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Health Conditions Prediction in Cardiac Patient Using Deep Ensemble Learning Based IoT Systems

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Abstract: The ongoing transformation of the Internet of Things (IoT) is profoundly impacting businesses promoting healthier lifestyles through technology. This paper introduces a novel system utilizing machine learning to extract features from long-term health data, particularly beneficial for individuals with chronic illnesses. The prototype presented suggests potential for more affordable and effective healthcare, encouraging the medical industry to adopt and test such devices. By leveraging big data architecture, artificial intelligence, and IoT, the proposed system forecasts illness progression, a development with significant implications for healthcare. Employing data mining techniques, including genetic algorithms, the framework optimizes feature selection for real-time medical inputs. A proposed ensemble framework integrates various algorithms enhancing prediction accuracy and robustness. Training each algorithm individually and combining predictions through weighted averaging or voting results in a more reliable ensemble forecast. The ensemble DBN framework, incorporating multiple algorithmic predictions, demonstrates superior accuracy and resilience compared to individual algorithms.

***Keywords**: IoT, Health condition, Deep learning, prediction*

1. Introduction

Through the use of health prediction algorithms, it is feasible to accelerate the process of shifting outpatients to treatment facilities that have lower patient numbers. Patients are able to obtain care that is tailored to meet their particular need. Based on the data that is currently available, it is possible that a greater proportion of individuals will come to seek assistance. It is becoming increasingly common to make use of health forecasting systems since these systems are able to assist with the problem of unexpected shifts in hospital traffic. There are two primary factors that contribute to the majority of the demand for healthcare services at a hospital: emergencies, which may include the arrival of ambulances in the aftermath of natural disasters or traffic accidents, and routine outpatient demand [1].

Despite the fact that certain adjacent hospitals have a lower patient traffic than others, many hospitals continue to struggle to satisfy the demands of their patients since there is a dearth of real-time data on the flow of patients. It does not matter which hospitals have the fewest patients; this is a problem regardless of hospital. The term "Internet of Things" (IoT) refers to a network that offers the capability for digital devices and physical items to speak with one another and share data. Transferring this information between digital devices and physical artefacts is not only possible but also practicable. The collecting of data can be accomplished in a short amount of time because to the utilisation of microprocessors used in modern technology.

The provision of healthcare is of utmost importance since the primary objectives of healthcare are to improve the health of individuals and to safeguard them against illness. These days, diagnostic techniques make it possible to examine abnormalities, such as tumours, that are situated in the deepest parts of the body. In addition, it is possible to monitor unusual illnesses such as epilepsy and heart attacks [2].

There are a number of variables that have contributed to an increase in the burden that is being placed on healthcare systems all over the world. These causes include the ever-increasing global population as well as the inherent unpredictability that is associated with the progression of chronic diseases. To put it another way, the demand for medical professionals, nurses, and hospital beds is currently larger than it was in the past [3].

In order to keep the quality and standards of healthcare systems at a high level, it is very necessary to reduce the amount of stress that is placed on those systems [4]. There is a possibility that the opportunities offered by the Internet of Things will assist in reducing the burden that is now being placed on healthcare networks.

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Hospitals, for instance, make use of radio frequency identification (RFID) devices in order to improve their management of healthcare while simultaneously lowering the costs connected with it. Because they enable medical professionals to rapidly monitor the heart rates of their patients, healthcare monitoring devices significantly enhance the ability of medical professionals to arrive at accurate diagnoses [5].

2. Related works

Over the course of past decades, an unlimited number of different kinds of portable and wearable electronic gadgets have been developed. Concerns have been raised by professionals in the fields of information technology and medicine over the issue of data security in relation to the Internet of Things [6]. As a result of this, a significant amount of research activity has been directed towards investigating the efficacy of merging the Internet of Things (IoT) with machine learning (ML) in order to monitor persons who are experiencing health problems while simultaneously preserving the authenticity of the data that is collected. These investigations have been conducted in a variety of settings, including hospitals, clinics, and even people's homes.

