication systems must be able to support the rigorous requirements of new networks and devices to meet the rapidly expanding economic and cultural demands of human civilization. For 5G, B5G systems to be successful, they need to outperform their predecessors in a variety of ways, including throughput, latency, device connectivity, and quality of service (QoS). To fulfill all these needs, 5G/B5G systems must tackle the more difficult challenges in the presence of uncertain, partial, or nonexistent a priori information. In light of this, it is critical to develop even more cutting-edge means of communication. Researchers in both academia and business are beginning to combine artificial intelligence (AI) with 5G/B5G because of the wide variety of successful applications in other sectors [3]. E-health IoMT-based apps have grabbed the lead in wellness services, pushing large numbers of people to live better lives. To get the most out of healthcare apps via IoMT, some issues must be overcome. IoMT devices (e.g., medical wearable and implanted sensors) are subject to security attacks and represent a danger to patient privacy and safety. Adversaries may hack IoMT devices and change stored data or functionality. For the effective implementation of IoMT technology into widespread healthcare systems, unique security techniques are needed to safeguard the IoMT edge network's security. First, analyze and categorize present and future IoMT edge network risks. IoMT devices have comparable capabilities and technological features to IoT devices; hence attacks against IoT networks may likewise threaten the IoMT 5G network.

- Datasets from Framingham, Health, and the Hungarian heart sickness dataset were collected for this study.
- The reliability of the data prepared for result creation and information pre-processing is improved by normalizing.
- Linear discriminant analysis is used to predictive algorithm for feature extraction.
- Feed forward Bi-directional LSTM algorithm improved to predict heart disease for classification.

Study [4] discussed that “5G communication networks and mobile edge computing (MEC)” are two potential technologies that may bring many advantages to drone-enabled settings and help address some of the problems that have been expressed. The research [5] separated the Internet of Medical Things (IoMT) into two sub-networks, namely intra-Wireless Body Area Networks (WBANs) and beyond-WBANs, to create a cost-effective in-home health monitoring system. The cost of patients varies on medical importance, the Age of Information (AoI), and energy usage, underscoring an aspect of IoMT. According to study [6], the centrally operated network's "individuals" and movement individuals; environmentally conscious FDMA framework (Flow-enabled Distributed Mobility Pinning)" functioned better. Study [7] focused on how energy-efficient communication, as well as the user's quality of experience “(QoE) level”, The UT device's transmission of multimedia content might be intercepted. The major distinctions “between the tactile internet and the Internet of Things” are discussed [8] this research considering the 5G revolution. Study [9] focused on how AI has contributed to recent developments in IoMT. They look at the hardware needed and some of the recent studies that have proposed solutions for IoMT utilize AI. The main benefits and drawbacks are properly outlined. Study [10] analyzed “identity-based seamless privacy-preservation (IB-SPP)” to allow smart device communication. Speedy user authentication is the only determinant of how quickly access may be granted in urgent circumstances. Study [11] described that 5G and IoT have improved the quality and efficiency of wearable medical equipment. A 5G-based sensor nodes design is also suggested for patient health monitoring.

## 2. Method

The research, we suggested the feed forward Bi-directional LSTM. The term "Internet of Medical Things" (IoMT) means a group of related things that work together healthcare IT systems, including Internet-connected medical equipment, hardware infrastructure, and software applications. Because the 5G network can connect with IoMT devices at a 100 times higher ability than the 4G network, medical providers may rely on remote medical monitoring or wearable technology to continuously collect, record, and transfer crucial information to a distant monitoring centre. In Figure 1 depicts the proposed methodology.

