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Deep learning used in IoT-enabled healthcare transformation to provide better patient monitoring and diagnostics

Bhavishya Katta *

Senior System Analyst, Information Technology (Masters in Computer Science, Masters in Information System Security, Masters in IT), University of the Cumberland's, Austin, Texas.

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Abstract

Deep learning's and the internet of things' revolutionary capabilities are generating a dramatic shift in the healthcare sector. An examination of the possible monetary chaos that may ensue from healthcare systems implementing deep learning for patient identification and monitoring through the internet of things is undertaken in this study. Wearable sensors, smart devices, and internet-connected medical equipment have made it possible for medical personnel to monitor their patients' respirations, heart rates, and other physiological indicators in real time. But the massive amounts of complicated data produced by these gadgets make analysis and diagnosis difficult. Deep learning algorithms do a great job of sifting through this ever-growing heap of medical records. Data collected from sensors, electronic health records (EHRs), and patient reports can be automatically analyzed for complex patterns and relationships using Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. Clinicians can use this ability to better diagnose patients, identify warning signals, and tailor therapies to each individual's needs. This study presents the specifics of an Internet of Things (IoT) healthcare system that employs convolutional neural networks (CNNs) and long short-term memories (LSTM) for tasks such as feature extraction, data classification, prediction, and development. When it comes to healthcare settings, using real-time updated deep learning models raises questions about interpretability, privacy, and accessible resources. The study demonstrates that the Internet of Things (IoT)—specifically, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM)—can enhance healthcare. These systems enable optimization of therapies, real-time diagnosis of diseases, and risk predictions. Healthcare that is both accessible and inexpensive can improve with the application of these ideas. Through networked devices and sophisticated analytics, the combination of the Internet of Things (IoT), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) can significantly improve disease detection, individualized therapy, and patient monitoring.

Keywords: Internet of Things (IoT); Convolutional Neural Networks (CNNs); Long Short-Term Memory (LSTM); Deep learning; Data.

1. Introduction

In order to alleviate treatment facility congestion, hospitals can quickly reassign outpatients with the use of health prediction algorithms. They improve access to healthcare by increasing the number of people who get treatment. One frequent problem with hospitals is unexpected shifts in patient volume; a health prediction system helps with this. A combination of routine outpatient demand and emergency events, such as the arrival of ambulances in the aftermath of natural catastrophes or traffic accidents, drives the demand for healthcare services in many hospitals [1]. Without up-to-the-minute information on patient flow, hospitals sometimes struggle to satisfy demand, even while neighboring

* Corresponding author: Bhavishya Katta

facilities may be understaffed. The IoT establishes a link between digital computers and physical objects to enable communication. New microprocessor chips make it possible to instantly collect data.

Keep in mind that healthcare is all about improving and maintaining health by identifying and preventing diseases. The use of diagnostic imaging modalities such as SPECT, PET, MRI, and CT allows for the examination of lesions or ruptures occurred deep within the skin. In a similar vein, epilepsy and heart attacks are observable abnormalities [2].

Contemporary healthcare systems are under pressure from both the population boom and the unpredictable rise of chronic diseases. Medical professionals, such as nurses, physicians, and hospital beds, are in great demand [3]. Therefore, it is necessary to reduce healthcare schemes' workloads without compromising healthcare facilities' quality or standards [4]. Potential steps toward relieving healthcare systems of some of the burden are laid out by the Internet of Things (IoT). Medical institutions, for instance, use RFID technologies to improve healthcare delivery while decreasing costs. In particular, healthcare monitoring networks facilitate the observation of cardiac impulses by clinicians, enabling them to arrive at precise diagnoses [5]. Many different kinds of wearable electronics claim to be able to transmit data wirelessly all the time. Concerns regarding the security of patient data when utilizing the Internet of Things (IoT) in healthcare are valid concerns for both medical and information technology experts [6]. For this reason, data integrity has been the focus of many investigations into the potential of IoT and ML for patient health monitoring. The Internet of Things has ushered in a new age in healthcare by enabling proactive connections between patients and experts. Through the use of machine learning and the Internet of Things, we can assess the urgency of the situation and plan accordingly for certain seasons. There is a common issue with waiting rooms being too full in many outpatient departments [7]. Hospitalized patients come from all areas of life, and some of them require emergency surgery. Making people wait in a long line who need medical help right now makes the situation much worse. Patients' conditions deteriorate more when hospitals in underdeveloped countries lack sufficient personnel. Overcrowding in hospitals often results in patients not receiving treatment after they leave. A WMS platform with several apps and services was developed by Yuvaraj and SriPreethaa [8]. While comparing WMSs' performance to that of other platforms, the authors conducted a thorough analysis of their usage and advancements. Professionals have pointed out a number of benefits to employing these devices to track the vitals of people suffering from diseases like Alzheimer's and heart attacks.

