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An IoT enabled computational model and application development for monitoring cardiovascular risks

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ABSTRACT

Technological advancement in the rise of the Internet of Things (IoT) and computational modelling and application development has revolutionized medical care. Monitoring cardiovascular risks is faster, easier, and more accurate than ever. Using IoT-enabled computational modelling and application development, medical professionals can detect, monitor, and predict certain conditions more efficiently. That paper explores the Internet of Things (IoT) enabled computational model and application development that can be used to monitor cardiovascular risks effectively. Cardiovascular diseases are the leading cause of death globally, and currently, there is a lack of comprehensive and reliable monitoring systems to assess the risk of such diseases. IoT enables the integration of different data sources, such as physical activity, diet, BMI and the environmental context, to form a comprehensive tracking tool that can provide accurate cardiovascular risk assessment. The developed application can offer personalized health coaching, leveraging machine learning algorithms to identify patterns and adapt a user's healthcare journey. Ultimately, this paper assesses the potential of IoT technology for monitoring cardiovascular risks and integrating it into current healthcare systems.

Introduction

The increasing proportion of people in their later years has made providing remote health monitoring an absolute need. In health monitoring, healing, and supported living for older people and therapeutically tested folks, one of the most pressing challenges is maintaining consistent system administration between individuals, various pieces of medical equipment, and specialized organizations [1]. As a consequence of this, there is a need for wearable, low-control, inexpensive, and dependable medical technology that has the potential to enhance the quality of life of specific people who are afflicted with certain disorders [2].

To properly monitor cardiovascular risks, IoT-enabled computational models and applications must be able to receive, analyze, store, and process real-time data from sources such as wearable devices, mobile phones, and fitness trackers. AI and machine learning algorithms can be applied to these data to classify risk factors associated with CVDs [3]. That analysis can be used to detect and monitor CVDs, develop prevention strategies, and reduce mortality and disability from CVDs. These IoT-enabled computational models and applications can be used in various ways. For example, a wearable device can measure a user's heart rate, blood pressure, and other vital signs. The collected data can generate personalized individual risk profiles and track health trends over time [4]. In recent years, cloud computing frameworks have also offered support for new applications by providing reliable and robust infrastructure and services [5]. Moreover, fog computing utilizes gateways, nodes, and routers to provide services with the most minor energy consumption, network latency, and response time. Recent research studies explore the problems of fog computing in medical applications and recognize that response time and latency are the most challenging and significant for optimizing the quality of service constraints in practical fog environments [6].

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The existing approaches may need help with these complexities in healthcare and equivalent IoT applications, where they face complexities in getting the accuracy rate in real-time applications [7]. As edge computing has given the immense benefit of minimizing response time, it provides a novel way of conducting research with integrated edge computing and complex ensemble deep learning models for getting high-accuracy results in practical applications. Because of the emergency requiring healthcare applications, there is a need to adopt automatic heart disease diagnosis models using IoT and fog computing technologies and enhanced deep learning applications [8]. As the number of connected devices grows and data-driven insights continue to evolve, developing these models and applications is critical for creating a healthy and safe environment. The construction diagram is shown in the following Fig. 1.

The benefit of IoT-enabled computational models and application development to monitor cardiovascular risks is immense [9]. Physicians can now easily track and record vitals and other medical data without using invasive measures like wires or straps. Moreover, because of the accuracy with which these systems collect patient data, physicians can make informed decisions about treatments or devices that may help improve or prevent the condition. That saves time and money, as diagnosing a patient can be quick and inexpensive. As more health records are stored digitally, physicians can access a patient's medical history and data quickly and efficiently to make more informed decisions about preventive treatments and medication [8–9]. That enables better long-term management of the patient's condition and helps avoid further medical risk.

Furthermore, IoT Enabled Computational Model and Application Development can also work with Wearable Devices, such as Fitbits, to monitor and track all the physiological data, such as heart rate, blood pressure, oxygenation, and respiration [10]. That makes each patient's data available to anyone in the medical team, thus allowing for a fast, accurate, and informed assessment of the patient's condition. The increased use of IoT-enabled computational models and application development for monitoring cardiovascular risks is a breakthrough in modern medical care [11]. The combination of sensors, data analysis, and medical decision-making has allowed physicians to assess risk factors more accurately and comprehensively and make more informed medical decisions. In turn, it can help reduce the possibility of further medical complications and costs while improving patient care overall [12].

The main contribution of the research has the following,

- The paper proposes a monitoring system equipped with an ECG device for patients with cardiovascular diseases, specifically arrhythmias. The system can send the ECG signal to a service located in the Fog layer using the LoRa communication protocol.
- The article contains an intelligent e-health system for heart disease detection using artificial intelligence and the Internet of Things. A biosensor-enabled stethoscope collects the heart sounds of a patient. A wireless sensor network is used to connect all sensors and IoT devices.
- IoT devices connect with a centralized cloud server, where all heart sound files are accumulated. Heart sound signal is separated from other noises using the blind source separation algorithm. The PASCAL data set trains and tests the deep convolutional neural network.

Related works

IoT-enabled computational models and applications for cardiovascular risk monitoring face several issues that must be addressed to ensure they work as intended:

1. There is a need to develop data collection and storage standards to ensure compliance with privacy laws.
2. Security is a significant issue facing these models, particularly concerning malicious actors gaining access to sensitive data.
3. Algorithms and software used for analytics must be reliable and accurate to ensure accurate results. It is also essential to ensure that the data collected is suitable for predictive modelling and risk stratification [13].
4. It is necessary to ensure that the models and applications are user-friendly and easy to understand so that users can benefit from the insights they provide.

Implementing an IoT-enabled computational model and application development to monitor cardiovascular risks is a powerful tool for improving public health [14]. It leverages the advantages of IoT to monitor, record, and track patients' real-time health data and use predictive analytics to identify potential risks. Such an application can help healthcare providers identify any fluctuating behaviour or activity