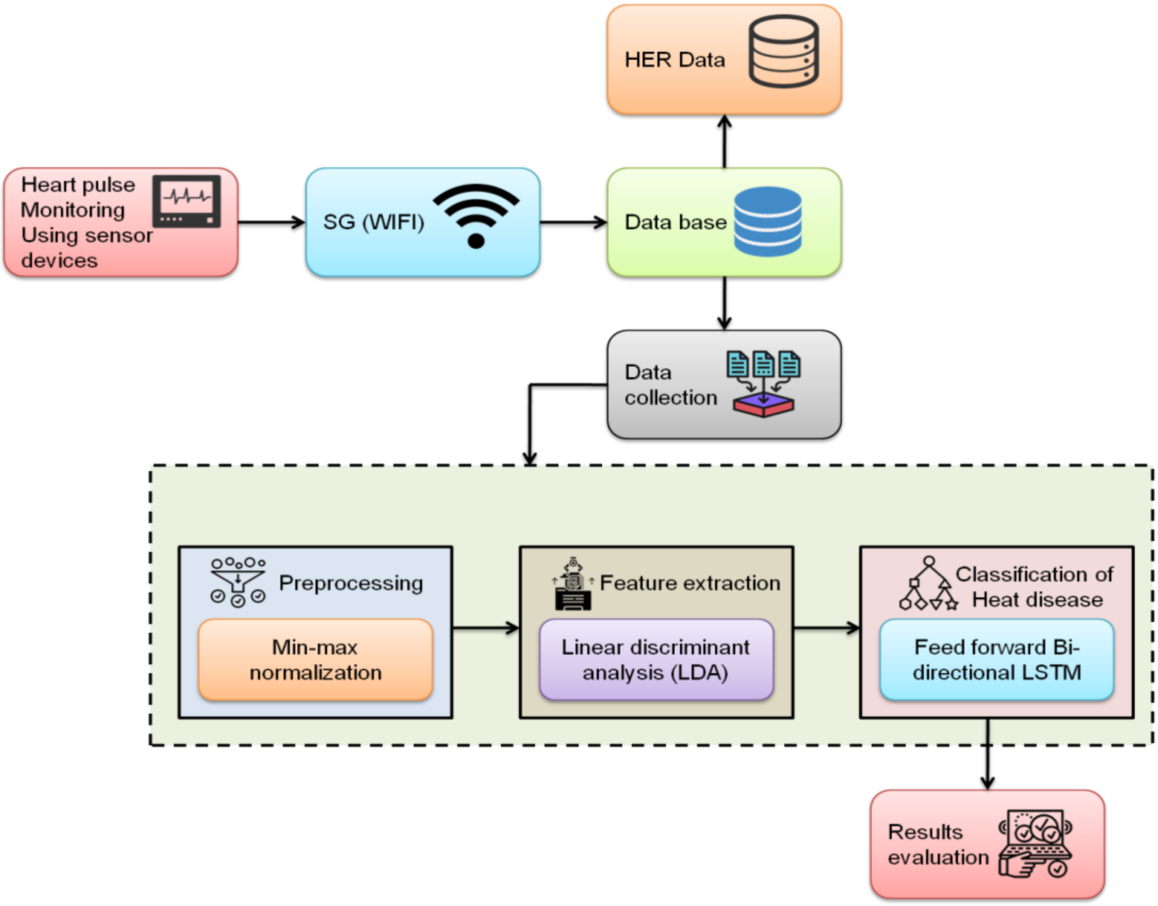


Figure 1. The suggested technique is shown schematically

## 2.1 Data collection

The UCI Machine Learning Repository, the Framingham and Health Datasets, and other resources were utilized to train and evaluate the disease. The UCI resource includes datasets from Switzerland, Cleveland, Hungary, and the VA Long Beach [13]. Data collection and analysis are performed using the Raspberry Pi single-board laptop. The necessary equipment is listed in Table 1 for this study. Three freely available internet datasets Framingham, Public Health, and the Hungarian heart disease dataset are used in the suggested methodology. Table 2 demonstrates that the roughly 76 attributes and 14 features of the information base were only partially exploited in the investigation.

Table 1. The equipment utilized in the mode

| Hardware | Explanation |
|---|---|
| Heart Guide BP8000m | Omron's wrist that measures blood pressure |
| AD8232 | Analogue Technologies' visual display of an electrocardiogram |
| SX 1272 | devices for LoRa at 900 MHz, including the transmitter and receiver |
| Customer Computer | 3.10 GHz PC with an Extra Fundamentals TM i5-2400 CPU |
| Raspberry Pi-IV | CPU with four cores, ARM Cortex-A72, 64 bits, and 1.5 GHz |