Because of the IoTs, medical professionals are now able to successfully maintain communication with their patients, which has made it possible for advancements to be made in the sector. A machine learning system is utilised by the IoTs in order to determine whether or not emergency medical treatment is required in order to prepare for the next seasons. In the event that medical attention is required in the event of an emergency, the plan must be put into effect without unnecessary delay. A significant proportion of outpatient clinics have the same challenge, which is an excessive number of patients sitting in the waiting room or waiting area [7].

It is common for patients who are hospitalised to suffer from a wide range of significant health conditions, some of which are life-threatening and require immediate medical attention. When people who are in need of medical assistance right now are forced to wait in queue, the situation has the potential to become extremely alarming very quickly. This is because of how quickly things can deteriorate. When it comes to organisations that are headquartered in less developed countries and do not have sufficient funding, the problem is much more pressing. Patients are frequently discharged from hospitals and other healthcare facilities without receiving the necessary care because of the overpopulation that exists in these facilities. Because of the high number of patients that are treated there, this is a rather typical event.

The platform is home to a number of useful software that are designed for wearable medical devices (WMS) [8]. *It is important to note that the authors conducted an exhaustive investigation into WMSs, looking into their numerous applications, newly developed capabilities, and overall efficiency in comparison to other platforms. There was a discussion about the possible advantages of utilising these devices for patient monitoring in the treatment of diseases and disorders such as Alzheimer's disease and cardiac arrest [9].

The authors of the study utilised a body sensor network (BSN) in order to determine the health problems the patients were experiencing. Utilising a wireless sensor network (WSN) in conjunction with a micro-electro-mechanical system architecture allowed for the realisation of this possibility. The researchers came up with a method for monitoring clinical data by utilising a number of different components, such as a microprocessor, a temperature sensor, and a heartbeat sensor [10]. As an additional component of this method, the author additionally carried out their own research.

It was hypothesised that a device may be developed that could directly regulate the patient's heart rate and temperature, and then broadcast that information to the healthcare provider's phone. Through its integration with the appliances located in the base station, this technology was developed to achieve both of the aforementioned goals. It is possible for the system to send a text message to the patient's loved ones as well as to competent medical personnel in the event of an emergency [3]. By employing this method, the patient is able to acquire their medicine orders from their physician when they are not physically present.

In addition, the IoTs (IoT) device has made it possible for medical facilities to keep track of the health of patients who are receiving treatment for chronic illnesses [11, 12]. As a result of this, the algorithm is able to produce multiple predictions on the current state of the patient's health. IoTs (IoT) devices are surgically implanted into the bodies of patients so that medical professionals can monitor their vital signs and make educated decisions on their treatment. People who have diabetes, for instance, are monitored by the sensor system that is a component of the IoTs (IoT) in order to anticipate potential patterns of sickness and any irregularities that may occur. Everyone is able to make use of the health prediction system in order to determine which companies are able to provide them with the most suitable services according to their individual requirements. They are thus in a position to make more informed decisions regarding their healthcare based on this information. Individuals who would rather continue to receive treatment in their current facility have the option to do so if they so choose, despite the fact that doing so may result in extended periods of waiting for therapy or even the prospect of being discharged without receiving treatment. Individuals who would prefer not to make use of other amenities have the option to do so. It is possible that individuals will opt to remain in the same institution for their whole stay if they do not wish to visit any other facilities.

This BSN healthcare surveillance platform, which depended on Zigbee technology, was proposed by the authors of the study that was cited in [13] in order to facilitate the remote monitoring of patients through the utilisation of clinical sensor data. A few examples of health assessment standards are the Zigbee IEEE 802.15.4 protocol, temperature measures, readings from spirometers, readings from heart rate monitors, and readings from electrocardiograms [14]. The fact that the data is transferred over radio waves makes it possible for portable electronic devices such as computers, smartphones, and other electronic gadgets to access the final product. It is possible to locate these screens in any location where data is being transported.