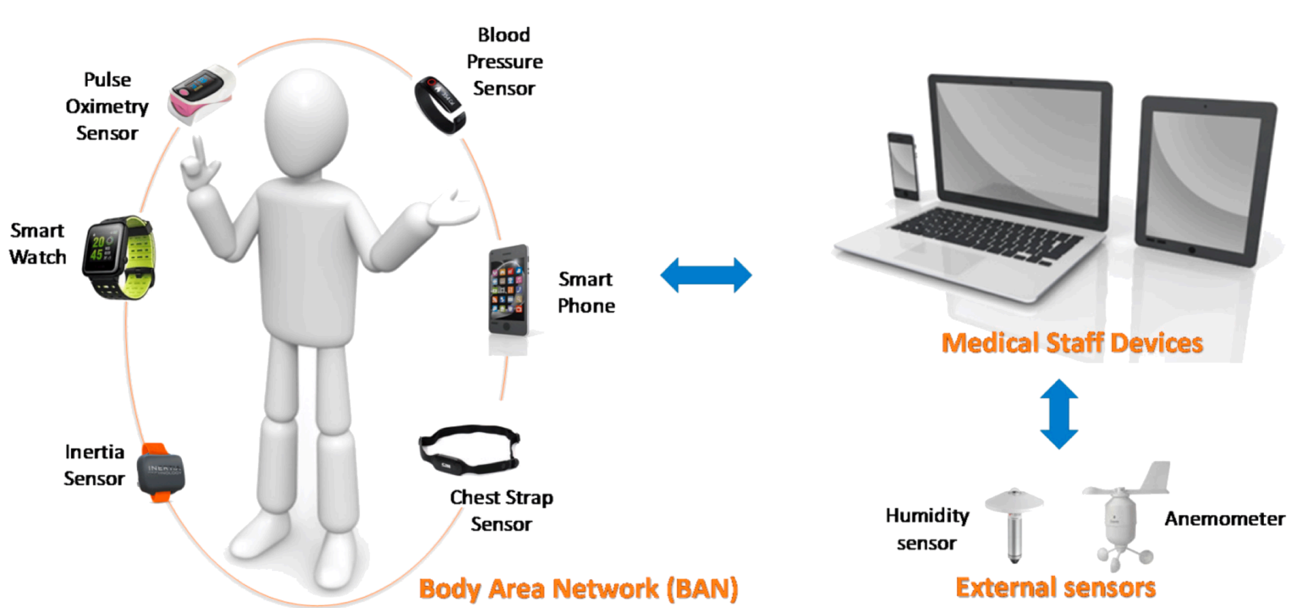

Fig. 1. Construction diagram.

linked to a rise in cardiovascular risks [15]. It can also be used to track the patient's health history to review any fluctuating patterns or activities that could increase risk. To develop such an application, acquire the necessary IoT hardware and software, such as a Raspberry Pi, Arduino, or similar electronic device [16].

A new framework named HealthFog was introduced as an edge computing device through an integrated ensemble deep learning technique for automatically assisting practical applications of heart disease diagnosis [17]. This healthcare service model has served as a fog service by managing the data of heart patients and gathering data using IoT devices. The integrated fog-derived cloud scheme was termed FogBus. It was used to deploy and test the efficacy of the suggested model regarding execution time, accuracy, jitter, latency, network bandwidth, and power consumption [18]. Heart disease increases the mortality rate around the world. Thus, predicting heart diseases is necessary, but identifying heart diseases is challenging and requires both sophisticated and expert understanding. The Internet of Things (IoT) has frequently been implemented in various medical systems to collect sensor readings to identify and predict heart diseases [19]. Even though many researchers have concentrated on heart disease diagnosis, the accuracy of the outcomes could be better.

An IoT structure for accurately evaluating heart diseases through "Modi7ed Deep Convolutional Neural Network (MDCNN)" was suggested [20]. The heart monitoring device and smartwatch were fixed to the patient for monitoring the electrocardiogram (ECG) and blood pressure. The gathered sensor data was classified using MDCNN to get the classes as abnormal and usual. An IoMT scheme was implemented to diagnose heart disease through "Modified Salp Swarm Optimization (MSSO) and an Adaptive Neuro-Fuzzy Inference System (ANFIS)," which has enhanced the searchability through the Levy Light technique [21]. The MSSO algorithm was used to optimize the learning parameters to get superior results for ANFIS. The designed MSSO-ANFIS model has given promising results in precision and accuracy compared with other methods [22].

This model considered ECG readings and monitored the high- or middle-risk level of heart disease [23–25]. If any abnormalities in ECG readings were observed, then alerts were instantly forwarded to the mobile phones of users and to the healthcare service providers to take necessary and immediate action early to track patients' wellness [26-27]. The simulation results have shown that the designed model has effectively and efficiently categorized the risk levels in less response time.

Problem Definition

In recent years, remote monitoring systems are becoming more efficient. Algorithms for Remote monitoring systems have evolved from simple to more complex and informative algorithms. Now, they don't just provide simple information about a patient, like sleeping hours, but they can also provide more informative data to the end user. In recent studies, more complex information related to CVD is presented using machine learning techniques. Data acquisition for disease prediction remains a challenging task. Acquiring accurate data is crucial for decision-making, especially in diagnosing CVD. An e-health system aims to detect CVD in its early stages to reduce the risk associated with disease and mortality. It also aims to accurately detect disease and provide an appropriate patient health improvement recommendation. There is a need to generate a customized and suitable recommendation for CVD patients to improve their health in remote areas, especially in the absence of a cardiologist. The system can also be helpful for a new cardiologist. The existing recommender systems for cardiovascular disease use machine learning (ML) classification techniques to classify disease in one of the available diseases.

Proposed model

The IoT-enabled computational model and application development for monitoring cardiovascular risks are essential tools for medical practitioners. However, several challenges can arise in developing such models and applications. These challenges include:

- Accurate and consistent data collection: Data collected from various sources, such as wearable devices, can be unreliable due to incorrect readings and incompleteness. Additionally, variation consistency in data collection processes and protocols across different regions can lead to consistency and poor application performance.
- Complex and time-consuming models: Building models from large, multivariate datasets is very difficult and time-consuming. The development process must involve specialists with a strong understanding of statistical techniques, machine learning, and the domain at hand.
- Determining the right features and metrics: Determining the right features and metrics to monitor cardiovascular risks is challenging. Models must be carefully tuned to identify outliers without artificially inflating false positives.
- Hardware limitations: To monitor cardiovascular risk effectively, the application must be able to capture large amounts of data. Increasing hardware limitations make it difficult for applications that require storage and processing resources.
- Privacy and security: Storing and processing sensitive health data requires reliable security measures. These can also involve regulatory compliance to protect the privacy of patients.

These challenges, however, can be addressed by leveraging existing research and implementing data collection and processing best practices. Developing successful and robust applications to monitor cardiovascular risk can tremendously benefit patients at risk.

Construction of proposed model

The health industry is undergoing unprecedented changes with the enhanced capabilities of the Internet of Things (IoT). The integration of IoT technology has offered a range of opportunities for efficient and cost-effective monitoring of different diseases. The development of IoT-enabled computational models and applications can revolutionize how cardiovascular diseases can be monitored and treated. The IoT-enabled computational models and applications can be used for various applications related to cardiovascular diseases. These applications include monitoring patients' vital signs, tracking and analyzing exercise and dietary data, and personalized risk assessments. Monitoring systems such as coronary artery bypass grafts (CABG) using these models is also possible. Moreover, these models can be utilized for continuous vital sign monitoring and telemetry applications. The data collected from these computational models and applications can provide information regarding the patient's health status and risk profile. The collected data can then be used to develop personalized risk assessments. The data can also be used to identify areas of improvement in treatments and lifestyle decisions. Additionally, the collected data can be used to compare the effectiveness of different treatment strategies. The use of IoT-enabled computational models and applications can also help in the diagnosis and assessment of cardiovascular risks. These models can compare patient data and physiological parameters and suggest appropriate interventions. The functional block diagram is shown in the following Fig. 2.