Table 2. Descriptions of the UCI dataset's characteristics

| Attribute | Explanation |
|---|---|
| slope | The ST segment of the pinnacle workout's perspective<br>➢ down sloping<br>➢ up sloping<br>➢ flat |
| num | Heart disease classification<br>0.existence (diameter reduction of 50% or less)<br>1-4. A heart condition exists (diameter has shrunk by more than 50%) |
| sex | Sex (1 = male, 0 = female) |
| ca | Major vessel count (0–3) colored by fluoroscopy |
| thalach | reached maximum heart rate |
| Age | Age in years |
| chol | Mg/dl of serum cholesterol |
| cp | Chest pain type<br>➢ asymptomatic<br>➢ non-angina pain<br>➢ typical angina<br>➢ atypical angina |
| fbs | Rising blood sugar more than 120 mg/dl (1 = true; 0 = false) |
| restecg | A rested electrocardiogram's findings<br>0. normal<br>1. having an aberrant ST-T wave (T wave inventions and/or ST elevation or depression of more over 0.05 mV)<br>2. according to Estes' Criteria, exhibiting either definite or probable left ventricular hypertrophy |
| trestbps | resting blood sugar levels |
| exang | (1 = yes; 0 = no) Exercise-induced angina |
| thal | 3 (normal); 6 (fixed defect); 7 (reversible defect) |
| old peak | Exercise-induced ST depression compared to rest |

### 2.2 B. Data pre-processing using normalization

We present data-preprocessing, which include standardization, manage any incorrect data, error, and comparable information since the information from the tool set includes some absent or inaccurate information as well as duplicated in form throughout individual potential by both sets of information. The level of computation was reduced by using a formula standardized data from medical data $GE^{gm}$ inside the context [0, 1]:

$$Data\_S_{norm} = \frac{GE^{gm} - Data\_S_{min}}{data\_S_{max} - data\_S_{min}} \times [max_{value} - min_{value}] + min_{value} \quad (1)$$

where $Data_{S_{norm}}$denotes the normalize assessment of a information source, Data_$S_{min}$ denote the lowest value of a information source, Data $S_{max}$ denote the highest column of a database, $GE^{gm}$ denote the unique column of the medical information source, “min-value and max-value” stand for the range of a normalize input information, with “max-value = 1 and min-value = 0”, and *GE* denote the original cost of a medical information basis.

### 2.3 Utilizing linear a discriminant analysis removes features

In the domain of data processing, multi-linear discriminant analysis (M-LDA) is a typical feature extraction method. Controlled complexity reduction is possible with M-LDA. The idea of M-LDA is to maximize variance across classes while simultaneously decreasing variation within them. As expected, the identical categories' values are as close as they come once the data are shown in a near-bottom region, but the two independent data continue to be in separate possible positions. Linear analysis of a diverging matrix of the supplied data sets may be used to get a visual angle value of M-LDA. For m values, the equation provides a well-known and managed LDA.

$$a^* = \underset{a}{argmax} \frac{a^q S_c a}{a^q S_x a} \quad (2)$$

$$S_a = \sum_{k-1}^{a} h_k \left(\mu^{(l)} - \mu\right)\left(\mu^{(l)} - \mu\right)^q \quad (3)$$

$$S_x = \sum_{k=1}^{a}\left(\sum_{i=1}^{h_k}\left(z_i{}^{(k)} - \mu^{(k)}\right)\left(z_i{}^{(k)} - \mu^{(k)}\right)^q\right) \quad (4)$$

An is the set of numerous possibilities carriers, and is the average value over each data set. H k is the quantity of data in the $k^{th}$ group, $k$ is the $k^{th}$ class's mean vector, and $z^{(k)}$ is the $i^{th}$ sample in the $k^{th}$ category. The symbols $S_x$ and $S_a$, which stand for the intra-class diverging matrices and the inter-class divergence matrix, accordingly, are used to identify these matrices. We get a fully diverging matrix ($S_t = Sa+S_x$) when the LDA assessment result from the formula (1) to The formula (5).

$$a^* = \underset{a}{argmax} \frac{a^q S_c a}{a^q S_x a} \quad (5)$$

The previous expanded matrix equation has a close approximation in equation (5).

