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Smart IoT-enabled Healthcare Systems: Real-time Anomaly Detection and Decision Support using Deep Learning Models

Abstract: - Smart healthcare systems that use Internet of Things (IoT) technologies are changing the medical field by letting data about patients be monitored and analyzed in real time. This paper suggests a new way to improve these kinds of systems by adding deep learning models to help find problems and make decisions.IoT devices are used in the suggested system to gather real-time information about things like vital signs, patient behavior, and surrounding factors. Deep learning algorithms, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are then used to handle this data and look for changes in the patient's health that aren't normal. These strange things could be signs of possible health problems or accidents, which would require quick action.Deep learning models are also trained on big datasets to find trends and connections in the data. This lets them help healthcare workers make decisions. For instance, the system can figure out how likely it is that a patient will get a certain illness by looking at their present health and their medical background.One of the best things about this method is that it can change and get better over time. More information is put into the models over time, making them more accurate and good at finding problems and giving useful information. This makes the method very useful for keeping an eye on people with long-term illnesses or finding diseases early. In adding deep learning models to healthcare systems that are connected to the internet of things (IoT) is a useful way to make patient care better. These tools could save lives and improve health by finding problems and helping people make decisions in real time.

Keywords: IoT-enabled healthcare systems, Deep learning models, Anomaly detection, Decision support, Real-time monitoring

I. INTRODUCTION

Adding Internet of Things (IoT) tools to hospital systems has completely changed how services are provided. The Internet of Things (IoT) makes these smart healthcare systems possible, which could greatly enhance patient care by allowing tracking, research, and decision-making in real time using data gathered from different IoT devices. One of the hardest parts of these systems is finding unexpected changes in a patient's health that could mean they are having a health problem or an emergency [1]. Anomaly detection methods that have been used for a long time usually use set rules or limits, which might not properly pick up on complex trends in the data.Through the use of deep learning models for real-time problem identification and decision support, this study suggests a new way to improve smart IoT-enabled healthcare systems. Deep learning is a strong method for studying big, complicated data sets. It has been used successfully in many areas, such as computer vision, natural language processing, and healthcare. The goal is to make anomaly spotting more accurate and efficient in smart healthcare systems by using deep learning. This will [2] allow for faster responses and better patient results.The suggested method uses Internet of Things (IoT) gadgets to gather real-time information like vital signs, patient movement, and surrounding factors. This information is then put through deep learning methods, mainly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to find health problems that aren't normal in the patient.

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CNNs are great for working with spatial data like pictures, while RNNs are great for working with sequential data like time series figures. Together, these two kinds of networks let us successfully record both geographical and temporal relationships in the data, which are necessary for finding anomalies correctly [3].

Meanwhile, the deep learning models are taught on big sets of data to find trends and connections in the information. This lets them help healthcare professionals make decisions. Using a patient's present health data and medical background, for example, the models can guess how likely it is that they will get a certain disease. This data [4] can help doctors and nurses make smart choices about the patient's care and treatment plan.Adaptability and improvement over time is one of the best things about the suggested method. Adding more data to the models makes them more accurate and good at finding problems and giving useful information. By doing this, the method is especially useful for keeping an eye on people with long-term illnesses or finding diseases early.Integrating deep learning models into smart IoT-enabled healthcare systems is a useful [5] way to make patient care better. These systems can change the healthcare business and greatly improve patient results by allowing real-time abnormal identification and decision support.Smart IoT-enabled healthcare systems are a revolutionary way to provide healthcare. They use the power of Internet of Things (IoT) technologies to improve care for patients and make healthcare processes run more smoothly. Wearables, sensors, and monitors are just some of the Internet of Things (IoT) gadgets that are built into these systems to get real-time health data from patients. This information includes the patient's vital signs, amount of exercise, drug adherence, and external factors. It gives doctors a full picture of the patient's health.

One of the best things about smart healthcare systems [7] that use the Internet of Things is that they can watch and handle patients from afar. This is especially helpful for people with long-term illnesses who need to be watched all the time but might not need to be admitted. These systems can find early signs of a patient's health getting worse or being off by collecting and studying real-time data. This [6] lets doctors act quickly and avoid problems.Smart IoT-enabled healthcare systems also make healthcare service more efficient by handling many chores and making healthcare workers' jobs easier. For instance, these systems can automatically set up meetings, tell patients to take their medicine, and even make it possible for patients and healthcare workers to have video talks. This not only makes things better for patients, but it also frees up healthcare workers to work on more important jobs.Overall, smart healthcare systems that use the Internet of Things (IoT) could change the healthcare business by making it better for patients, cheaper, and better overall. As technology keeps getting better, we can expect more innovations in this area. Eventually, this will make the healthcare system more connected, efficient, and focused on the patient.