Once the data from the sensors has been transmitted to the Zigbee network, it is then transmitted to a different network, which enables medical professionals and loved ones to view it on their mobile phones and other electronic devices [15]. Through the utilisation of the IoTs and machine learning, the administration of healthcare could become significantly less difficult. Increasing the amount of communication that goes in both directions between patients and primary care physicians is one strategy to accomplish this objective.

IoTs make available tools that can be used for patient surveillance and supervision. These tools can be used to monitor and supervise patients. The instrument in question is a sensor network, which can be constructed using either software or electronic components. The Raspberry Pi board is one of the products that are included in the second category of home appliances. Other products that are included in this category include devices that measure heat, blood pressure, and pulse rate. The first category of home appliances consists of things like these devices and other similar products. There are several components that make up the software approach [16], including the gathering of data from sensors, the storage of that data in the cloud, and cloud analysis to search for abnormalities in patient health.

3. Proposed Method

The IoT is already causing a revolution in the information technology industry; however, a breakthrough that has the potential to further alter the course of events is the ability to accurately forecast the development of disease without the involvement of humans. We design an artificial intelligence (AI) and IoT enabled system out of a big data architecture in order to forecast how an illness would progress. The artificial intelligence into a process that involves disease forecasting is particularly original, despite the fact that the usage of IoT sensors in disease forecasting is not unique.

Data mining strategies [17] – [19] are utilised extensively throughout this research project in order to contribute to the development of deep learning. The technique for training an Ensemble DL, also known as a convolutional neural network, is illustrated in Figure 1. This procedure involves using data collected from IoT devices belonging to a patient.

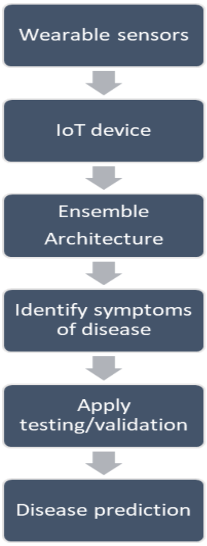

Figure 1: Proposed Framework

3.1. Feature Selection

For the purpose of customising feature selection for medical inputs that are utilised in real-time IoMT, this work proposes the utilisation of a genetic algorithm. This dataset is an example of one that use this method for the purpose of stroke prediction.

Chromosome Representation:

Among the various sets of features that are believed to be of great significance for stroke prediction in real-time

IoMT medical inputs, chromosomes are one of the most crucial. By examining the positions of genes on chromosomes, it is possible to determine whether or not an input feature is present in the medical data collected by the IoMT (1) or not (0). The depiction of chromosomes would be something along the lines of [1, 0, 1, 0]. The age of the patient and their glucose levels are likely to be considered prognostic indicators, in addition to other metrics that are included in the dataset, such as cholesterol, blood pressure, and glucose levels. It is also possible that the dataset might include glucose levels.

Fitness Function:

During the process of evaluating the expected performance of a deep learning model, the fitness function has the responsibility of selecting a collection of features to be utilised. There are a number of criteria that might be used to construct a fitness function for stroke prediction. Some examples of these criteria are the F1 score, specificity, accuracy, and sensitivity. Through the utilisation of a fitness function, we are able to evaluate the effectiveness of the model in recognising instances of stroke by utilising the essential characteristics.

Initialization:

A population of chromosomes is initialised by the genetic algorithm; each chromosome represents a possible subset of features for stroke prediction. The algorithm is used to estimate stroke frequency. At this point in time, the algorithm is in its initialization phase. The process of genomic analysis (GA) begins with the definition of the population size, while also taking into account the crossover likelihood and the mutation probability.