$$R_a X = \lambda S_q \quad (6)$$

Therefore, we may change Equation (6) to get Equation (7):

$$S_a = \sum_{k-1}^{a} h_k \left(\mu^{(k)} - \mu\right)\left(\mu^{(k)} - \mu\right)^q = \sum_{k-1}^{a} h_k \left(\frac{1}{h_k}\sum_{j=1}^{h_k}\left(x_i{}^{(k)} - \mu\right)\right)\left(\frac{1}{h_k}\sum_{i=1}^{h_k}\left(x_i{}^{(k)} - \mu\right)\right)^q = \sum_{k-1}^{a} \frac{1}{h_k}\left(\sum_{i=1}^{h_k}\left(\bar{x}_i{}^{(k)}\sum_{i=1}^{h_k}\left(\bar{x}_i{}^{(k)}\right)^q\right) = \sum_{k=1}^{a} \bar{k}^{(k)} Y^{(k)} \left(\bar{x}^{(l)}\right)^P = \bar{X} Y \bar{X}^P \quad (7)$$

$Y^{(k)}$is a$h_k * h_k$ a matrix with identical values $1/h_k$. X is a mm matrix that appears as follows:

$$X = \begin{bmatrix} X^{(1)} & 0 & \dots & 0 \\ 0 & X^{(2)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & X^{(a)} \end{bmatrix} \quad (8)$$

$x_i = x_i$ represents a centralized data point, and $X^{(l)}$=$\overline{X1}^{(l)}$,….,$\bar{X}{n_k}^{(l)}$represents the centralized data matrix of the $l^{th}$ class. And $\bar{X}^{(k)}$=$\overline{X1}^{k}$,…., $\bar{X}{h_k}^{k}$. represents the cth class's centralized data matrix. Since $S_a$=$\bar{X}Y\bar{X}^Q$, the following transformation applies to the extended value solution in Equation (6).

$$\bar{Y} Z \bar{Y}^P c = \lambda \overline{Y} \overline{Y}^P \quad (9)$$

Here, we describe a multi-linear discriminant analysis that effectively navigates the challenge posed by M-eigenvalues LDA's in Equation (9). When this is the case $\bar{X}^q$ $a$=$\bar{y}$, Equation (9) may be rewritten as

$$X\bar{y} = \lambda \bar{y} \quad (10)$$

The eigenvalues in equations (9) and (10) are equivalent to the eigenvalues a that are created and modified when $\bar{X}^q$ $a$=$\bar{y}$ Use of the observed data method, as shown by the equation, is an excellent substitute for $\bar{X}^q$ $a$=$\bar{y}$.

$$a = \underset{a}{argmin} \sum_{j=1}^{n}\left(a^q \bar{x}_I - \bar{y}_I\right)^2 \quad (11)$$

By solving (10), we may generate the mappings matrix a= [a1, a2,:::,a$^q$] (11). After features are extracted, the characteristics are calculated as $a$=$a^q \bar{x}_I$ where X is a1 linear transformation produced via prediction.

### 2.4 Classification of heart disease using feed-forward Bi-directional LSTM

With the aid of a predetermined set of weights and activation processes, the FNN is a specific kind of inferences model 22 that transforms its inputs. Before using the weights in a prediction, a set of T instances Z= [$Z_1$….$Z_D$, $Z_d$] are used to train the model with the help of their training labels (classes). W-dimensional binary vectors represent the training labels for W classes in the w true input type.

$$v_d^w = \begin{cases} 1, w = w_{true,} \\ 0, w \neq w_{true,} \end{cases} w = 1, \ldots, w \quad (12)$$

At each time d, FNN produces a likelihood-like distribution of W classes $\hat{v}_d^w$ where M is the number of classes.

$$\hat{v}_d^w = a\left(\sum_{q=1}^{T} m^{q,w} z^q\right) = a\left(M^{wD} Z_d\right) w = 1, \ldots, W \quad (13)$$

In this expression, mw is a weight vector, and a is a function chosen at random. Through inversion, the locally optimum weights mw; w 14 1;...; W is determined by minimizing a cost function, Q, across a collection of input samples, d 14 1;...; D.

$$\widehat{M}^w = arg \min_{M^w} \{\textstyle\sum_{d=1}^{D} (B(v_{d,} v_d (M^{w,} Z_d)))\} \quad (14)$$

The Bi-LSTM consists of two independent LSTMs that can integrate and summarise data coming from both the forward and backward directions. For successful sequence labeling tasks, it is useful to have access to both historical and prospective contexts. To learn about both the present and the past, the Bi-LSTM suggests forward and reverses each progression two different unknown states, which are then concatenated to get the output.