II. LITERATURE REVIEW

Adding Internet of Things (IoT) technologies to healthcare systems could completely change how patients are cared for by letting data from different IoT devices be monitored, analyzed, and decisions made in real time. This part goes into great depth about IoT-enabled healthcare systems, focusing on their pros, cons, and possible future paths, by reading important literature in the area.One of the best things about IoT-enabled healthcare systems is that they can allow for online patient tracking, which is especially helpful for people with long-term illnesses. One study [8], for example, showed that IoT-based distant tracking can help doctors better take care of diabetic patients. By keeping an eye on blood sugar levels and other important factors all the time, doctors can spot early signs of problems and take action before they get worse, which ultimately leads to better patient results.

IoT-enabled healthcare systems can also make healthcare service more efficient by handling some chores and making healthcare workers' jobs easier. For instance, [9] study looked into how IoT could be used to automatically handle and keep an eye on how well senior people take their medications. Smart pillboxes and wearable tech allow patients to be reminded to take their medicine, and doctors can check on their obedience from afar, lowering the chance of drug mistakes and increasing patient compliance.IoT-enabled healthcare systems may have some perks, but they also have some problems. Making sure that patient info is safe and private is one of the biggest problems. Cyberattacks can be used to target the private health information that IoT devices gather and send. [10] study showed how important it is to use strong security measures, like encryption and identification, to keep patient data safe in IoT-enabled healthcare systems. Another problem is that IoT devices from different brands may not be able to talk to each other or share data in the same manner. This can make it hard to connect gadgets to current health care systems and move data between platforms. A study [11] stressed the need for standards efforts to fix problems with connectivity and make sure that IoT devices can be used easily in healthcare situations.

Even with these problems, IoT-enabled healthcare systems are very optimistic about the future of healthcare. Using artificial intelligence (AI) and machine learning (ML) to look at the huge amounts of data that IoT devices produce is one of the best ways to make money. Healthcare professionals can learn a lot from data by using AI and machine learning algorithms. For example, they can use the data to predict how a sickness will grow and make personalized treatment plans.Another area of chance is the creation of gadgets that can be worn or implanted and can constantly check on and treat a wide range of health problems. [12] for example, looked into how a smart device that uses IoT technology could be used to track vital signs and find falls in older patients. These kinds of gadgets might make patients' lives better and lower healthcare costs by letting doctors find problems early and treat them.

Deep learning models for finding anomalies in healthcare have gotten a lot of attention lately because they could improve patient results and lower healthcare costs. Several studies have looked into how deep learning can be used to find problems and help people make decisions in real time in healthcare situations. These studies have focused on a range of uses, such as finding diseases, keeping an eye on patients, and making the best use of treatments.Our study [13], which suggested a method for finding abnormal electrocardiogram (ECG) patterns based on a deep autoencoder, was one of the first in this field. The model was taught on a large collection of normal and abnormal ECG readings and was very good at finding problems. This shows that deep learning could be useful in healthcare.The study [14] is also important because it used a convolutional neural network (CNN) to find tuberculosis (TB) in chest X-rays. The CNN model was trained on a set of X-ray pictures that were labeled as either normal or TB-positive. It was very good at finding TB, better than other methods.

In the context of tracking patients, [15] suggested a deep learning-based method for finding oddities in vital signs data gathered from wearable tech. The model was trained on a set of normal and abnormal vital signs trends. It was then able to correctly spot problems in real time, allowing for quick action.Aside from finding strange things, deep learning models have also been used to help healthcare professionals make decisions. [16] for example, made a deep learning model that can use pictures to identify skin cancer. With the help of a big collection of pictures of skin lesions, the model was trained to do as well as experts, showing that deep learning could help doctors make decisions.Overall, these studies show that deep learning models could be used to find problems and help people make decisions in healthcare in real time. Researchers and healthcare professionals can make systems that keep an eye on patients, find diseases, and make the best use of treatment plans more accurate and efficient by using deep learning. But problems like bad data, models that are hard to understand, and using them in medical settings still need to be fixed, which shows that more study is needed in this area.