In [9], the authors propose a system for monitoring that integrates WSNs and fuzzy logic networks. In order to establish a body sensor network (BSN) that consistently tracks patients' unusual health changes, the researchers combined WSN with micro-electro-mechanical systems (MEMS). Using components like a temperature sensor, pulse oximeter, and microprocessor, the authors created a system for measuring clinical data [10]. It was also possible to remotely control the patient's temperature and pulse using the suggested system's integration with base station equipment, and the data could be sent to the doctor's phone. In the event of an emergency, the system can notify the patient's loved ones and healthcare providers by text message. Consequently, this technology allows patients to obtain prescriptions remotely from doctors.

In addition, hospitals may now track the vital signs of patients with chronic diseases thanks to the Internet of Things application [11,12]. In order to make various predictions about the patients' health, the system uses this data. Implanted Internet of Things (IoT) sensors monitor the patient's vitals, identify their movements, and provide prognoses for their health. One application of IoT sensors is the tracking of diabetic patients, which allows for the prediction of disease trends and the detection of abnormalities. Alternative hospitals that patients might seek treatment at can be suggested to them using the health prediction system. Those who would rather not go elsewhere can remain at the current institution, but they may have to wait in long lines or go home untreated. In order to remotely monitor patients utilizing data from clinical sensors, a healthcare surveillance platform was proposed by [13] that makes use of Zigbee technology and BSN. Data from Zigbee IEEE 802.15.4 protocols, spirometer readings, temperature signals, and electrocardiograms were specifically analyzed in order to determine patients' well-being [14]. After that, visual devices like desktop computers or mobile phones are used to display the data that has been transmitted via radio waves. Consequently, the suggested system might track vital signs like respiration rate, temperature, glucose, electroencephalogram (EEG), and blood pressure, and then transmit this information to a server via GPRS or Wi-Fi connectivity. Zigbee transmits the received data to another network so that devices like emergency devices and doctors' and family members' phones can display the sensor data. By enhancing the connection between patients and their caregivers, the integration of machine learning and the Internet of Things (IoT) simplifies healthcare management.

2. Literature review

2.1. Machine Learning Algorithm Classification

This study will examine supervised learning, semi-supervised learning, and unsupervised learning, the three primary models in machine learning.

2.1.1. Supervised Learning

Among machine learning models, supervised learning stands head and shoulders above the others. Satisfying the requirements of real-world applications is its principal role [15]. Based on specific sets of inputs and instances of input/output pairs, we can predict outputs using this approach. Every supervised training dataset consists of two input objectives, where each includes an input vector and an expected output value, also known as a supervisory signal. These examples are used to teach machine learning algorithms how to use training datasets to create a classifier function. Predicting the value of one or more outcomes from input information is the goal of training algorithms in supervised learning.

The presence of humans is a defining characteristic of supervised learning models. Building a dataset requires human intervention at the outset, but once it's up and running, it can generalise and learn from input samples autonomously. The first steps in building a dataset involve feeding the ML model inputs and desired outputs in pairs. After that, it figures out how to operate autonomously to produce results. When the model is required to anticipate the outcome for an unknown input without human intervention, the primary issue emerges. Verifying the accuracy of the provided model is, hence, of paramount importance.

While the benefits of supervised learning are obvious, one drawback is the vast amount of labelled data required to construct a large-scale labelled dataset [16]. Classification and regression make heavy use of supervised learning models. The categorization strategy, though, is all that this study will cover.

