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DEEP REINFORCEMENT LEARNING FOR DYNAMIC TREATMENT REGIMES

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Abstract:
Aim: To explore the interactions between machine learning, healthcare, and the IoT . They study the intersection of these three disciplines and the related methods, difficulties, and opportunities. Studying the ways that data-driven insights and technological advancements are combining to create improved health is the aim of this article in order to deliver better health and to rethink healthcare.
Background: Traditional healthcare systems offer an attainable level of performance when it faces numerous patient data volumes.
Contribution: Internet of Things (IoT) provides a seamless data collection and the selection of correction application for data is considered challenge in creation of a precise health forecasts.
Methodology: Complex algorithms are essential for extraction of relevant details from the patient data and this includes medical IDs, pulse rates, medical reports, and symptoms. Hence, dependable and accurate estimates are needed for ensuring the health quality of the patients. The proposed work provides the development of an IoT healthcare prediction using Generative Adversarial Networks (GANs) based Dynamic Reinforcement Learning (DRL). These features patterns including medical reports, the sequences, and the trends are noticed in pulse rates. The network initially learns to maintain connections among patterns in pulse rates and its associated symptoms in medical data to generate accurate forecasts.
Findings: The experimental results are based on training the RNN model with historical patient data and validate it using DRL. The trained RNN-DRL model may identify likely medical issues if consistent real-time patient data is fed to it.
Recommendation for Researchers: Furthermore, in terms of computing efficiency and accuracy of prediction, our method beat those of previous methods. Furthermore improved interpretability of the learnt characteristics gave important new perspectives on the underlying patterns in dynamic treatment methods.

Future Research: In future research, this work can be enhanced using several deep learning algorithms for achieving better accuracy and performance.

Keywords: IoT, Healthcare, RNN, Medical Treatment

1. INTRODUCTION

A revolutionary service delivery within the healthcare industry has been brought about by the convergence of machine learning, healthcare, and the Internet of Things (IoT) within the last few years. Wearables connected to the IoT for tracking and enhancing human health (Shen et al., 2020). Machine learning has shown its efficacy in diagnosis, disease courses, and treatment plans; due to its capability on solving complex data patterns in healthcare industry (Saravanan et al., 2023).

The Internet of Things (IoT) wearables were the ones that revolutionized the gathering and use of data in the healthcare industry (Yadav et al., 2024). Within the healthcare industry, this is a major breakthrough. This change also creates new possibilities for early intervention and preventive measures (Saravanan et al., 2023; Uniyal et al., 2023; Rao et al., 2024; Saravanan & Malarvizhi, 2023).

There is a convergence of machine learning, healthcare, and the Internet of Things (IoT) that could be quite advantageous (Gorantla et al., 2024). The critical healthcare industry may revolutionize the provision of healthcare by fusing the analytical powers of machine learning algorithms with the data-rich inputs from wearable devices. More proactive, effective, and individually tailored care might be made feasible by this (Baz et al., 2024; Naeem et al; 2021)

This work aims to explore the interactions between machine learning, healthcare, and the IoT (Li et al., 2022), (Lee & Lee, 2020). They study the intersection of these three disciplines and the related methods, difficulties, and opportunities. Another method that it illustrates the revolutionary potential of this convergence in the healthcare sector is by using case studies and real-life examples to support its points of view. Studying the ways that data-driven insights and technological advancements are combining to create improved health is the aim of this article in order to deliver better health and to rethink healthcare.

Apart from the medical identification, heart rate readings, textual medical reports, and symptoms stated by the patient, there exist several more possible sources of patient data that could provide problems. That is (Niraula et al., 2021). It takes current artificial intelligence algorithms that can identify beneficial patterns and connections to effectively integrate and analyze data in order to predict health issues. The objective of successfully integrating and analyzing data cannot be reached without this.