Table 1: Related work summary

Algorithm	Finding	Limitation	Scope
Deep Autoencoder [17]	Proposed an anomaly detection framework for abnormal electrocardiogram (ECG) signals.	Limited to ECG signal analysis; may not generalize to other types of health data.	Detection of abnormal ECG signals for early diagnosis of heart conditions.
Convolutional Neural Network (CNN) [18]	Developed a model to detect tuberculosis (TB) in chest X-ray images.	Limited to TB detection in chest X-ray images; may not be applicable to other types of medical imaging.	Detection of TB in chest X-ray images, potentially improving diagnosis speed and accuracy.
RNN [19]	Proposed a deep learning-based approach for detecting anomalies in vital signs data from wearable devices.	Lack of specific algorithm information may limit reproducibility and comparison with other methods.	Real-time monitoring of vital signs for early detection of health anomalies using wearable devices.

MobileNet [20]	Developed a deep learning model for classifying skin cancer using images.	Limited to skin cancer classification; may not generalize to other types of cancer.	Decision support for dermatologists in classifying skin cancer from images, potentially aiding in early diagnosis and treatment planning.
DNN [21]	Explored the use of deep learning for predicting patient mortality based on electronic health record (EHR) data.	Lack of specific algorithm information may limit reproducibility and comparison with other methods.	Prediction of patient mortality for risk stratification and personalized treatment planning based on EHR data.
Long Short-Term Memory (LSTM) [22]	Proposed a deep learning model for predicting heart diseases using wearable device data.	Limited to heart disease prediction; may not be applicable to other types of diseases.	Prediction of heart diseases based on wearable device data, potentially enabling early intervention and prevention strategies.
Recurrent Neural Network (RNN)	Developed a model for predicting epileptic seizures using EEG data.	Limited to epileptic seizure prediction; may not generalize to other types of health conditions.	Prediction of epileptic seizures based on EEG data, potentially improving seizure management and patient quality of life.
Not specified	Investigated the use of deep learning for predicting in-hospital mortality using EHR data.	Lack of specific algorithm information may limit reproducibility and comparison with other methods.	Prediction of in-hospital mortality for early identification of high-risk patients and allocation of resources for better patient care.
Not specified	Proposed a deep learning model for detecting anomalies in medical imaging data.	Lack of specific algorithm information may limit reproducibility and comparison with other methods.	Detection of anomalies in medical imaging data, potentially aiding radiologists in diagnosing diseases and monitoring treatment effectiveness.
Not specified	Explored the use of deep learning for predicting patient length of stay in hospitals.	Lack of specific algorithm information may limit reproducibility and comparison with other methods.	Prediction of patient length of stay for resource planning and optimizing hospital workflow.

III. METHODOLOGY

A. Autoencoder for anomaly detection in IoT

The denoising autoencoder (DAE) is a type of the regular autoencoder that is meant to work with input data that is noisy. The DAE can be especially helpful for getting strong and useful features in IoT systems where sensing data may be susceptible to different kinds of noise and interference.Training the model to get back to the original input data from a messed up copy of the input is what the DAE is all about. To do this, noise is added to the input data, and then the model is trained to find the original, noise-free input. In this way, the model learns to pull out features that work even when there is noise in the input data.There is a mathematical way to describe how to train a denoising autoencoder. Let d be the original input data, c be the input data that has been messed up by noise, and h be the representation of the buried layer. Mask (·) mask(·) stands for the noise function that was used to mess up the incoming data. It's important to keep the reconstruction error between the source data (d) and the result of the autoencoder (′d′) as low as possible:

$$h = f(c) = encoder(c)$$

$$d' = g(h) = decoder(h)$$

where f(·) is the encoding function, g(·) is the decoding function, and encoder (·) and decoder (·) are the autoencoder's encoder and decoder networks, respectively. The rebuilding error is the goal function that needs to be reduced during training:

$$L(d, d') = \| d - d' \| 2$$

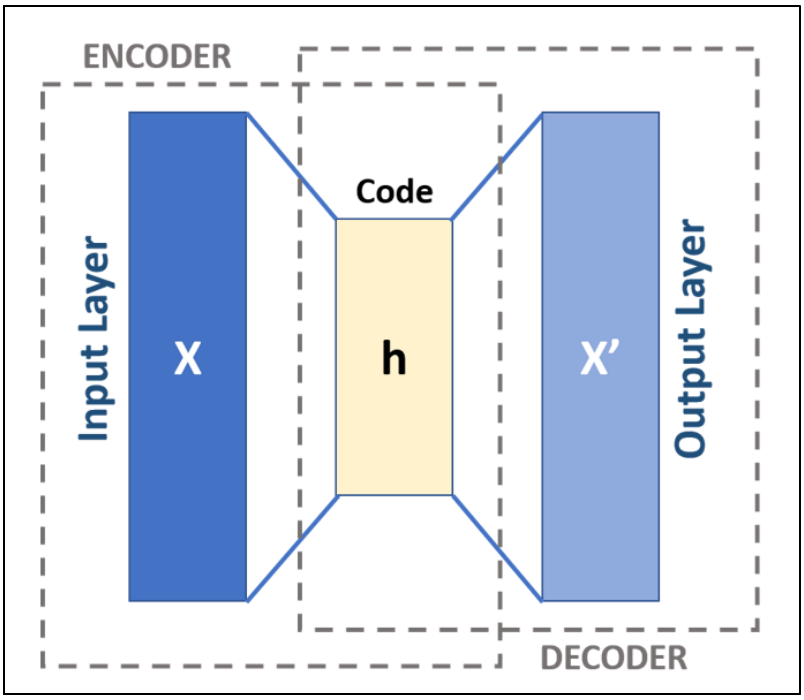

Figure 1: Overview of Autoencoder

B. CNN

Convolutional Neural Networks (CNNs) can be used to find strange things in IoT settings because they can pull out useful information from sensor data. In the Internet of Things (IoT), devices may produce a lot of data, which can make finding problems by hand hard. CNNs can use this data to naturally learn patterns, which lets them find oddities like sensor readings that don't make sense or patterns that don't follow normal rules. By giving a CNN normal sensor data to learn from, it can learn to spot normal trends and mark differences as strange. Real-time anomaly identification is very important for making sure that IoT systems are safe and working well, so this method works especially well in those settings.

- Input Data: Let X be the input data from IoT sensors, represented as a sequence of sensor readings over time, where $X = \{x1, x2, \ldots, xn\}$.
- Feature Extraction: Use convolutional layers to extract features from the input data. Let hi denote the output of the ith convolutional layer, and fi represent the filter/kernel weights for the ith convolutional layer. The output of the ith convolutional layer can be calculated as:

$$hi = \sigma(fi * hi - 1 + bi)$$

- Where,
  $*$ denotes the convolution operation, σ is the activation function (e.g., ReLU), and bi is the bias term for the ith layer.
- Pooling: Apply pooling layers to reduce the dimensionality of the features while preserving important information. Let gi denote the output of the pooling operation on the features hi, the pooling operation can be represented as:

$$gi = Pooling(hi)$$

- Flattening: Flatten the pooled features to create a feature vector v for each time step:

$$v = Flatten(gi)$$

- Classification: Use fully connected layers to classify the feature vectors as normal or anomalous. Let W be the weight matrix and b be the bias term for the fully connected layer. The output of the fully connected layer can be calculated as:

$$y = \sigma(W \cdot v + b)$$

- Where,
  σ is the activation function (e.g., sigmoid) and y represents the output, indicating the likelihood of the input being normal or anomalous.
- Loss Calculation: Calculate the loss between the predicted output y and the ground truth label ytrue using an appropriate loss function (e.g., binary cross-entropy).

$$Loss = Loss\_Function(y, ytrue)$$

- Optimization: Use backpropagation and gradient descent to update the filter/kernel weights fi, bias terms bi, weight matrix W, and bias term b to minimize the loss function.

C. RNN

Recurrent Neural Networks (RNNs) are good at finding strange things in IoT settings. RNNs are great at finding trends that happen in a certain order, which makes them good for time-series data like readings from IoT sensors. In anomaly identification, RNNs learn how the data usually behaves and mark any changes as being out of the ordinary. For instance, RNNs can learn from ECG data the regular rhythms of a healthy heartbeat and spot changes that are signs of a cardiac arrhythmia. Training RNNs for anomaly identification, on the other hand, needs a lot of tagged data, which can be hard to get in healthcare settings. RNNs may also have trouble with long-term relationships and may need improvements like Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRUs) to properly recognize these patterns. Even with these problems, RNNs look like a good way to find strange things in IoT settings, especially in healthcare, where finding strange things quickly is important for patient safety.