Selection:

In order for a person to have the capacity to reproduce, their fitness values, which are the result of natural selection (chromosomes), are taken into consideration. Using selection methods such as tournament selection or roulette wheel selection, it is feasible to enhance the probability of picking chromosomes with higher fitness values to act as progenitors for the next generation. This can be accomplished by increasing the probability of selecting chromosomes with higher fitness values.

Crossover:

It is necessary for parents to make a decision on which chromosomes they will present to their offspring before a new generation of genetic material may be produced. In the context of real-time Internet of Medical Things (IoMT) medical inputs, the term "crossover" refers to the process of transferring genetic material, specifically specific characteristics, from one parent unit to another by mixing genes at specific locations to complete the transfer.

Mutation:

It is possible for a population to preserve its genetic diversity through the process of mutations, which are arbitrary changes to the DNA that are passed down from generation to generation. The objective of the research on mutations in stroke prediction is to randomly alter specific chromosomal genes, which are characteristics of the stroke. Consequently, this paves the way for the investigation of a wide variety of permutations of characteristics on various chromosomes.

Fitness Evaluation

After each mutation or crossover, the fitness function is utilised to determine whether or not the progeny chromosomes are suitable for reproduction for the organism. A method that can be utilised to ensure that positive characteristics are passed down from one generation to the next is to ensure that the chromosomes of the most successful individuals are preserved from one generation to the next. It is possible that elitism is a process that meets this description.

Termination:

Following the completion of a predetermined number of generations or the occurrence of a termination event, the genetic algorithm will proceed in a sequential manner through the stages of selection, crossover, and mutation. Whatever transpires is contingent upon the particulars of the situation. The GA is able to keep an eye on the feature subset and make modifications when fresh data comes in since it receives medical inputs from the IoMT in real time. The evolutionary algorithm is able to alter the feature selection process to take into account new inputs from IoMT medical devices as they change. This is made possible by the fact that it can process data in real time.

3.2. Proposed Ensemble Framework

The Ensemble Framework allows for the construction of a prognostic model that is both accurate and reliable. This is accomplished by merging ResNet, RBF, DBN, and RBN. By taking into account the specific qualities that are associated with each algorithm, the ensemble technique enhances the overall effectiveness and dependability of the prediction framework. RBN, RBF, ResNet, and DBN itself are some of the algorithms that are utilised by the ensemble DBN architecture. This is done in order to make the most of their individual strengths. By combining the skills of all of the algorithms that are included in the ensemble, the ensemble is able to enhance the accuracy of its predictions and take into consideration the finer-grained characteristics of the data. It is the purpose of the integration process to improve the overall prediction efficacy and durability of the ensemble. This is accomplished by utilising the specific characteristics that each algorithm possesses.

Each individual algorithm in the ensemble makes use of the model that it has acquired in order to enhance the final prediction in a manner that is distinctive to itself. In order to acquire the ensemble forecast, it is required to incorporate all of the individual projections. In this particular investigation, we make use of the weighted combination methodology, however there are a number of different approaches of integrating predictions that are still available.

The purpose of a weighted combination is to ensure that the predictions provided by each algorithm are taken into consideration in an equitable manner. This is accomplished by assigning varying amounts of weight to each of the algorithms. When deciding whether or not to use static weights, the performance of the algorithm on the training dataset is taken into consideration. To calculate the weighted combination, you must first collect all of the weighted forecasts and then put them all together.

For the sake of argument, let us assume that the ensemble is comprised of N algorithms, which are labelled as A1, A2,..., AN. For each instance of the input, each algorithm Ai generates a prediction, which is represented by yi, as the output. We are able to derive the ensemble forecast, denoted by yp, by utilising the integration approach.

$$y_p = w_1 * y_1 + w_2 * y_2 + ... + w_n * y_n$$

where

$w_1, w_2, ..., w_n$ - weights

The performance of ensembles is improved by algorithms because they make it possible for the various viewpoints and capabilities of the individual algorithms to collaborate more effectively with one another. By integrating forecasts by voting, averaging, or weighted combining, the ensemble model increases the accuracy of predictions, as well as their generalizability and robustness. Before deciding on an integration strategy, it is important to take into consideration the characteristics of the problem, the requirements of the application, and the properties of the algorithm.