Most applications of machine learning techniques aim to either classify data or make predictions. Using a predefined collection of samples, these techniques categorize and predict class labels. Classification samples might be fully or partially classified as belonging to a given class. Partially, they do not fit within any category. Classification and prediction procedures suffer when values are missing

Binary and multiclass categorization are the two main types. There are two sets of classifications used in binary classification, and the input data is organized according to these sets. Predicting whether an email is spam or not is one example of using a yes/no decision. For the purposes of this classification, the numbers 0 and 1 are sufficient. Alternatively, when dealing with three or more predictable classifications, multiclass classification comes into play. The determination of cancer stage is one such example. The numbers 0, 1, 2, etc., serve as the classes here.

Figure 1 demonstrates the process of applying supervised learning to resolve a specific problem. It is common for there to be specific procedures to follow. Finding out what kind of training example to use is the first step. Gathering the training set—which can be done by measuring data or by consulting human experts—is the next step. Furthermore, it should demonstrate the practical application of the function. First things first: figure out how the input feature is represented. For the representation to make an accurate output prediction, it requires a sufficient amount of data. Choose a learning algorithm thereafter. Once the design is finalized, we execute the learning algorithm on the training set. Nowadays, supervised learning methods are required for users to find the best control settings, particularly when dealing with prediction problems. Every parameter that has been optimized for performance on a subset of the training set or through cross-validation is part of the validation set. Both exhaustive and nonexhaustive cross-validation methods are used often. All potential ways of splitting the original sample into training and validation sets are investigated and tested by the algorithms in exhaustive cross-validation. In terms of thorough cross-validation procedures, leave-p-out and leave-one-out are good examples. When it comes to initial sample partitioning, nonexhaustive cross-validation methods do not compute every possible alternative. On the other hand, exhaustive methods do. Approximate forms of leave-p-out cross-validation are these techniques. Two- and k-fold cross-validation, along with repeated random subsampling validation, are methods that fall under this category. The effectiveness of the learning function should be checked last. Using a distinct test set from the training set, the user can check the function's performance after learning and modifying its parameters.

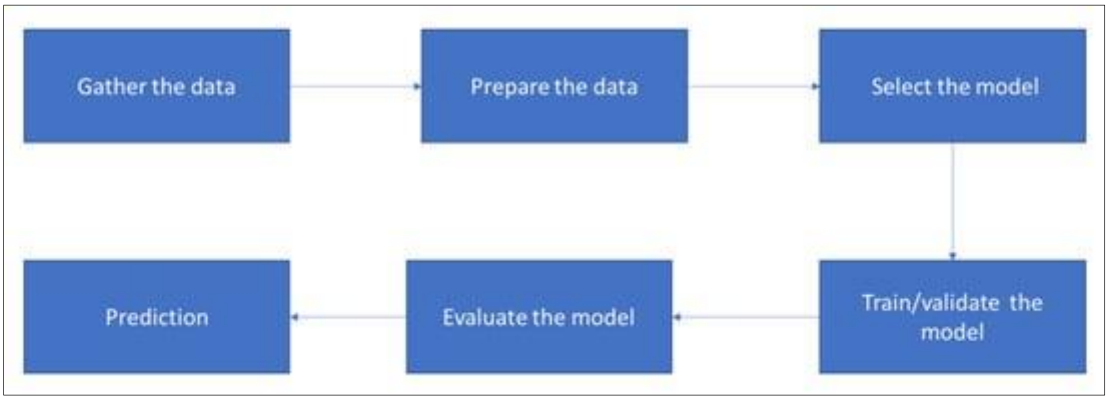

Figure 1 Steps to fix an issue using supervised learning.

2.1.2. Unsupervised Learning

Discovering previously unmarked structures in data is one use case for unsupervised machine learning. Many useful apps have made use of this, but evaluating them can be a real challenge. A lack of education on how to apply unsupervised ML is to blame. Consequently, there are no metrics to measure success or failure while evaluating potential remedies. In this case, supervised ML is differentiated from unsupervised ML by the reward signal. The statistical domain makes use of unsupervised learning for density approximation. Unsupervised learning is also used by models in adaptive resonance theory (ART), self-organizing maps (SOMs), and neural networks (NNs) [17].