The assessed risks can be monitored continuously over time, thus enhancing the success of treatments. In addition to using IoT-enabled computational models and applications for monitoring cardiovascular risks, research and technological advancements must go hand-in-hand. For example, machine learning algorithms can be used for enhanced accuracy and rapid development of personalized risk assessments. Moreover, the need to assess various combinations of risk factors and their effects on the occurrence of cardiovascular diseases needs to be explored. Furthermore, applications must be developed to track activity levels and promote lifestyle modifications. These developments can be used to enhance the collective health of the population, as well as to reduce cardiac diseases. The advancements in IoT technology have made it possible to establish efficient and cost-effective monitoring of

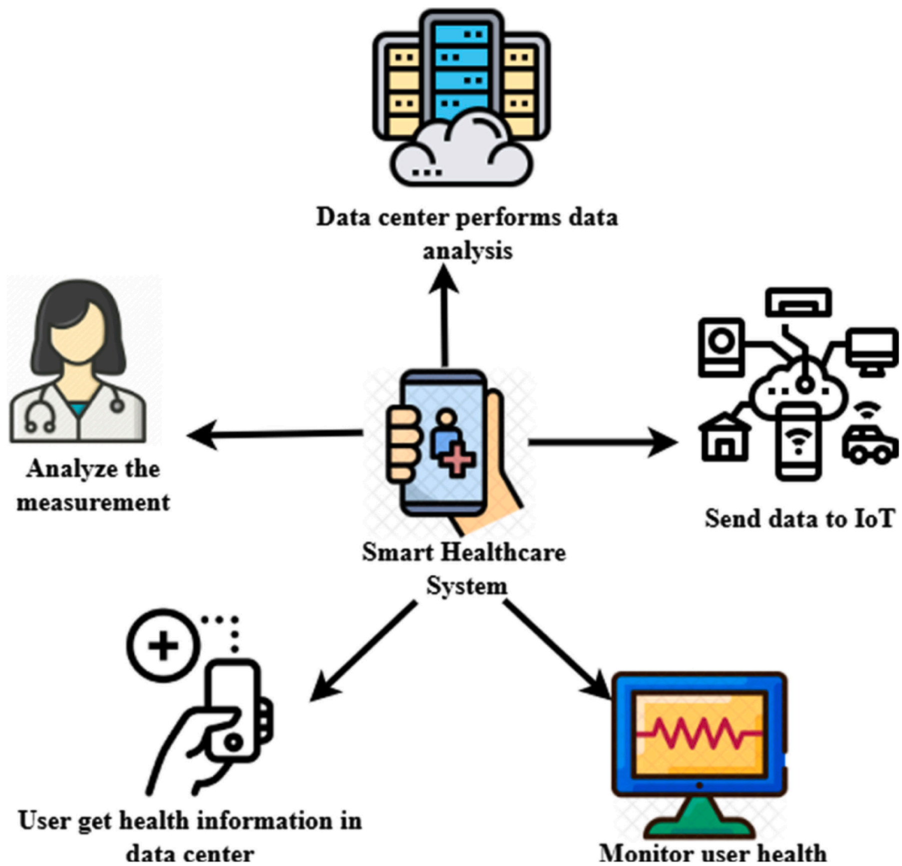

Fig. 2. Functional block diagram.

cardiovascular risks. Using IoT-enabled computational models and applications, personalized risk assessments can be developed and monitored for better management of cardiovascular diseases. Additionally, various factors must be studied to assess and manage these risks appropriately. These advancements will undoubtedly revolutionize the healthcare industry and improve the quality of life of countless individuals.

Functional working

The world of technology is rapidly changing the way we conceptualize healthcare. IoT-enabled computational models and application development for monitoring cardiovascular risks offer perspectives on improved healthcare diagnostics to provide more prompt and efficient diagnoses.

IoT-enabled Computational Models: This model combines a sensor embedded within the patient's device, such as an implantable device, with the patient's body metrics (heart rate, blood pressure, pulse oximetry, and other measurements). These metrics are analyzed and assessed within the computational model to allow healthcare providers to provide precise and prompt diagnoses of patients' cardiovascular health conditions. Additionally, the device can provide feedback to the patient through alerts or alarms and help patients monitor their health metrics and respond to the data accordingly.

Application Development: Application development for monitoring cardiovascular risks involves using mobile and web applications to store and analyze health metrics and provide patients with the necessary tools to take control of their cardiovascular health. In a mobile application, patients can access their health information and view visualizations of their data to identify trends in their health condition.

Healthcare providers can use these applications to provide patients with personalized preventive care instructions for optimum health maintenance. The operational flow diagram is shown in the following Fig. 3.

The combination of IoT-enabled computational models and application development for monitoring cardiovascular risks modifies how healthcare providers approach screening and diagnosis for cardiovascular health. These technologies help create a comprehensive model for patient diagnostics and reduce the need for costly visits to healthcare providers. Additionally, this model allows patients to take control of their health, making it easier to actively monitor and maintain cardiovascular health in the long term. The operating principle of IoT-enabled computational model and application development for monitoring cardiovascular risks is to detect, monitor, and prevent cardiovascular events by utilizing data acquired from smartwatches and other wearable devices. The system collects real-time physiological data such as heart rate, activity, and sleep patterns. It uses machine learning algorithms to analyze the data to detect signs of cardiovascular disease. The system can also alert users when their readings are abnormal, helping them take preventive measures. Additionally, these models can be combined with existing medical research and clinical guidelines to provide personalized insights into the individual's cardiovascular health.