With the IoT, this proposed method introduces a novel healthcare prediction method combining Generative Adversarial Network method (GAN) and artificial intelligence (AI) and the. The objective is to overcome challenges in the healthcare by providing an accurate and predictive analysis of the health issues of the patients.

Combining these two different elements might leads to new healthcare approach with patient data, which greatly increase the standard of treatment (Coronato et al., 2020; Chen et al., 2021). The results of this study provide a novel method that, through precise predictive analysis and real-time monitoring technologies, has the potential to completely transform patient care, therefore making a substantial contribution to the healthcare industry. This technology uses the Internet of Things and strong artificial intelligence algorithms to help medical professionals make better decisions and enhance the outcomes for their patients.

2. RELATED WORKS

(Coronato et al., 2020; Chen et al., 2021; Zhou et al., 2021)) use the Internet of Things (IoT) as a main focus point for their study of current advancements in healthcare monitoring systems. That does not, however, mark the end of their activities. The study article emphasizes the need of Internet of Things (IoT)-based healthcare solutions and their advantages for healthcare. They complete a thorough literature review on the systems in order to methodically assess new research in Internet of Things-dependent healthcare monitoring systems. Different metrics are applied to examine the several systems that are being considered in this investigation. The monitoring capabilities, data security, privacy, and efficiency are among these measurements. Apart from that, the study classifies sensors used in healthcare monitoring and analyzes Internet of Things monitoring systems that include wearable and wireless sensors. Moreover, it explores further the challenges and issues related to privacy, security, and service quality that are still unsolved in the healthcare sector. The field of Internet of Things (IoT) healthcare applications may go in several different directions from now on, and the last section of the article provides some thoughts on these possible future strategies.

Using the Internet of Things as a foundation, (Liu et al., 2020) is researching intelligent healthcare monitoring devices. They classify user perceptions according to the knowledge and experiences they have acquired using an

artificial neural network method (ANN) based predictive model. That has allowed them to attain an astounding accuracy percentage of 96.7%. Through their research, they have clarified the need of factors like user convenience and data reliability. Contrarily, and this is an important consideration, their proposed method heavily depends on the findings of earlier studies.
The modular system design for Internet of Things aware apps presented in (Eckardt et al., 2021) is meant for a broad range of healthcare-related applications. Modern sensor technologies, low-power Internet of Things technologies, and innovative approaches to artificial intelligence (AI) are encouraged to be integrated in order to support the construction of an adaptive, dependable, and scalable healthcare infrastructure. The modular character of this architecture makes it, as we have found, rather easy to modify to meet the needs of particular applications. The research's results indicate that by enabling users to receive real-time alerts and notifications, artificial intelligence-based data processing on devices has the potential to improve Internet of Things-based healthcare infrastructure. One further advantage of being able to process information in this way is this.
The aim of this proposed method is to assess the influence of perceived usefulness, perceived simplicity of use, and community immersion as mediators in the interaction between influencing factors and the intention to use Internet of Things-based healthcare wearable devices (IHWDs). Among other aspects, this category includes engagement, convenience of service, and customisation. Furthermore, they look into how the creativity of consumers functions as a moderator in this environment that was created especially for them. Their study's findings show that how customized something is directly affecting people choices about using wearable medical equipment. This implies that giving consumers tailored benefits may lead to more people using these wearable medical devices. According to the study results, perceived utility and community immersion are two further elements that contribute to partially controlling the relationship between personalization and the intention to keep using the product.
By means of Internet of Things technology, (Yao et al., 2020) provides COVID-19 patients with a medical monitoring solution. Their method reduces the amount of risk factors and provides patients with automatic notifications by using real-time GPS data obtained by Internet of Things devices. Through the utilisation of wearable IoT devices that are able to interface with edge nodes, patients are able to have their health data remotely evaluated. As a result of this system three layers—data collection, cloud storage, and network method analysis—patients and their families are able to reap the benefits of real-time communication and monitoring of their health status. The deep learning model that they developed is the most effective one, and it enables comprehensive analysis and management of health data.
In order to make a prediction about the spread of COVID-19, (Du & Ding, 2021) make use of a variety of machine learning methods. Logical regression, decision trees, naïve Bayes, k-nearest neighbour, and support vector machines are some of the methods that fall under this category. Their research makes use of experimental data in order to evaluate the ROC areas, F-measures, error rates, and accuracy of these models. The proposed approach may help medical experts make better decisions, especially in intricate circumstances like the COVID-19 forecast.