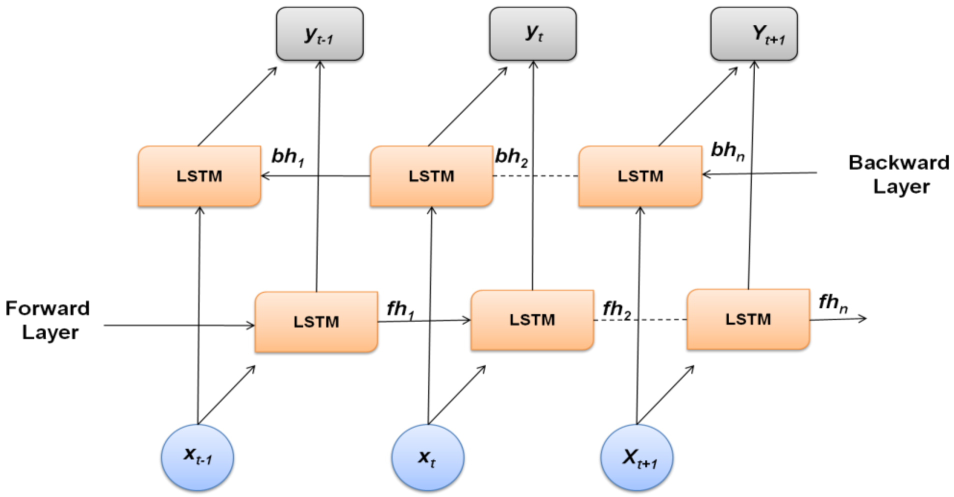


Figure 2. Basic design of the Bi-directional LSTM

The next LSTM produces the concealed column fht using the words that decode xt at each time t and the prior hidden column fh (t-1), but the opposite LSTM produces the hidden column bht-1 using the phrases that decode *xt (t-1)* and the prior hidden column *bh*. By combining the forward hidden column *(fh)* and reverse hidden column *(bh)*, the Bi-LSTM model's final hidden column is produced. The following LSTM creates the hidden column $fh_t$ using the input words that encode xt at each time t and the prior hidden column $fh_{(t-1)}$whereas the reverse LSTM generates the hidden column $bh_{t-1}$ using the previous hidden column bh and the input words that encode $xt_{(t-1).}$ The final hidden column of the Bi-LSTM model is created by adding the backward hidden column (*bh*) and forward hidden column (*fh*). Parameters of the two opposite directions in the Bi-LSTM framework are distinct, even if the sentence embeddings themselves are similar. The basic elements of the Bi-LSTM model are shown in Figure 2, where $fh_1$, $fh_2$... $fh_n$ stands for the forward hidden column and $bh_1$, $bh_2$... $bh_n$ for the backward hidden column. The vector generated when $fh_n$ *and* $bh_n$ intersect is designated by the symbol $h_n$.

## 3. Result and discussion

Heart disease diagnosis has expected a lot of consideration from researchers; however, findings are often inaccurate and fall short of what patients would consider to be of high quality of service (QoS). With improved QoS in IoMT based on 5G, this work offers a new "feed-forward Bi-directional long-short term memory (FF-Bi-LSTM)" method to forecast heart illness more accurately. By considering the recommended "technique's accuracy, precision, recall, and f1-score," its performance is evaluated. Additionally, the suggested approach is contrasted with certain already in-use methods. These findings demonstrate that suggested method performs the competition of raising QoS. The existing methods such as "Decision Tree Algorithm (DTA), Naïve Bayes (NB), Modified Deep Conventional Neural Network (MDCNN), and Long Short Term Memory (LSTM)" are used.The degree to which a size outcome conforms to a cost or average is "accuracy." To acquire the best measurement, accuracy and precision are needed. A precise set of measurements need not be accurate. Because the compilation of measurements may be arranged by their values.

$$\text{Accuracy} = \frac{(TP + TN)}{(FP + FN + TP + TN)} \quad (15)$$

Where,

"TN=True Negative; TP=True Positive; FP=False Positive; FN=False Negative"