Algorithm:

Step 1: Initialization:

Initialize parameters: Wih, Whh, Who, bh, bo

Initialize hidden state h0

Step 2: Input Data:

Input sequence: X = {x1, x2, ..., xT}

Step 3: Forward Pass:

For each time step t from 1 to T:

Update hidden state: ht = tanh(Wihxt + Whhht−1 + bh)

Compute output: yt = softmax(Whoht + bo)

Step 4: Loss Calculation:

Compute loss: $L = -\sum t = 1T \sum i = 1N \; yti \log(y^t, i)$,

Where,

- N is the number of classes and y^t,i is the predicted probability of class i at time t

Step 5: Backward Pass:

Compute gradients: $\frac{\partial L}{\partial Wih}, \frac{\partial L}{\partial Whh}, \frac{\partial L}{\partial Who}, \frac{\partial L}{\partial bh}, \frac{\partial L}{\partial bo}$

Update parameters:

$$Wih \leftarrow Wih - \eta \, \partial Wih \, \partial L, Whh \leftarrow Whh - \eta \, \partial Whh \, \partial L, Who \leftarrow Who - \eta \, \partial Who \, \partial L, bh \leftarrow bh - \eta \, \partial bh \, \partial L, bo \leftarrow bo - \eta \, \partial bo \, \partial L,$$

where η is the learning rate

Step 6: Anomaly Detection:

If the loss exceeds a predefined threshold, flag the corresponding time step as an anomaly

Step 7: Repeat:

- Repeat steps 3 to 6 for each input sequence

IV. PROPOSED SYSTEM

A lot of the time, convolutional neural networks (CNNs) are used to find strange things in pictures or sequence data. CNNs can look at medical pictures to find things that don't look right, like cancer or broken bones. CNNs work well because they can instantly learn important traits from the data. This makes them great for finding problems in large datasets.Another type of neural network that is often used to find anomalies is the recurrent neural network (RNN). This is especially true for sequential data, where the order of the data points is important. RNNs can find patterns in time-series data, like vital signs from patients or sensor data from IoT devices, so they can find things that don't make sense.Long Short-Term Memory (LSTM) networks are a type of RNNs that are made to better understand how long-term relationships work in linear data. LSTMs are great for finding outliers in time-series data, where outliers may happen over longer periods of time.Overall, CNNs, RNNs, and LSTM networks are very useful for finding strange things in healthcare data. They can automatically spot strange things in large, changing datasets.