Analytical discussion

The Performance analysis of an enabled Computational Model and Application Development for Monitoring Cardiovascular Risks refers to studying how well an Internet of Things (IoT) enabled computational model and application can detect and predict cardiovascular risks. This performance analysis examines the accuracy, reliability, scalability, and usability of the IoT-enabled computational model and system. It also has a detailed assessment of the performance results, including the number of false positives and other misclassifications. Additionally, it looks at the cost associated with the implementation of the system, as well as any other associated risks or potential issues. Performance analysis is essential to any system development project, mainly when dealing with

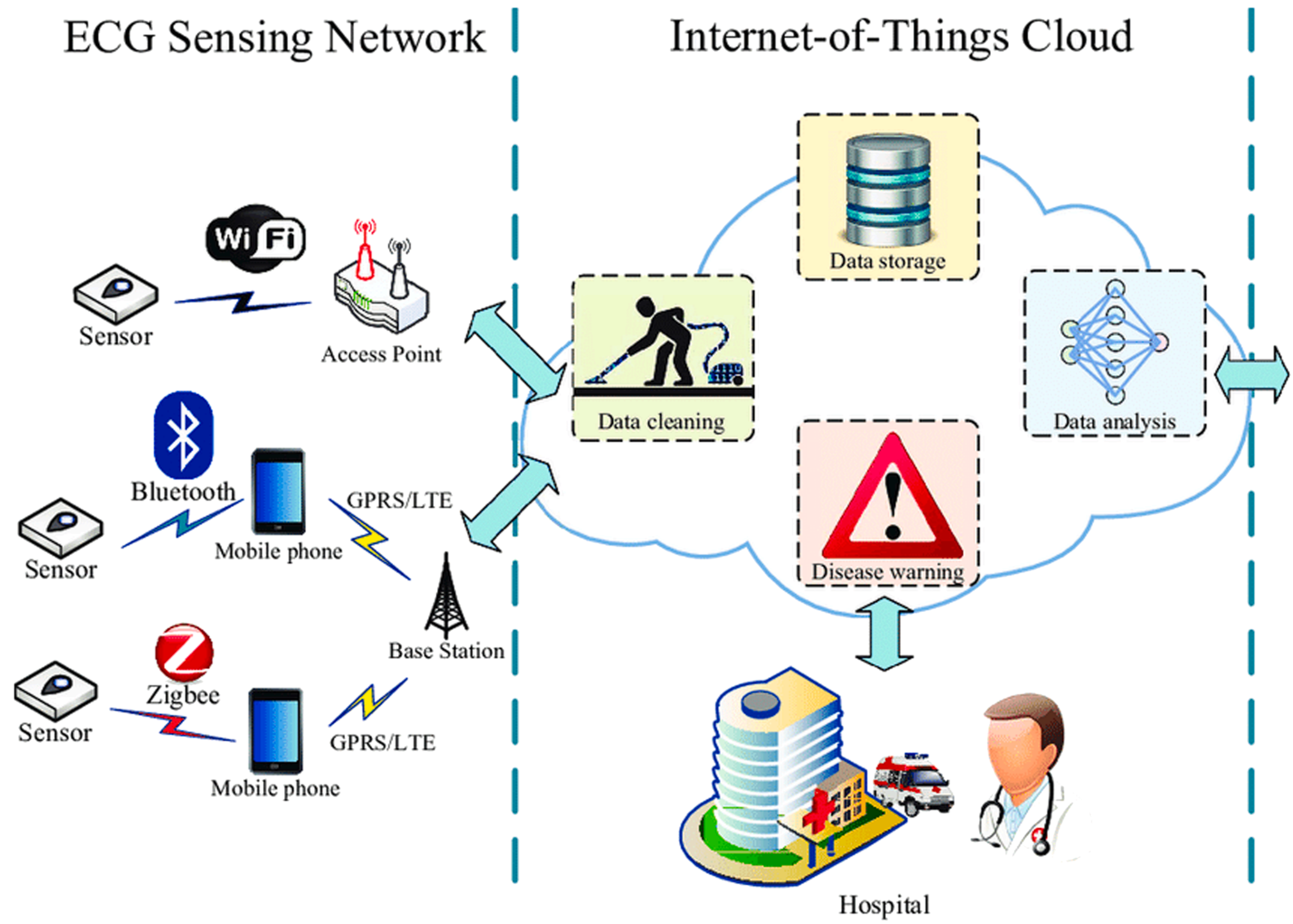

Fig. 3. Operational flow diagram.

sensitive health information applications. By understanding the system's performance, developers can plan for potential risks and develop solutions to minimize or mitigate them in advance. This performance analysis also shows areas of improvement should the system require further refinement. The functional, analytical diagram is shown in the following Fig. 4.

Optimized performance

The Internet of Things (IoT) has revolutionized how we interact with the world. We have seen almost every aspect of life become increasingly automated through the development of connected devices, commonly called 'Smart' devices. This trend has extended into the health and medical realm, which has become more accessible than ever before. IoT-enabled computational models for monitoring cardiovascular risks allow users to receive tailored health recommendations while preserving their data's privacy.

$$\frac{dm}{dn} = \frac{d}{dn}(e^m * \sin ij) \tag{1}$$

The rising popularity of intelligent consumer products combined with advancements in communication technologies has enabled the development of IoT-enabled computational models for various purposes. These models are built to analyze large amounts of big data, often collected through third-party applications such as fitness trackers. Utilizing this data, the models identify and monitor trends of cardiovascular risk indicators, such as high blood pressure, and develop personalized recommendations based on the user's risk profile.

$$\mathrm{S} = i^*\mathrm{j} \tag{2}$$

However, the development of IoT-enabled computational models for monitoring cardiovascular risks comes with its own performance challenges. Although the data collected by IoT devices is often accurate and helpful, the sheer amount of data can make it challenging to process promptly. If the model is to be used in a real-time setting, such as a medical emergency, optimizing its performance is imperative to avoid delays, which could seriously affect the user's health.

$$\frac{dn}{dm} = \left(i * \frac{dj}{dm}\right) + \left(j * \frac{di}{dm}\right) \tag{3}$$

To address this issue, organizations developing IoT-enabled computational models for monitoring cardiovascular risks must first assess their current infrastructure. Here, two key components must be identified: the hardware and the software. The former refers to the physical components used to collect data from the user through their connected device. At the same time, the latter focuses on the algorithms used to analyze the data and develop tailored recommendations. To ensure optimal performance, the hardware and software components must be optimized to ensure they can efficiently process data.

$$\frac{dn}{dm} = \left(e^m * \frac{d}{dm}\sin in\right) + \left(\sin in * \frac{d}{de}(e^m)\right) \tag{4}$$

This can include using more powerful processors and more efficient algorithms or ensuring no bottlenecks in the user's device. Additionally, organizations should aim to use the latest technologies available, such as artificial intelligence and natural language processing, to interpret the data collected better and generate more relevant insights and more accurate risk profiles. Although the available technologies can vary greatly, the key to performance optimization remains the same:

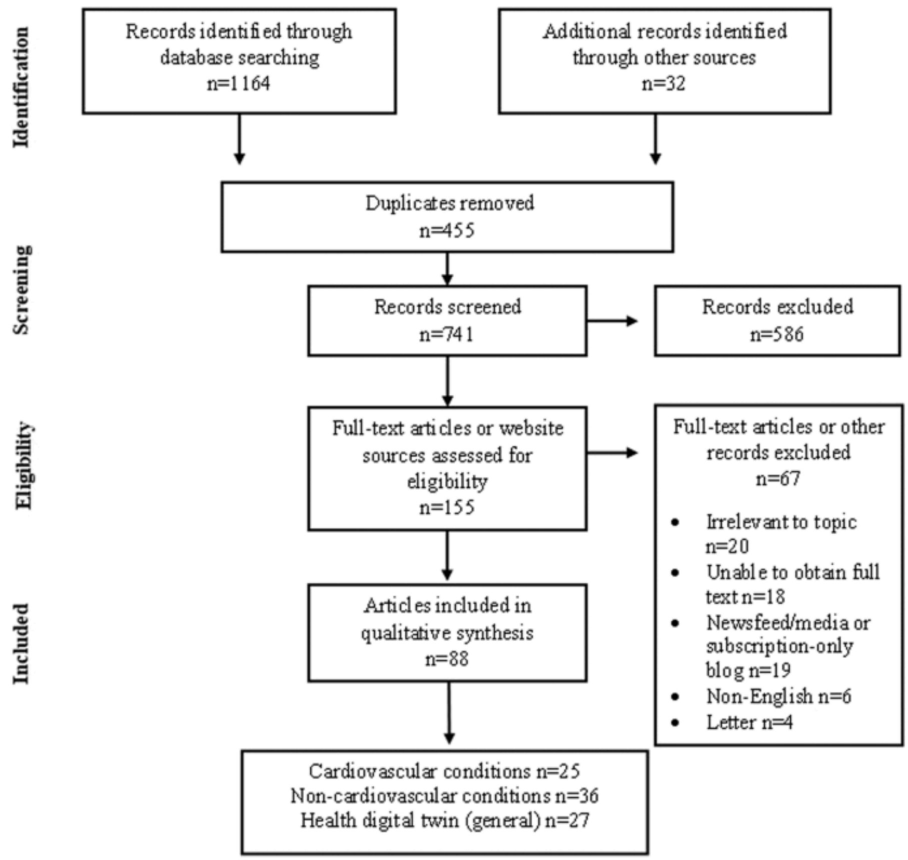

Fig. 4. Analytical diagram.

understanding the data and ensuring it is being used and interpreted correctly. As such, organizations developing IoT-enabled computational models for monitoring cardiovascular risks must continuously assess their models to ensure that they accurately measure users' risk without incurring delays.

$$\frac{dn}{dm} = (I * e^{m}\cos in) + (e^{m}\sin in) \tag{5}$$

This can be done by periodically conducting tests to identify and rectify potential performance issues. Organizations developing IoT-enabled computational models for monitoring cardiovascular risks must take the necessary steps to optimize their models to ensure accuracy and performance. By assessing their infrastructure, using the latest technologies available, and conducting regular tests, they can ensure that their risk profiles and tailored recommendations are up-to-date and relevant to the users' needs.

Enhanced performance

The performance enhancement of IoT-enabled computational models and applications for cardiovascular risk monitoring has revolutionized the healthcare industry. IoT-enabled technologies allow physicians to transfer and receive sensor data, diagnose accurately and detect early health problems. The market comprises cardiovascular risk monitoring systems enabling medical professionals to monitor and manage cardiovascular diseases such as hypertension, diabetes, and other heart-related illnesses.

$$S = e(n) = q^{m} \tag{6}$$

Due to the increased data transmission rate of IoT-enabled systems, medical professionals can access and analyze data from various sensor systems, including wearables, calibration techniques, and more. That enables medical professionals to develop more sophisticated computational models and applications to diagnose and monitor cardiovascular risks accurately.

$$n^{''} = \lim_{m\to 0}\left(\frac{o(m+n) - o(m)}{n}\right) \tag{7}$$

IoT-enabled systems allow medical professionals to transmit data securely, integrating and deploying data from multiple sources, including the patient's EHR, medical imaging technologies, and wearable devices. Medical professionals can now use advanced algorithms to interpret data from wearable devices, monitor vital signs, identify patterns in the data, and develop predictive models to assess cardiovascular disease risk accurately.

$$n^{''} = \lim_{m\to 0}\left(\frac{o^{m+n} - o^{m}}{n}\right) \tag{8}$$

$$n^{''} = \lim_{m\to 0}\left(\frac{(o^{m} * o^{n}) - o^{m}}{n}\right) \tag{9}$$

$$n^{''} = \lim_{m\to 0}\left(\frac{o^{m} * (o^{n} - 1)}{n}\right) \tag{10}$$

These applications and predictive models can also identify when lifestyle changes are needed to reduce cardiovascular risks. IoT-enabled technology also makes it easier for medical professionals to collect data from remote patients, making it easier to identify and track signs of heart disease from different geographical locations and in different time frames. IoT technologies for cardiovascular risk monitoring have proven invaluable assets for medical professionals. The data transmission rate of these systems allows medical professionals to collect and monitor more data than ever before, allowing them to create more accurate predictive models and applications for healthcare. With this technology, medical professionals can identify and monitor a patient's risk for heart disease and take the necessary measures to reduce the risk.

Comparative analysis

The proposed IoT-enabled computational (IoT-EC) has been compared with the existing ensemble deep learning (EDL), Cloud-based IoMT framework (CIoMTF) and IoT-based computational framework (IoT-CF). The comparative analysis of IoT-enabled computational models and application development for monitoring cardiovascular risks is a study that compares different approaches and technologies for developing IoT applications that can track and monitor a person's cardiovascular risk. This analysis focuses on the advantages and disadvantages of other technologies and how they can be used in cardiovascular risk monitoring. The goal is to find the most cost-effective and efficient way to monitor cardiovascular risks among different people. The analysis looks at various technologies, such as wireless sensors, wearable devices, RFID tags, and others, to see how well they perform regarding accuracy, sensor range, accuracy of results, and cost. It also evaluates the different technologies in terms of the types of data they can collect, including vital signs and other biometric data.

In our first experiment, we evaluated the performance of the different classifiers for the collected dataset using a feature selection technique. The performance is also considered for two publicly available datasets from the UCI repository. UCI repository contains two datasets: an arrhythmia dataset and a heart disease dataset. The heart disease dataset contains four databases to diagnose heart disease. The Cleveland dataset is extensively used as a standard for the classification of heart disease. It is used for binary classification to identify the existence and nonexistence of heart disease. The database contains 303 instances and 76 attributes, but all published experiments use only 14 attributes to identify cardiovascular disease. The UCI arrhythmia dataset contains 452 cases and 279 characteristics. This dataset is used to determine the presence or absence of arrhythmia and to classify arrhythmia disease in one of the 16 classes.

A wireless sensor network is used to connect all sensors and IoT devices. IoT devices connect with a centralized cloud server, where all heart sound files are accumulated. Heart sound signals are separated from other noises using the blind source separation algorithm. Many of the gadgets connected to the Internet of Things (IoT) are created to monitor a person's vital signs, such as their blood pressure, heart rate, blood sugar levels, and level of pain. These monitors, surgically placed within the patient's body, keep track of the subject's vital signs throughout the experiment.