Accuracy comparison among the suggested and current approach is depicts in Figure 3. The recommended approach is more accurate when compared to the current method. DTA has a 53% accuracy rate, NB has a 74% accuracy rate, MDCNN has a 65% accuracy rate, LSTM has a 81% accuracy rate, and the suggested FB-Bi-LSTM has a 93% accuracy rate. The term "recall" refers to the percentage of cases in which the classifier properly identified them as positive, and it is used in the process of determining whether or not the data set is comprehensive. When determining which model is superior to others, one performance parameter that is used is called recall. The recall comparison between the new technique and the current methods is shown in Figure 4. DTA has a score of 63%, NB has a score of 72%, MDCNN has a score of 58%, LSTM has a score of 86%, and the suggested FB-Bi-LSTM has a score of 97%.

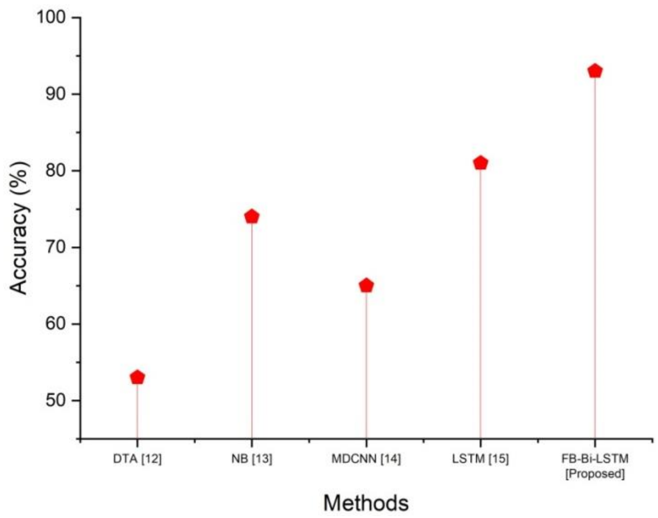


Figure 3. Comparison of Accuracy

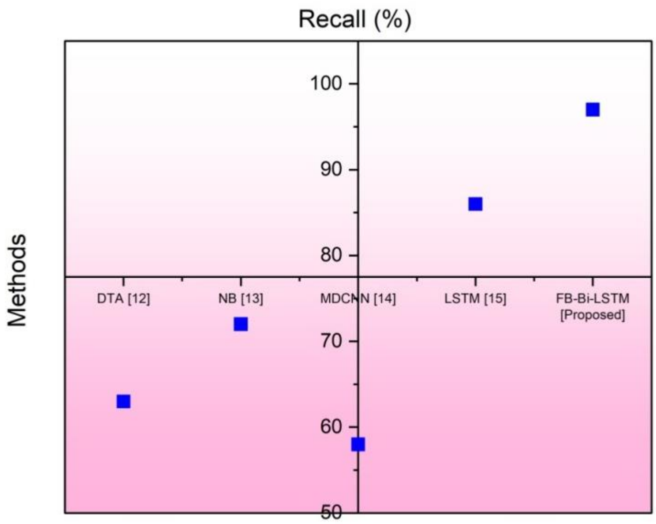


Figure 4. Comparison of Recall

One of the most important measures of reliability is the proportion of cases that are correctly categorized to all examples of data that are predictably optimistic. This ratio can be found in Equation 16, and it is one of the most important measurements of precision.

$$\text{Precision}=\frac{A}{A+B} \quad (16)$$

A = True positive; B = False positive

Figure 5 presents a comparison of the new method's accuracy with that of the approaches that are currently being used. The DTA received a score of 53%, the NB received a score of 65%, the MDCNN received a score of 75%, the LSTM received a score of 82%, and the FB-Bi-LSTM was recommended, which received a score of 97%. F1-score is measured by taking the standard of the recall and precision scores. Through this process, the percentage of false positives and false negatives may be determined. Regardless of whether or not your classes are equally distributed, F1 will almost always prove to be more beneficial than accuracy, even though it is more difficult to understand and implement. Figure 6 depicts the F1 score for existing and proposed methodology. The prior method, such as DTA, NB, MDCNN, and LSTM, had the F1 score of 55 percent, 74 percent, 68 percent, and 82 percent, respectively. The suggested FB-Bi-LSTM has an F1 score of 98 percent.