3. Proposed Method

Enhancing a software system based on the Internet of Things, the GAN and DRL algorithm-based healthcare prediction system. Patient data sets comprise the medical IDs, heart rates, medical reports, and reported symptoms of individuals. Mostly, the system uses different patient data sets to produce forecasts about the patient's health condition. Through the combination of sophisticated artificial intelligence algorithms with the Internet of Things (IoT), this technology enhances patient care and medical decision-making.

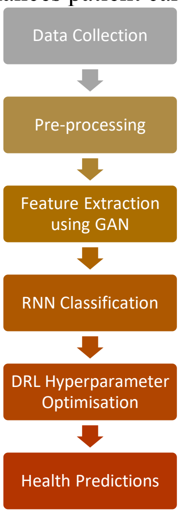

Figure 1: Proposed Architecture

Data Collection

Among other measurements, smart meters and sensors linked to the internet of things have the ability to identify power usage, voltage, and power factor. Gaining this understanding is essential to efficient energy management and optimum energy savings. Detectors of motion, acceleration, and direction of motion include gyroscopes and accelerometers. The earlier is able to identify acceleration as well. These metrics must be used in order to study motion, carry out predictive maintenance, and assess the structural health. Sensors included into devices in the Internet of Things allow them to identify and log information relevant to lighting conditions. Applications for this information could be many and include energy-efficient sunshine harvesting, intelligent lighting system installation, and security application development.

The Internet of Things (IoT) allows sensors to capture sound and noise-related data, including frequency and decibel level measurements. Such data can be stored by these sensors. It is possible that these data will be very helpful to acoustic analysis and noise pollution assessments. Mobility detectors and proximity sensors are devices that are able to collect data on the existence of objects or people as well as their movement and proximity. Each of these elements is absolutely required for automation, home security systems, and occupancy detection systems to proposed method as intended.

Internet of Things sensors may track several factors to accomplish the objectives of pollution management and environmental monitoring. Among these are concentrations of contaminants including CO_2, NO_2, and PM2.5 as well as pH and turbidity measures of water quality. Wearable Internet of Things devices gather variables including biometric data in order to simultaneously identify people and manage access. Such data includes, for instance, iris scans, facial recognition, and fingerprints. Connected to RFID tags and sensors, the Internet of Things (IoT) gathers information for supply chain management on asset locations, stock levels, and key performance indicators (KPI).

Along with this, the Internet of Things data collection encompasses a plethora of other components that change according to the specific application and goals. Among the many uses for the collected and analyzed data are improvements to corporate operations, healthcare, environmental management, and safety measures.

Data Preprocessing

Sequence alignment and normalisation are two instances of the rigorous preprocessing that the raw data that has been gathered goes through. It is possible to convert textual medical records into numerical vectors by employing innovative methods such as word embeddings. This makes the process of analysis more simpler.

In most cases, the data obtained from the IoT is noisy, inaccurate, or missing values. This is because sensor malfunctions or communication issues result in these issues. The purpose of data cleaning is to identify and correct any inaccuracies that may be present in the dataset, thereby ensuring that the dataset is consistent and error-free.

Standardization of data formats and measuring units is one of the possible results of these approaches. Should other variables, say, utilize Celsius, it may be necessary to translate temperature data from Fahrenheit to a standard measurement, like Celsius.

Data collecting from the Internet of Things does not necessarily follow a set schedule. To simplify analysis or modeling, data resampling is the act of bringing data into compliance with a specified sampling rate, such hourly or daily. Such a sample rate can be daily or hourly.