PASCAL data set [25] contains heart sound samples. It has 449 records and five classes. The classes are standard, noisy, normal, extrasystole, and murmur. Heart sound signals are separated from other noises using the blind source separation algorithm. PASCAL data set is used to train and test the proposed convolutional neural network. Three hundred images are used to prepare the proposed model, and 149 images are used to test the CNN model. Framework was implemented in the Jupyter tool. It is a Python-based tool. An I5 7th-generation processor with 3.2 GHz and 8GB RAM was used in the experimental setup.

The accuracy of a classification method may be evaluated based on the percentage of a given group of test files that have been correctly assigned to their respective categories. The total number of occurrences in which the model correctly classified the data as positive is called the true positive. If a number is described as a true negative, it has been unequivocally established as having a value in the negative range. To elaborate, a false positive is the occurrence of an incorrect positive classification when the underlying data is harmful. That is referred to as an erroneous positive classification. A false positive is often referred to as a type 1 error. A false negative is a number incorrectly labelled as having a negative value, regardless of how long it takes to arrive at that conclusion. That phenomenon is also called the type 2 error, which is also often referred to as the false negative. These parameters define the classification accuracy, precision, recall, and F1 score of deep convolutional neural networks and other contemporary machine learning and transfer learning methodologies as shown in Fig. 5.

The k-fold cross-validation method was used to train the proposed system. In this method, at each run, 1/k of the data is randomly considered as a test set, and the rest as a training set, and the evaluation criteria are calculated on the test set. This process is performed k times, and finally, the mean of the calculated values is reported as the result of each evaluation parameter.

In stage three, the digital value corresponding to the amplified analogue signal is transmitted to an ESP-32 board via an I2C protocol. This board is responsible for receiving and transmitting the ECG data to the Fog device using a built-in SX1276 LoRa chip. The data structure with the LoRa protocol is shown in Figs. 6 and 7.

Computation of accuracy (A)

The accuracy of the IoT-enabled computational model for monitoring cardiovascular risks depends on the data accuracy of the available sensor data and the quality of the algorithm used. The model's accuracy can be measured using a combination of validation techniques. These techniques include using a hold-out set, cross-validation, and accuracy scores like the Matthews Correlation Coefficient (MCC). The hold-out set technique involves splitting the dataset into training and testing datasets. Table 1 shows the comparison of accuracy between existing and proposed models.

Fig. 8 shows the comparison of accuracy. In contrast, the proposed IoT-EC has reached 94.72 % accuracy. The existing EDL has obtained 56.72 %, CIoMTF has gained 72.72 %, and IoT-CF has achieved 71.97 % accuracy. The training dataset is then used for model training, and the testing dataset is used to measure the model's accuracy. Cross-validation is another method used to measure the model's accuracy, which involves partitioning the dataset into multiple subsets and using each subset for training and testing. The Matthews correlation coefficient (MCC) is an accuracy measure that requires computing the true positive, false positive, true negative, and false negative values to calculate the accuracy. The model's accuracy can thus be measured using a combination of these techniques.

Computation of precision (P)

The precision of an IoT-enabled computational model for monitoring cardiovascular risks would depend on several factors, such as the accuracy of the sensors it uses, the algorithms used to process the data, the number of inputs, and so on. However, it isn't easy to calculate the precision of any such model without knowing all of these factors. Developing a precision metric for such a model would require detailed testing and evaluation. Table 2 shows the comparison of precision

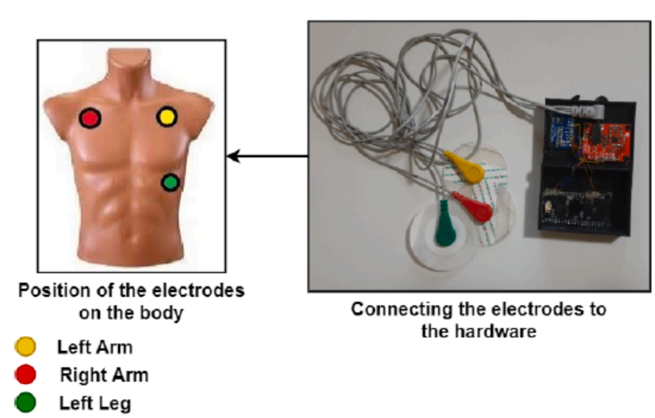

Fig. 5. Hardware Deployment.

```
{"device_1": {
  "User_ID": "0001",
  "Type_Sig": "ECG",
  "Data": [1.86569055 1.85442996 1.84230676 ... 1.81078644 1.80
    318612 1.80656663],
}}
```


Fig. 6. The data structure employed by ESP-32 to send the signal.

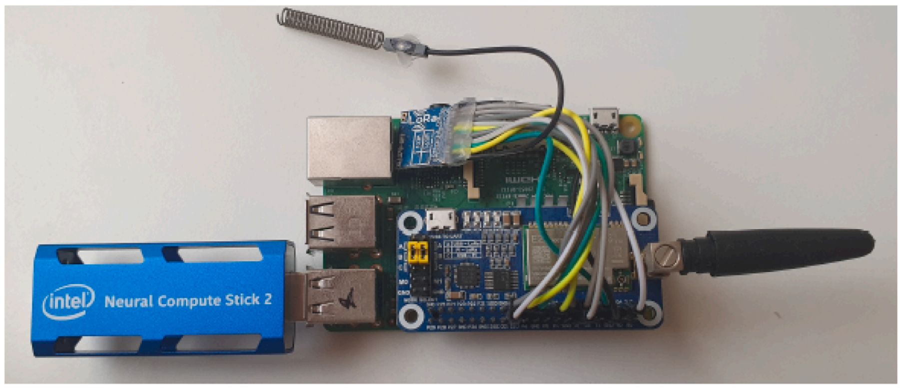

Fig. 7. IoT based CVD prediction system.

Table 1
Comparison of Accuracy (in%).

Samples	EDL	CIoMTF	IoT-CF	IoT-EC
100	59.33	74.29	74.67	95.89
200	57.83	73.70	72.80	94.88
300	56.72	72.72	71.97	94.72
400	56.34	71.51	71.06	93.76
500	55.33	70.37	70.14	94.19

Table 2
Comparison of precision (in%).