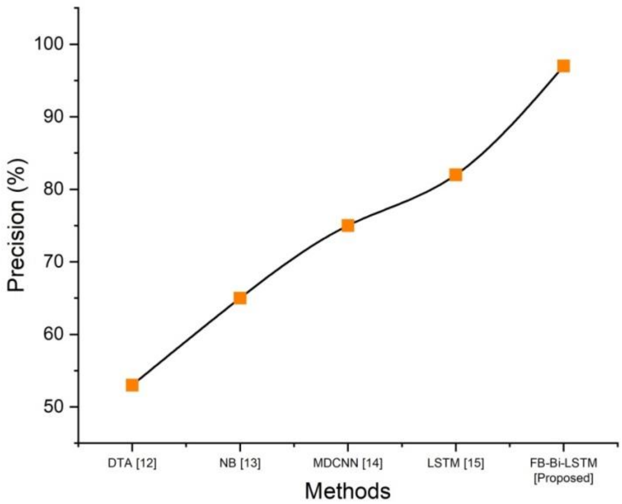


Figure 5: Comparison of precision

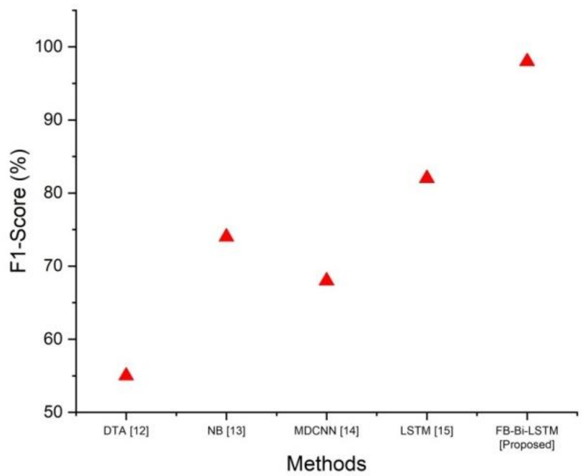


Figure 6. Evaluation of F1- score

DTA (existing) are given the ability to split to a granular degree; they are more likely to learn every point exceedingly well, leading to flawless categorization, which is an example of over fitting. A major problem with decision trees is that they are not as accurate as other methods of predicting which option a user would choose.

The result of a forecast using a continuous variable may be less accurately predicted using this method [12]. NB (existing) data mining approach to creating a model that may predict cardiovascular illness. This method is a statistical classifier that does not make the individual properties reliant on one another in any way. To decide on the class, the posterior probability has to be significantly increased. In this development, the "Naive Bayes" classifier has worse performance and a lower level of effectiveness when it comes to illness prediction [13]. MDCNN (existing) has been integrated into healthcare systems to gather sensor readings to diagnose and predict cardiac disease. Although there have be a lot of studies focusing on the analysis of cardiac infection, the findings of such diagnoses are not very accurate [14-19]. The ability of LSTMs to circumvent the issue of vanishing gradients contributed to their meteoric rise to prominence in the field of illness prediction for heart disease [20-26]. To address such issues, we introduce a novel "feed-forward Bi-directional long-short term memory (FF-Bi-LSTM)" algorithm to predict heart disease more accurately with enhanced QoS in IoMT based on 5G.

## 4. Conclusion

The security and privacy of an "Internet of Medical Things (IoMT)" health service are very difficult to ensure. 5G networks have developed a wide range of authentication and authorization mechanisms to prevent and protect sensitive data utilize of wearable "Internet of Medical Things devices". The study examined the Framingham, Public Health, and Hungarian cardiac disease datasets. Normalization was used for data preprocessing. Linear discriminant analysis is a heart disease predictive algorithm for feature extraction. We proposed feed-forward using a Bi-directional LSTM for heart disease detection to improve the metrics performance. The experimental results are provided as 93% accuracy, 97% of precision, 97% of recall, and 98% of F1-score. We emphasized 5G's significance and the technologies that enable its usage in addressing the challenges and limitations of existing networks. Finally, we briefly discussed how 5G networks may be used to foresee future predictions for heart disease and build a society prepared to deal with them by increasing digitalization and adopting widespread automation.

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**Declaration of competing interest**

The researchers certify that none of the information described in this research is subject to any known financial or non-financial competing priorities.

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