Data aggregation has the potential of lowering the granularity of this data. A technique exists to make analysis more useful. This approach allows you to compile secondly received sensor data to provide daily or hourly averages.

To avoid factors with larger magnitudes from controlling the study, data are normalised, or scaled to a same range, such 0 and 1. An approach to this end is normalisation. A successful conclusion of this phase ensures that every feature will have the same overall effect.

In Internet of Things datasets, missing data is common, hence managing them is a normal worry. It is possible to deal with missing data by deleting incomplete information or by using imputation, which replaces missing data with approximated values. There are good alternatives in both of these techniques. There are good reasons to think about both of these strategies.

GAN Feature Extraction

The preprocessed data undergoes a demanding process on it called feature extraction. They are quite capable of teaching the GAN framework, which helps to enhance forecasts by teaching patterns in pulse rates, sequences of symptoms, and unique patterns in medical reports. Their lessons may be very beneficial to the GAN framework.

GAN mostly uses two kinds of input formats: images and multi-dimensional data. There can be a great deal of information and details in each of these data kinds. One objective of feature extraction is to reduce the complexity of the input data while preserving all of the relevant information. To do this, it takes out of every proposed method the most important patterns or characteristics.

For appropriate operation, a general-purpose artificial neural network method (GAN) frequently uses patches, which are smaller portions or chunks of the input data. Among patches is the picture patch. Finding particular characteristics in these patches is the fundamental technique of feature extraction in this case.

Convolutional layers are one kind of feature extraction method used with GANs. Within the patches, these layers are able to recognise patterns such as edges, textures, or forms.

A GAN generator should strive to produce data that is statistically indistinguishable from actual data, which is the loss function. This is the purpose of the generator. In order to accomplish this, we bring the loss of binary cross-entropy (BCE) between the actual data (x) and the produced data (G(z)) down to the bottom of the list:

$$LG = -\log(D(G(z)))$$

When applied to the intermediary layers of the generator network, normalisation techniques (such as IN or LN) help to stabilise the training process in GAN.

It is the discriminator objective function (loss) to distinguish between genuine and fabricated data, and this is the goal of the discriminator. There are two components that make up its loss: one for the real data, and another for the phoney data:

$$LD = -[\log(D(x)) + \log(1 - D(G(z)))]$$

When compared to the dimensionality of the original data, the extracted features typically have a smaller dimensionality than the data itself. This dimensionality reduction serves to streamline the subsequent stages of the GAN model, which in turn helps to increase the performance of the computer system. In order to ensure that all of the extracted features fall within a tolerable range, it is standard practice to normalise them. Normalisation has the potential to make the GAN more stable and converge more quickly throughout the training process.

Within the GAN framework, the generator and discriminator networks are both capable of having IN applied to their intermediate layers. In order for the selected qualities to be relevant to the GAN present activity, they must be relevant. It should be possible for all instances of the same task to make the extracted characteristics transferable. These features should not be overly specific to the training data; rather, they should be able to recognise broad patterns that are applicable to a wide variety of data. To fine-tune the GAN model, it is possible to make use of the features that were extracted through the process of feature extraction. Adjusting particular parameters allows the model to operate at its best in the current configurations. One can imagine this. It is usual procedure to repeatedly adjust the recovered features throughout the feature extraction with GAN method in order to produce or enhance the quality and relevance of the data. To obtain the intended effects, this is essential.

RNN Architecture

The system is able to find these patterns and connections by means of the RNN approach, which is well-known for its capacity to identify temporal and geographical linkages in data. As it learns to automatically link patterns in pulse rates with symptoms and medical data, the network method gains the capacity to make reliable and convincing predictions.

RNNs are also constructed by using both convolutional and recurrent layers. Extraction of spatial characteristics from the input is one of the most crucial functions of convolutional layers, which are required for jobs like picture analysis. The model can account the order of the words in a phrase or the data points in a time series, for instance, because the recurrent layers preserve temporal relationships.