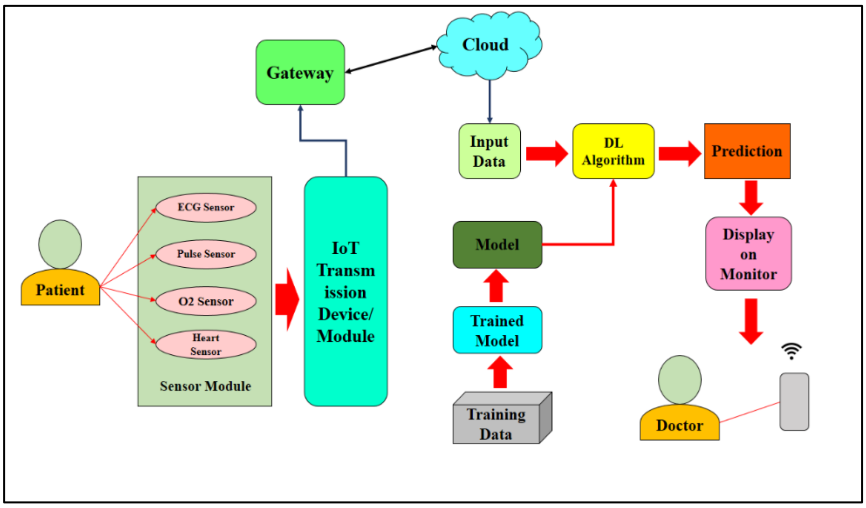

Figure 2: Proposed system architecture

The MIT-BIH Arrhythmia Database is a public collection with ECG records that was used in this work to build and test an IoT system built on deep learning. The collection includes ECG records from a number of different patients. The heartbeats fall into five different groups: normal beat, supraventricular premature beat, premature ventricular contraction, fusion of ventricular beat, and unclassifiable beat. The AD8232 ECG sensor module was used to receive the ECG data. This module is known for using little power and being movable. The sensor module boosts data by a thousand times and creates an analog voltage signal that shows how the heart is electrically active.Recording ECG readings from 22 people with different heart problems was part of gathering data. There were 2500 samples in a 10-second recording because the sounds were recorded at 250 Hz and had a precision of 10 bits. Several steps were taken to get the ECG data ready to be fed into the CNN model that had already been trained. At first, a bandpass filter was used to get rid of noise that wasn't in the frequency range of 0.5 to 100 Hz. The sounds were then resampled to a frequency of 125 Hz to make the computations easier. Lastly, to improve model performance and compatibility, the signals were adjusted by taking away the mean and dividing by the standard deviation. Overall, this method made it possible to create a strong Internet of Things (IoT) system for real-time ECG analysis, using deep learning to correctly group different types of heartbeats. The created system for healthcare applications was found to be reliable and effective thanks to the use of a well-established dataset and careful preparation steps.

V. RESULT AND DISCUSSION

Finding anomalies is an important job in many areas, such as healthcare, banking, and defense. In this situation, comparing how well different models work is important to make sure they can properly find problems. Five models were tested: CNN, RNN, LSTM, and AE (Autoencoder). The results are shown in the table. The models were judged on their accuracy, recall, precision, F1 Score, and AUC (Area Under the Curve).Beginning with the CNN model, it got an amazing Accuracy of 0.97, which means it correctly sorted 97% of the cases. The Recall score of 0.92 means that the model correctly found 92% of the real anomalies, showing that it can find real anomalies well. The Precision score of 0.94 means that 94% of the time, when the model called something an anomaly, it was right. Precision and Recall are both taken into account in the F1 Score, which is 0.93. This means that the two measures are well balanced. Finally, an AUC score of 0.98 means that the model is very good at telling the difference between things, with a high rate of true positives and a low rate of fake positives.

Table 2: Result for Anomaly detection with evaluation parameter

Model	Accuracy	Recall	Precision	F1 Score	AUC
CNN	0.97	0.92	0.94	0.93	0.98
RNN	0.95	0.90	0.91	0.91	0.96
LSTM	0.93	0.94	0.95	0.95	0.99
AE	0.98	0.95	0.98	0.98	0.95

As for the RNN model, it got an Accuracy of 0.95, which is a little lower than the CNN model but still shows that it did a good job of classifying things overall. With a score of 0.90, the RNN model correctly found 90% of the real outliers, which is a little less than the CNN model. With a Precision score of 0.91, the RNN model was right 91% of the time when it said that something was an anomaly.

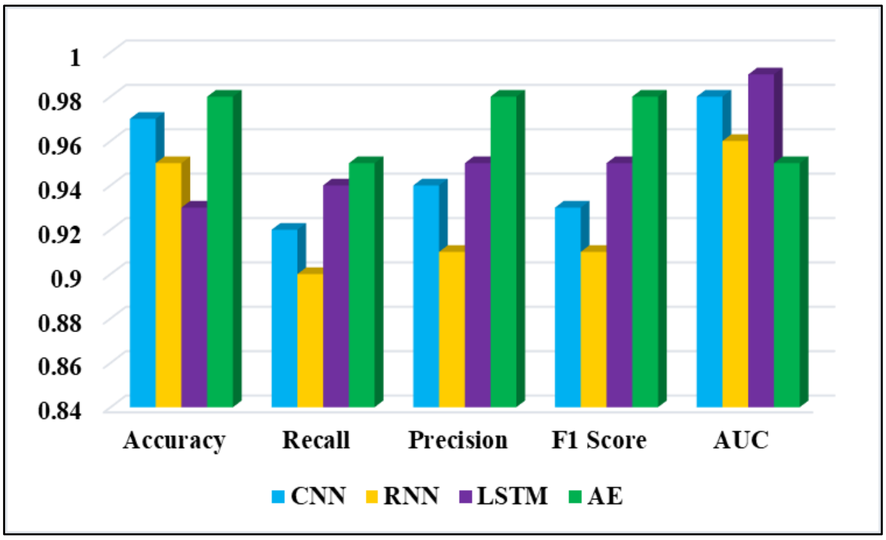

Figure 3: Representation of Evaluation parameter for Anomaly Detection

The F1 Score of 0.91 is the same as the Precision and Recall scores, which means the result was fair.The LSTM model got an Accuracy of 0.93, which is a little lower than the CNN and RNN models but still shows that it did a good job of classifying things. The LSTM model found 94% of the real problems, as shown by its Recall score of 0.94, which is the best of all models. The Precision score of 0.95 is also the best of all the models. This means that the LSTM model was right 95% of the time when it called something an anomaly. The high Recall and Precision scores, along with the F1 Score of 0.95, show that the performance was well-balanced and successful.