Training Phase:

During the training phase, every algorithm acquires new knowledge by doing an analysis of the dataset that has been given. When it comes to training the DBN, we employ the unsupervised learning technique that is layer-by-layer. As an alternative, we train RBF, ResNet, and RNN using the training techniques that are specific to each of these networks. In order to begin the process of constructing an ensemble of features, one of the first steps is to use feature selection methods, such as genetic algorithms, to the dataset in order to determine which characteristics are the most helpful and informative to extract.

Following the features that have been selected and the algorithm that has been trained, the next stage is the collective prediction step. In order to provide a forecast for each and every input instance, each and every algorithm makes use of the learnt model. The generation of an ensemble forecast can be accomplished by combining each individual prediction through the utilisation of a fusion strategy such as weighted average or majority vote.

The capacity to determine the relative importance or dependability of each algorithmic prediction can be achieved through the process of assigning relative values to each prediction. By analysing the performance of the algorithms on the training dataset, we are able to identify whether the algorithm weights are changing in a static or adaptive manner. The weighting method gives algorithms that have a history of making correct predictions on a consistent basis a greater value. This is done in order to encourage the use of these algorithms.

It has come to our attention that the ensemble DBN architecture employs fusion techniques or set weights in order to merge the predictions of RBN, RBF, ResNet, and DBN strands that are available. Based on the final forecast, it appears that the overall output of the ensemble appears to be more accurate and resilient than the output of any individual algorithm that is functioning alone.

4. Results and Discussions

During the process of creating the proposed model in Python, we make use of scikit-learn for classification and PyTorch for the generation of computational graphs. It is necessary to have a very powerful computer that is equipped with a large number of Intel i7 cores in order to execute the entire model.

Dataset:

It is possible to gain access to the dataset for the prediction of heart disease using the Kaggle repository. This dataset contains a number of different issues, one of which being the likelihood of an individual experiencing a heart attack. By utilising the characteristics of the dataset that are associated with a heart attack, it is possible to train deep learning models to make predictions about the likelihood of a heart attack occurring.

Table 1: Accuracy of Training

Test set	TN	TP	FN	FP
10	0.7452	0.9125	0.8046	0.9532
20	0.7416	0.9098	0.7989	0.9552
30	0.7391	0.9112	0.7806	0.9617
40	0.8221	0.9073	0.9093	0.8221
50	0.8657	0.9440	0.9390	0.9459
60	0.8992	0.9333	0.9364	0.8992
70	0.7418	0.9614	0.8433	0.7418
80	0.9499	0.9707	0.9512	0.9276
90	0.9138	0.9065	0.8663	0.7777
100	0.9773	0.9666	0.9292	0.8847
110	0.9562	0.9704	0.9519	0.9277
120	0.9666	0.9707	0.9469	0.9193
130	0.9620	0.9532	0.9089	0.8494
140	0.9552	0.9435	0.9057	0.8439
150	0.9654	0.8663	0.8353	0.7292

Table 2: Accuracy of Testing

Test set	TN	TP	FN	FP
10	0.7443	0.9115	0.8037	0.9520
20	0.7413	0.9095	0.7987	0.9549
30	0.7396	0.9119	0.7812	0.9623
40	0.8205	0.9055	0.9075	0.8205
50	0.8665	0.9448	0.9398	0.9468
60	0.9009	0.9350	0.9380	0.9008
70	0.7426	0.9624	0.8442	0.7426
80	0.9505	0.9713	0.9519	0.9283
90	0.9133	0.9060	0.8658	0.7773
100	0.9748	0.9641	0.9269	0.8825
110	0.9573	0.9714	0.9530	0.9288
120	0.9664	0.9705	0.9467	0.9191
130	0.9614	0.9526	0.9083	0.8488
140	0.9547	0.9430	0.9052	0.8435
150	0.9655	0.8664	0.8354	0.7293