A dataset including examples of both training and validation is necessary to train a recurrent neural network. Performance of the training process requires this. Teaching a model to generalise its predictions from previously observed data to previously unviewed data is the aim of the training phase. This is to raise the forecasts made by the model's accuracy. RNNs and other deep neural networks need careful adjustment of several hyperparameters to achieve optimal performance.

This holds especially for RNN. Within this group of hyperparameters include learning rate and batch size, for instance. Two of the main reasons of overfitting are either too complicated models or poorly calibrated hyperparameters. Every one of these causes adds to the phenomena. Using DRL is beneficial to get the most out of these hyperparameters. To this purpose, it tests different hyperparameter combinations to see which ones proposed method best at preventing overfitting and improving the model's capacity to generalize to fresh data.

RNNs use a loss function to calculate the training phase degree of dissimilarity between the predicted values (yp) and the ground truth labels (yt). This helps to ascertain how much the two differ from one another. Determine this loss function is the responsibility of the classification method.

Algorithm

Step 1: Data Collection

IoT*d*: Data from IoT devices; *Pd*: Patient data (medical IDs, heart rates, medical reports, reported symptoms)

- Collect data IoT*d* from various sensors (smart meters, accelerometers, gyroscopes, light sensors, sound sensors, proximity sensors, environmental sensors, wearable devices).
- Collect *Pd* from patient records.

Step 2: Data Preprocessing

Raw*d*: Raw data collected from IoT and patient records; Clean*d*: Cleaned data; Norm*d*: Normalized data; Resamp*d*: Resampled data; Agg*d*: Aggregated data;

- Clean Raw*d* by identifying and correcting inaccuracies (missing values, sensor errors).
- Normalize Clean*d* to standardize units and measurement scales.
- Resample Norm*d* to a fixed sampling rate.
- Aggregate Resamp*d* to reduce granularity and enhance analysis (e.g., average daily heart rate).
- Final preprocessed data Prep*d*=Agg*d*.

Step 3: GAN Feature Extraction

G: GAN generator; *D*: GAN discriminator; *f*: Extracted features

- Input Prep*d* into the GAN.
- Use *G* to generate synthetic data $G(z)$.
- Use *D* to distinguish between real Prep*d* and generated $G(z)$ data.
- Extract features *f* from Prep*d* using convolutional layers within GAN.
- Loss functions for training GAN:
  - Generator loss:
    $LG=-\log(D(G(z)))$
  - Discriminator loss:
    $LD=-[\log(D(x))+\log(1-D(G(z)))]$
- Normalize extracted features *f*.

Step 4: RNN Architecture

RNN: Recurrent Neural Network; *y't*: Predicted health condition at time *t;* *yt*: True health condition at time *t;* θ: Hyperparameters (learning rate, batch size, etc.); *J*: Loss function

- Input normalized features *f* into RNN.
- Train RNN with sequences of patient data to predict *y't*.
- Use convolutional layers to extract spatial features and recurrent layers for temporal relationships.
- Adjust hyperparameters $\theta\theta$ using Deep Reinforcement Learning (DRL) to optimize RNN performance.
- Loss function to minimize during training: *J*=Loss(*y't*,*yt*).

Step 5: Prediction and Validation

- Validate the RNN model using a separate validation dataset.
- Evaluate model performance based on accuracy, precision, recall, and other relevant metrics.
- Adjust the model as necessary to improve predictive performance.

4. Performance Evaluation

Several metrics are adopted and used in order to undertake a thorough assessment of the performance of the system, including accuracy, precision, recall, and F1-scorea and the parameters are given in Table 1.