Examples of unsupervised learning include grouping and dataset manipulation. The goal of the transformation process is to make the dataset more understandable for both people and machine algorithms by presenting the data in a new and distinct way. In contrast, clustering algorithms divide datasets into meaningful groupings of similar items. Among unsupervised algorithms, K-means clustering is the most popular and basic; it finds groups of data that are similar to one another. The first part of the procedure involves finding the cluster center that is geographically closest to each data point; the second part involves fixing each cluster center as the mean of the data points assigned to it. Assessing the efficacy of unsupervised learning presents a significant challenge. If the algorithm has learned something helpful, it will show in the results of its unsupervised learning efforts. Since unsupervised learning does not make use of labels or outputs, it is impossible to determine which output is correct. Because of this, evaluating the algorithms' efficacy becomes a challenging task. Because of this, unsupervised learning is reserved for exploratory purposes only, such as improving data comprehension. Supervised algorithms rely on preprocessing, which is another important aspect of unsupervised algorithms. To make supervised algorithms more accurate, it is necessary to find new ways to describe data.

2.1.3. Semisupervised Learning

The learning technique is a subset of ML models that uses both labeled and unlabeled data to train its models. The combination of little amounts of marked data with large amounts of unmarked data is necessary to achieve higher learning accuracy in the actual world. Humans are needed for the labeling of datasets. Completely tagged training could be difficult to create and costly due to the time-consuming tagging process. Consequently, semisupervised learning can end up being the superior choice in some cases.

To improve the model's performance when there aren't enough labelled data, semisupervised learning is commonly employed. There are a lot of unlabeled samples that are available right now. You can use these unlabeled samples to make the model better. Poor model performance, rather than improvement, results from using unlabeled sample data in semisupervised learning. Supervised learning, which excels at solving machine learning issues, is thus preferred, whereas semisupervised learning finds less practical value.

3. IOT and machine learning applications in healthcare systems to predict future trends

The statistical domain makes use of unsupervised learning for density approximation. Unsupervised learning is also used by models in adaptive resonance theory (ART), self-organizing maps (SOMs), and neural networks (NNs) [17]. The gadgets can track a patient's heart rate, respiration rate, and other vitals, and then report back to a designated database on their progress. Additionally, the system records and communicates any indications of pathogen presence. The healthcare system is able to better provide best practices thanks to this significant advancement. Smart medications, sensors, and wearable monitoring have all contributed to healthcare's recent upswing. By utilizing these tools, disease patterns may be more accurately monitored and forecasted. Automation of patient and disease monitoring tasks starts in when all doctors are occupied, which is commonly during times of crisis. Time is of the importance. It is crucial to apply intelligent technology in this field in order to preserve lives in the face of devastating pandemics like COVID-19.

Wearable monitoring devices send data to the doctor, who can then use that data to diagnose the patient or prescribe medication. In order to prepare for a pandemic, patients can wear Internet of Things (IoT) smart bands or take smart medications that record their vital signs.

By using these tools, both humans and machines (through machine learning) can better recognize symptoms, analyze them, and create safe and rapid diagnostics for a variety of diseases. Using machine learning to avoid direct touch with patients who may be carrying fatal airborne viruses is one way that quarantine protocols might improve patient and healthcare provider safety.

An additional effective component of the IoT market is cloud computing. To better comprehend data via analysis and storage, it facilitates the connection of numerous machine learning AI devices. Cloud computing's ability to store massive amounts of data is another essential aspect that can support healthcare system demands. Different devices can access the information thanks to cloud computing's data-sharing capabilities. The flip side is that cloud computing isn't without its problems right now. Despite these obstacles, scientists and researchers may find novel approaches to studying how ML and the IoT might enhance healthcare.

As an example, there is the issue of data privacy and security. Medical records kept by healthcare companies must follow strict security measures because of the sensitive information they contain. Consequently, laws such as HIPAA have been established to regulate the access to and analysis of this data. This is a major obstacle for data mining and machine learning methods like deep learning, which normally necessitate massive amounts of training data.

Patients' right to privacy may be jeopardized if this kind of sensitive information is shared in an effort to enhance healthcare delivery quality. There are now a number of options available for using ML technology to protect patients' privacy. The term "federated learning" (FL) describes one approach. The new ML paradigm uses deep learning to train and enable servers and mobile devices to construct a shared, strong ML model independently of one another, without the need to share data.