Samples	EDL	CIoMTF	IoT-CF	IoT-EC
100	61.63	70.89	71.93	96.80
200	60.13	70.30	70.06	95.76
300	59.02	69.32	69.23	95.63
400	58.64	68.11	68.32	94.67
500	57.63	66.97	67.40	95.10

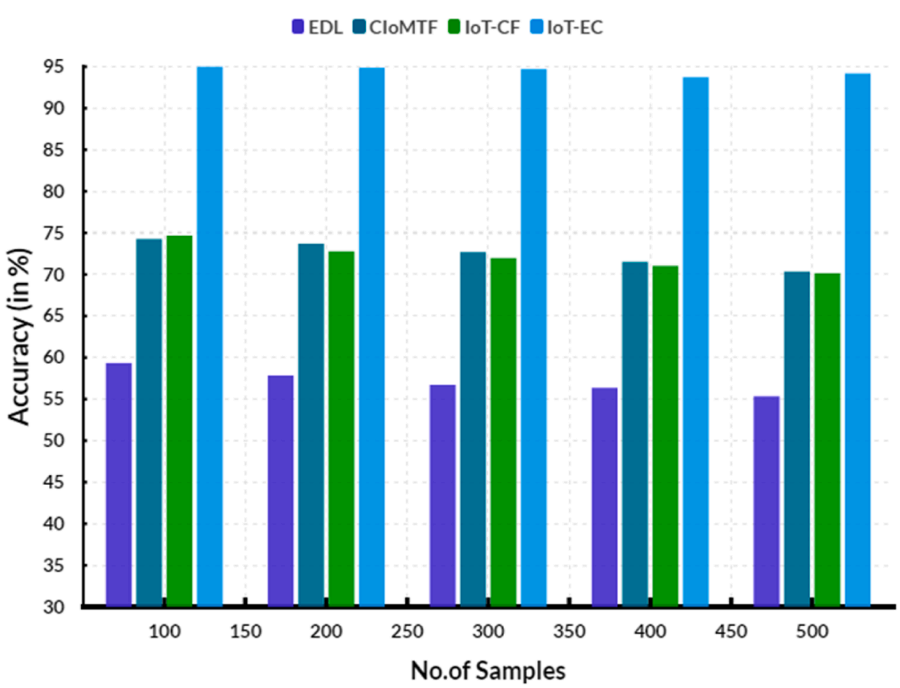

Fig. 8. Comparison of accuracy.

between existing and proposed models.

Fig. 9 shows the comparison of precision. In contrast, the proposed IoT-EC has reached 95.63 % precision. The existing EDL has obtained 59.02 %, CIoMTF has gained 69.32 %, and IoT-CF has achieved 69.23 % precision.

Computation of recall (R)

Recall measures how much pertinent information is correctly retrieved relative to all the information that should have been recovered. To calculate the recall for an IoT-enabled computational model for monitoring cardiovascular risks, we need to divide the number of correctly retrieved items by the total number of items to be rescued. For example, if the model perfectly recovered 10 out of 15 items, the recall would be 10/15= 0.67 or 67 %. Table 3 shows the comparison of recall between existing and proposed models. Fig. 6 shows the comparison of precision. In contrast, the proposed IoT-EC has reached 95.63 % precision. The existing EDL has obtained 59.02 %, CIoMTF has gained 69.32 %, and IoT-CF has achieved 69.23 % precision.

Fig. 10 shows the comparison of recall. In contrast, the proposed IoT-EC has reached 93.76 % recall. The existing EDL has obtained 65.29 %, CIoMTF has gained 74.67 %, and IoT-CF has achieved 77.69 % recall.

Computation of F1-Score (F1)

The f1-score is a metric used to assess the accuracy of a model on a classification problem. In this case, the f1-score must be computed on the dataset used to train the IoT-enabled computational model for monitoring cardiovascular risks. The data is expected to contain labels of either 'high risk' or 'low risk', and the f1-score can then be computed using this data. To add the f1-score, several metrics must first be calculated. These include:

- True Positive (TP): When the model correctly predicted a high-risk condition
- False Positive (FP): When the model incorrectly expected a high-risk condition
- True Negative (TN): When the model correctly predicted a low-risk condition
- False Negative (FN): When the model incorrectly predicted a low-risk condition

Table 3
Comparison of recall (in%).

Samples	EDL	CIoMTF	IoT-CF	IoT-EC
100	69.37	78.45	80.37	96.06
200	67.63	76.87	78.95	94.77
300	65.29	74.67	77.69	93.76
400	64.48	73.04	75.70	92.87
500	62.19	71.90	73.23	92.50

The f1-score can then be computed by taking the harmonic mean of the Precision and Recall scores, which are calculated as follows:

$$Precision = \mathrm{TP} / (\mathrm{TP} + \mathrm{FP}) \quad (11)$$

$$\mathrm{Recall} = \mathrm{TP} / (\mathrm{TP} + \mathrm{FN}) \quad (12)$$

$$\mathrm{F1\text{-}score} = 2 \text{ x } (Precision \text{ x Recall}) / (Precision + \mathrm{Recall}) \quad (13)$$

Table 4 shows the comparison of F1-score between existing and proposed models.

Fig. 11 shows the comparison of the F1-score. In contrast, the proposed IoT-EC has reached a 94.87 % F1 score. The existing EDL has obtained 62.17 %, CIoMTF has gained 75.46 %, and IoT-CF has achieved a 76.36 % F1 score.

The comparative analysis also looks at the different applications that can be developed with these technologies. For instance, the study looks at applications that can track a patient's heart rate, blood pressure, and other parameters over time and identify potential problems. It also evaluates the types of data that can be collected with each technology, such as environmental and behavioural information that can help predict a person's risk of cardiovascular disease. This comparative analysis can provide valuable insight into the most suitable and cost-efficient technologies for developing and maintaining cardiovascular risk monitoring applications. It can also lead to improved care outcomes for people who are at risk for cardiovascular problems.

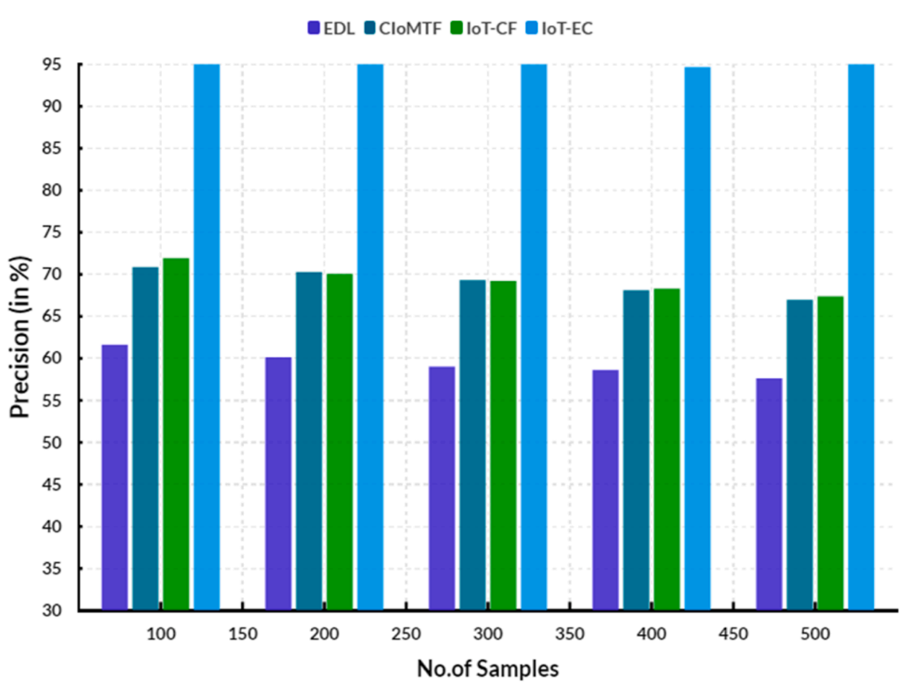

Fig. 9. Comparison of precision.