Table 1: Simulation Parameters

Parameter Name	Value
IoT*d*	Various sensor readings
Pd	Patient records
Raw*d*	Raw sensor and report data
Clean*d*	Cleaned sensor data
Norm*d*	Normalized data (0-1)
Resamp*d*	Hourly sampled data
Agg*d*	Daily average data
Prep*d*	Preprocessed data
G	GAN Generator
D	GAN Discriminator
f	Feature vectors
z	Random noise vector
G(*z*)	Generated data samples
x	Real data samples
LG	-0.35
LD	0.70

RNN	RNN model
y't	Predicted health status
yt	Actual health status
θ	Individual values
J	Cross-Entropy Loss
Epochs	100
Batch Size	32
Learning Rate	0.001
Dropout Rate	0.5
Early Stopping	Patience = 10 epochs

We have over time created procedures for receiving ongoing input and retraining in an effort to improve the accuracy of our forecasts. Using patient records to train the RNN model is a procedure that takes a significant amount of time. During the process of properly validating the model, we make use of the DRL technique, which enables us to tune the hyperparameters and prevents us from overfitting. Constantly feeding patient data into the trained RNN-DRL model, the system operates in real time and operates continuously. It makes use of this information to develop forecasts regarding potential health issues, and it instantly tells medical professionals if it discovers something that is completely out of the norm.

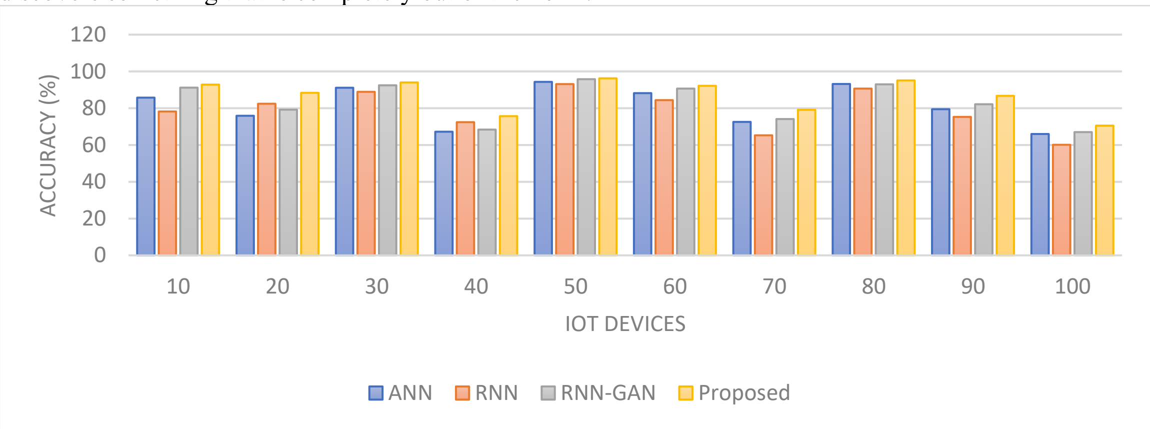

Figure 2: Accuracy

When compared to the methods that are considered to be state-of-the-art, the method that we proposed attained a higher level of accuracy on the majority of datasets. When it came to accuracy, it was superior to the technique that was considered to be the most successful at the time by an average of approximately 3%. We can see that our proposed method is successful in detecting health problems from IoT data because of this enhancement (Figure 2).