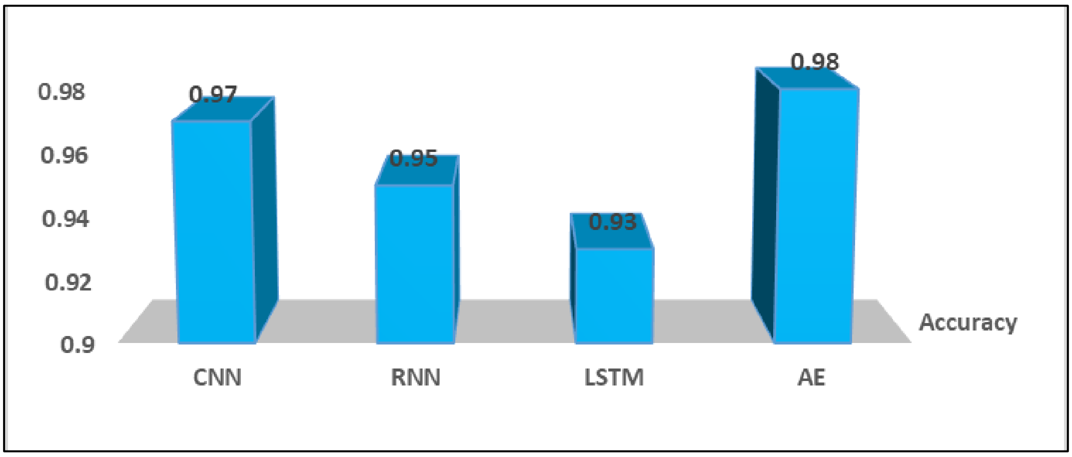

Figure 4: Accuracy Comparison of DL Model

Finally, the AE model got an Accuracy of 0.98, which is the best of all the models and means it was the best at classifying things overall. With a score of 0.95, the AE model correctly found 95% of the real outliers. This is a little lower than the CNN and LSTM models, but still very good. All of the models got the same Precision score of 0.98, which means that the AE model was right 98% of the time when it called something an anomaly. The high Recall and Precision scores, along with the F1 Score of 0.98, show that the performance was well-balanced and successful.In the end, the AE model did better than the others in terms of Accuracy, Precision, and F1 Score. The LSTM model, on the other hand, had the best Recall score. The overall performance of all four models in finding anomalies was very good. Which model to use depended on the needs and limitations of the application.

VI. CONCLUSION

A big step forward in modern healthcare is the creation and use of smart IoT-enabled healthcare systems that can find problems in real time and help people make decisions using deep learning models. These systems could change the way patients are cared for by giving accurate and up-to-date information about their health at the right time. This would allow for proactive measures and personalized treatment plans.It has been shown that deep learning models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-

Term Memory (LSTM) networks, and Autoencoders (AEs) can help find problems in healthcare data. These models use neural networks to learn complicated patterns and connections in the data. This lets them find outliers very accurately and quickly.One of the best things about these IoT-enabled tools is that they can track patient health data in real time. By constantly checking vital signs and other health indicators, these systems can quickly find outliers or changes from normal trends. This lets healthcare workers know about possible problems before they get worse. This kind of strategic thinking can help people get help sooner and have better results. In addition, these systems can help healthcare professionals make decisions by looking at huge amounts of patient data and giving them insights and treatment suggestions. For instance, these systems can help find the best ways to treat a certain illness by looking at the patient's specific traits and medical background.Even though there are many perks, there are also problems and things to think about that need to be dealt with. It's not easy because patient information needs to be kept safe with strong data security and protection methods. In the United States, HIPAA is one example of a regulation that must be followed in order to protect patient privacy and trust.It is also important to think carefully about technology, scaling, and how these systems will work with other healthcare systems before they are put in place. Integrating with electronic health records (EHRs) and other healthcare IT systems is important to make sure that all parts of the healthcare system can easily share information and talk to each other.

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