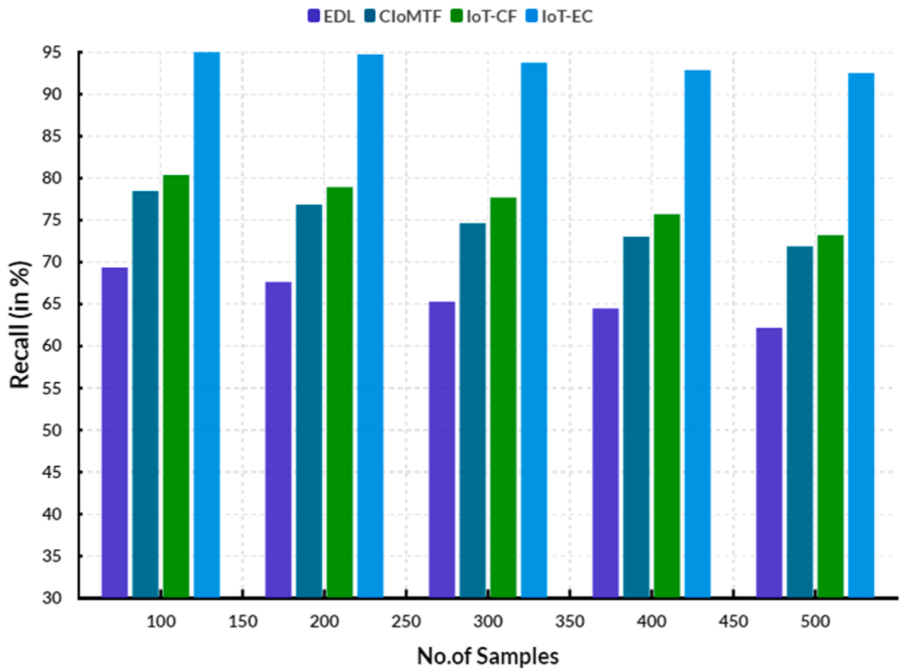

Fig. 10. Comparison of recall.

Table 4
Comparison of F1-score (in%).

Samples	EDL	CIoMTF	IoT-CF	IoT-EC
100	65.27	78.29	79.36	96.06
200	63.30	75.87	77.16	96.07
300	62.17	75.46	76.36	94.87
400	60.98	73.86	75.69	94.39
500	60.59	71.54	74.26	92.96

Conclusion

The Internet of Things (IoT) Enabled Computational Model and Application Development for Monitoring Cardiovascular Risks is an innovative approach to monitor and prevent cardiovascular disease. It is a comprehensive system that collects and analyzes data from multiple sources, such as wearable technology, electronic medical records (EMRs), and other sources. This information can generate a personalized risk profile for individuals based on age, sex, lifestyle habits, medications, and more. The IoT model can be programmed to detect changes over time and provide alerts when necessary. That helps healthcare professionals better monitor their patient's health and make timely and

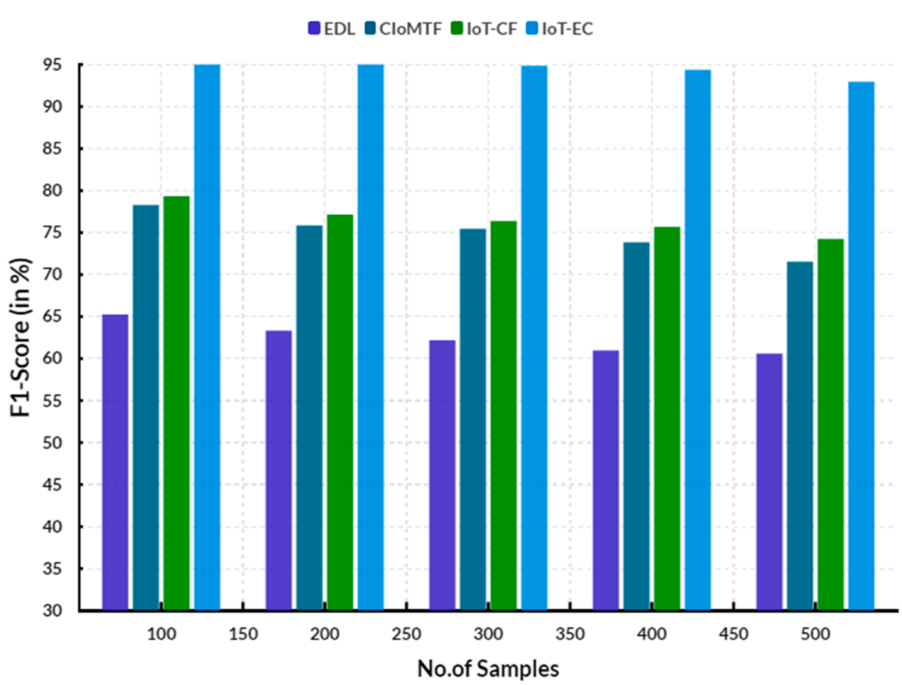

Fig. 11. Comparison of F1-score.

appropriate clinical decisions. The applications developed on this platform can be used by healthcare professionals to monitor risk levels in real-time and to create customized strategies for prevention and intervention. The proposed IoT-EC has reached 94.72 % accuracy. The existing EDL has obtained 56.72 %, CIoMTF has gained 72.72 %, and IoT-CF has achieved 71.97 % accuracy. The proposed IoT-EC has reached a 94.87 % F1 score. The existing EDL has obtained 62.17 %, CIoMTF has gained 75.46 %, and IoT-CF has achieved a 76.36 % F1 score.

CRediT authorship contribution statement

R. Rajaganapathi: Data curation, Conceptualization. **Radha Mahendran:** Software, Resources. **D. Sivaganesan:** Validation, Supervision. **Mr.R. Vadivel:** Methodology, Investigation. **M. Robinson Joel:** Visualization, Validation. **V. Kannan:** Project administration.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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