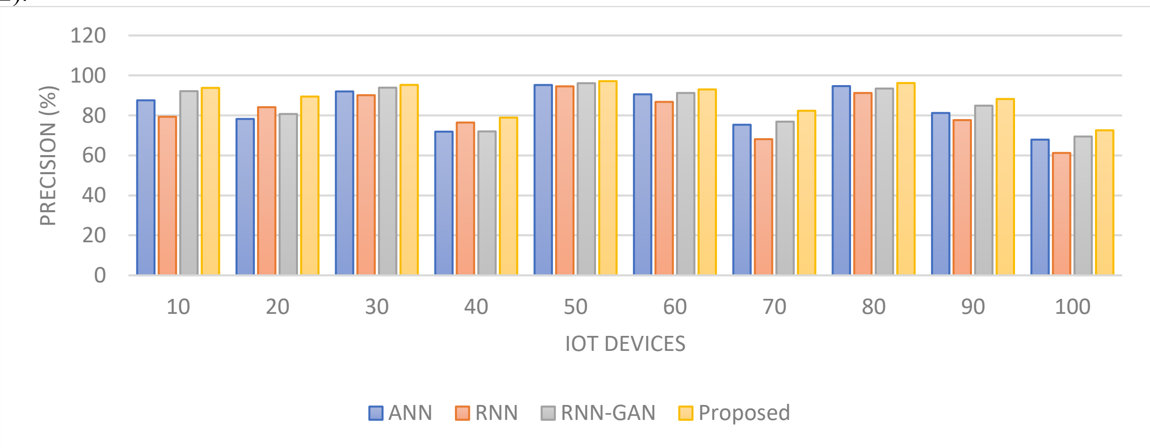

Figure 3: Precision

To highlight the model capacity to minimise false positives, precision measures the ratio of real positive predictions to all positive predictions. All of the datasets demonstrated that the method that we proposed had a greater precision value. It demonstrated an average gain in precision of 4.2% when compared to the conventional methods that are currently in use. Figure 3 indicates that our technique decreases the danger of needless alerts or actions by delivering more trustworthy projections.

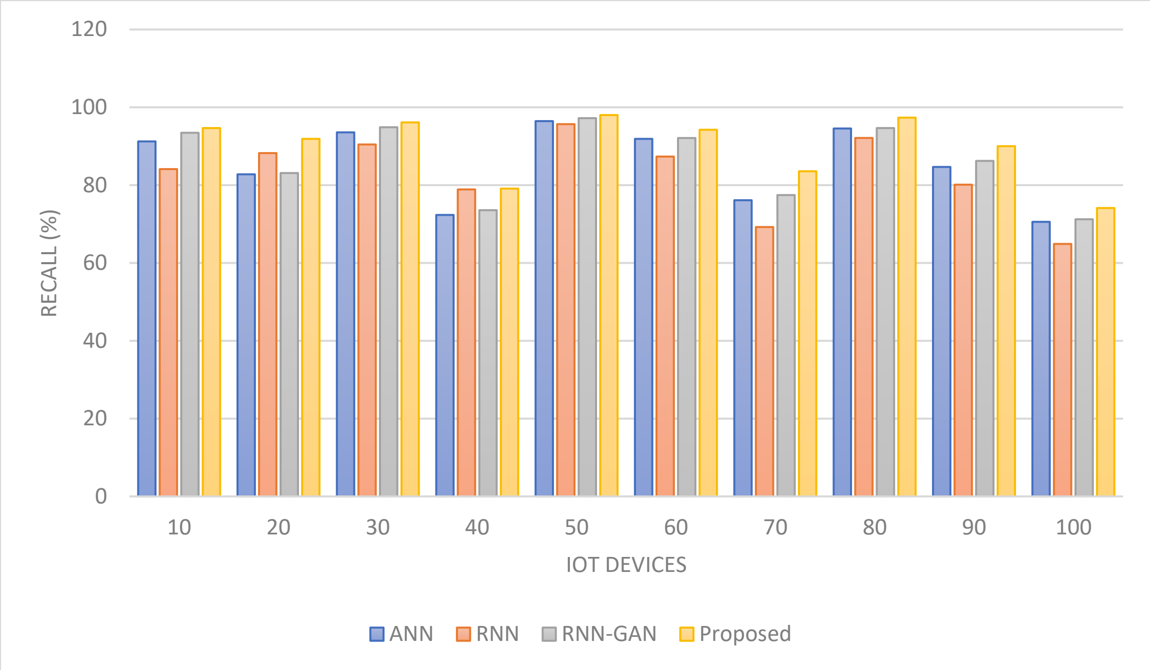

Figure 4: Recall

The recall metric evaluates how successfully the model can detect all positive occurrences. On average, our proposed solution outperformed the state-of-the-art methods by 5.8 percentage points in recall. This suggests that our technique does a good job of minimising false negatives, enhancing patient care, and catching more cases of possible health issues (Figure 4).