Table 2: Accuracy of Validation

Test set	TN	TP	FN	FP
10	0.7441	0.9112	0.8034	0.9518
20	0.7419	0.9102	0.7993	0.9557
30	0.7403	0.9126	0.7819	0.9631
40	0.8210	0.9061	0.9081	0.8210

50	0.8644	0.9426	0.9376	0.9446
60	0.9003	0.9344	0.9375	0.9003
70	0.7424	0.9622	0.8439	0.7424
80	0.9514	0.9722	0.9528	0.9291
90	0.9125	0.9051	0.8649	0.7765
100	0.9769	0.9662	0.9289	0.8843
110	0.9562	0.9704	0.9519	0.9277
120	0.9674	0.9714	0.9476	0.9200
130	0.9624	0.9535	0.9093	0.8497
140	0.9564	0.9447	0.9069	0.8450
150	0.9657	0.8666	0.8355	0.7295

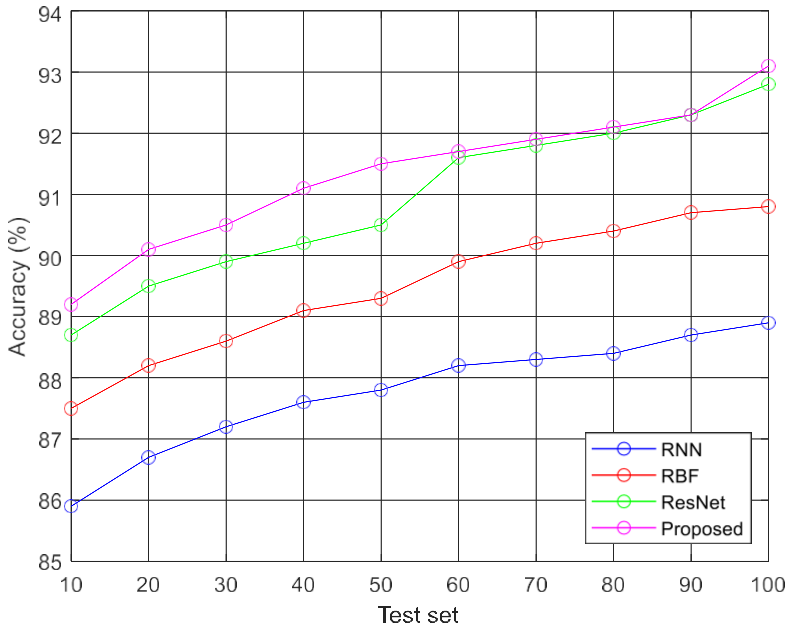

Fig 2: Accuracy

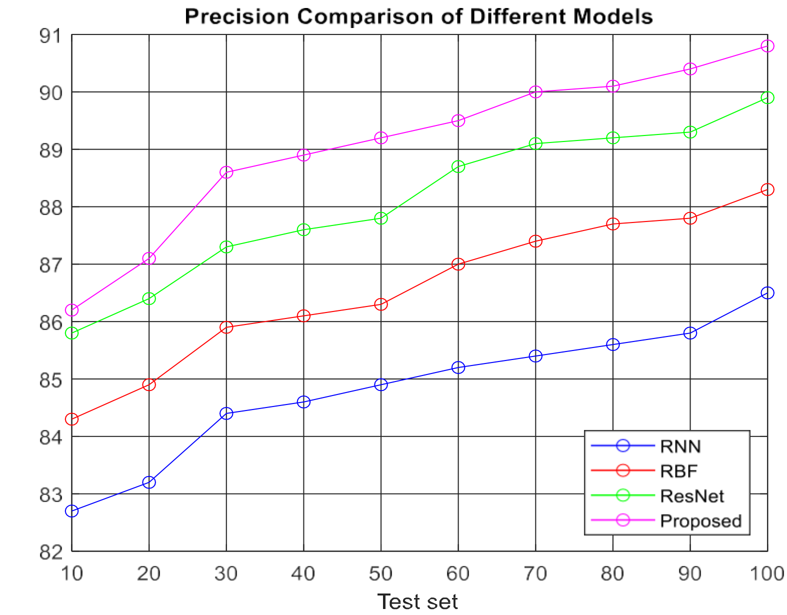

Fig 3: Precision

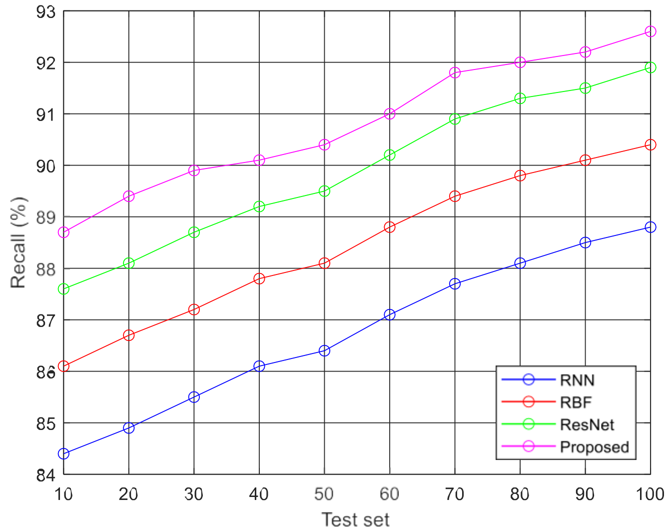

Fig 4: Recall

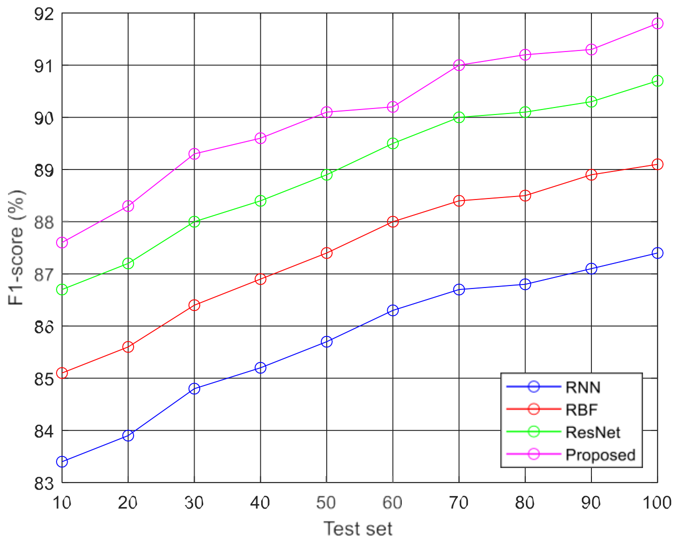

Fig 5: F1-Score

It is possible that patients will make progress in their prognosis based on the results in Figure 2 - 5. Early disease detection, when combined with a high level of sensitivity, makes it possible to treat patients with greater success. This result illustrates the validation performance indicators that were acquired in order to make any predictions regarding the health problems of patients. These metrics were produced by applying the number of repetitions to both sets of data, which can be found in Tables 1-3.

5. Conclusions

The heart disease prediction models for patients is found through the application of deep ensemble learning. In big data and data mining, this article explores the ways in which deep learning and the IoT are being utilised in the field of medical research. As far as IoT applications are concerned, there is reason regarding the ensemble architecture and these applications make use of real-time prediction of patient health condition. It is feasible that with its assistance, patient care and healthcare outcomes could be improved. This is due to its capacity to utilize a wide variety of algorithms for the purpose of making decisions in a timely and correct manner. There is a possibility that in the future, researchers would investigate various deep learning algorithms in order to enhance the framework and advance the implementation of predictive healthcare.

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