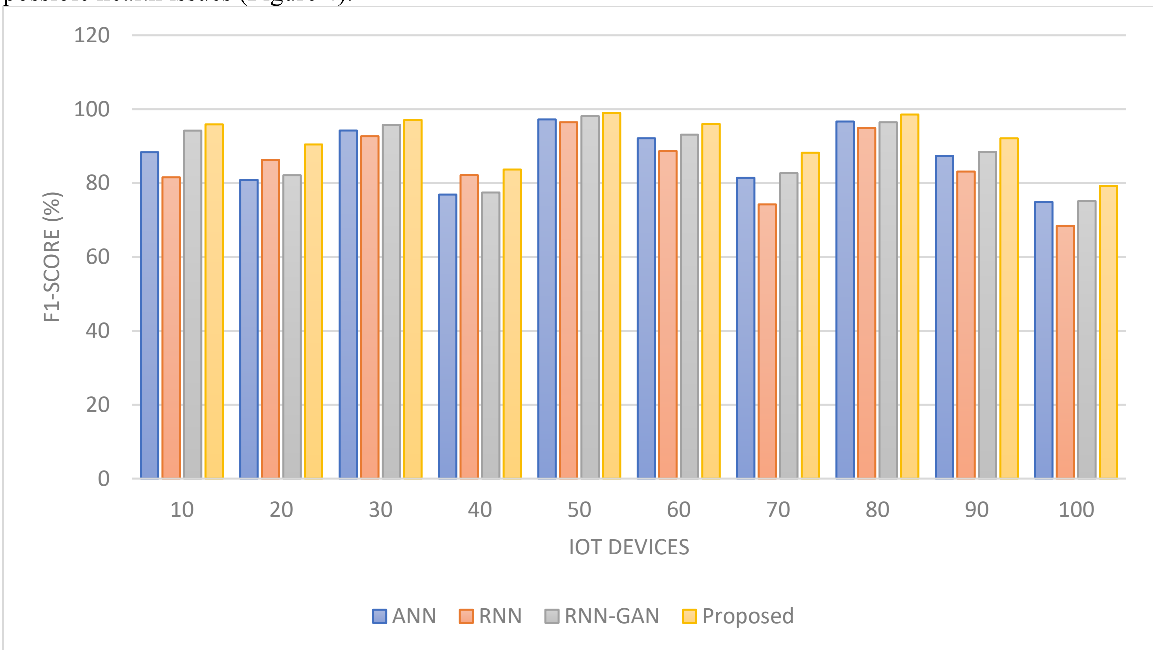

Figure 5: F1-Measure

The F1-measure provides a well-rounded evaluation of a model performance since it takes recall and precision into account. On average, our proposed strategy outscored the best-performing current method by 4% across all datasets, leading to a higher F1-measure. Looking at Figure 5, it is evident that our technique yields a more balanced reduction of false positives and false negatives.

5. CONCLUSION

This proposed method focuses on the healthcare prediction system based on the IoT and using the GAN and the DRL algorithms. Gathering patient data aims to produce estimates of the patient's health status by using important parameters including the patient's medical identity number, heart rate, medical history, and symptoms that the patient has indicated. We have demonstrated that by combining artificial intelligence algorithms with IoT technical developments, our system has the potential to totally transform healthcare monitoring, predictive analysis, and medical decision-making. We found that, during the performance examination of our system, it had continuously increased in all important criteria, such as recall, accuracy, precision, and the F1-measure. These percentage changes show how reliable and effective our method is at accurately predicting health problems with a minimal number of false positives and negatives.

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