One of the main issues that researchers can tackle using FL is heterogeneous data access, which includes data security and protection rights. With data stored in a centralized cloud, ML becomes even more complicated. This is due to the fact that generic models gather data from numerous devices through a single server, which could lead to bias or failure. An inaccurately trained model could also lead to less-than-stellar predictions. So, right now, the best course of action is to use decentralized data storage. Blockchain is an example of a decentralized system for storing data. A number of these gadgets are capable of taking readings of your heart rate, temperature, and blood pressure. They aid in the collection and storage of patient data, which is useful for diagnosis in the end. The ability of healthcare practitioners to stay current with the newest innovations is vital for a healthy society, and the Internet of Things (IoT) and machine learning can make that possible. Researchers and medical practitioners must be able to access, analyze, and exchange real-time results from COVID-19 symptoms and diagnostic data stored in a single database. This will help in the eradication of the disease or development of a vaccine.

4. Proposed methodology

Figures 2 and 3 show the process graphically of how Internet of Things devices gather data, send it to a hub, and then use sophisticated deep learning models to process it. In line with the transformational objectives shown in the figures, this integration improves healthcare quality by allowing for precise and prompt medical interventions. The steps of the suggested method, which combines deep learning with IoT devices, are shown in Figure 4. It includes steps like collecting and cleaning up data, making CNN and LSTM layers, and then running the model.

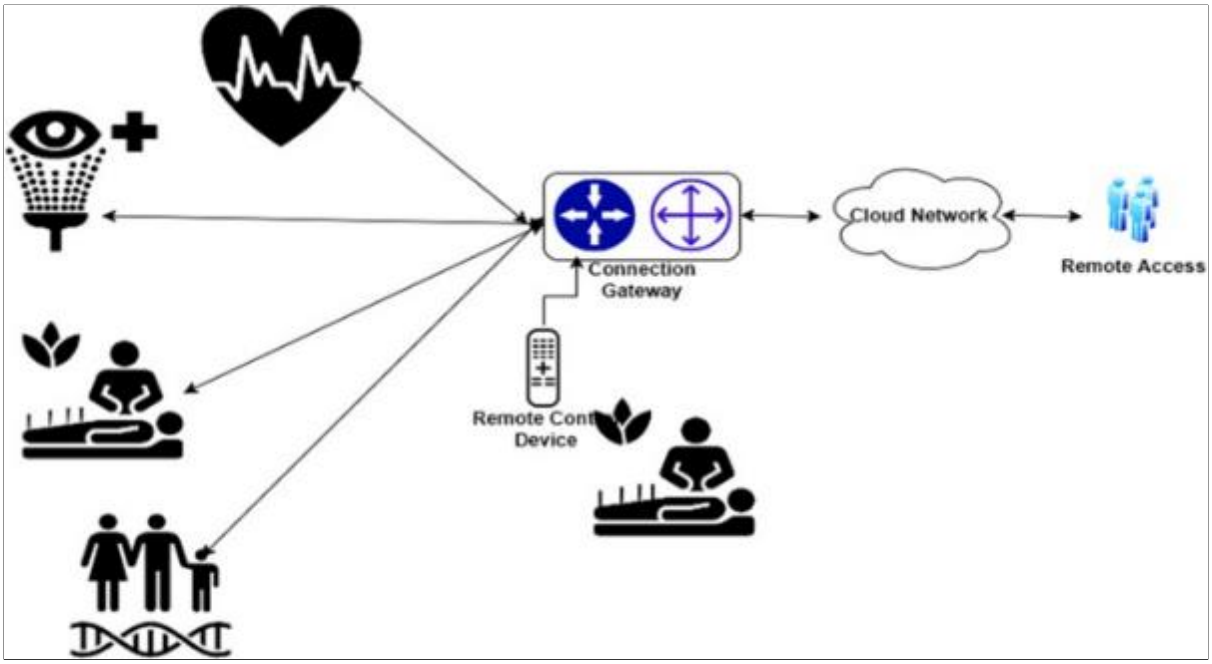

Figure 2 Smart health care with the Internet of Things

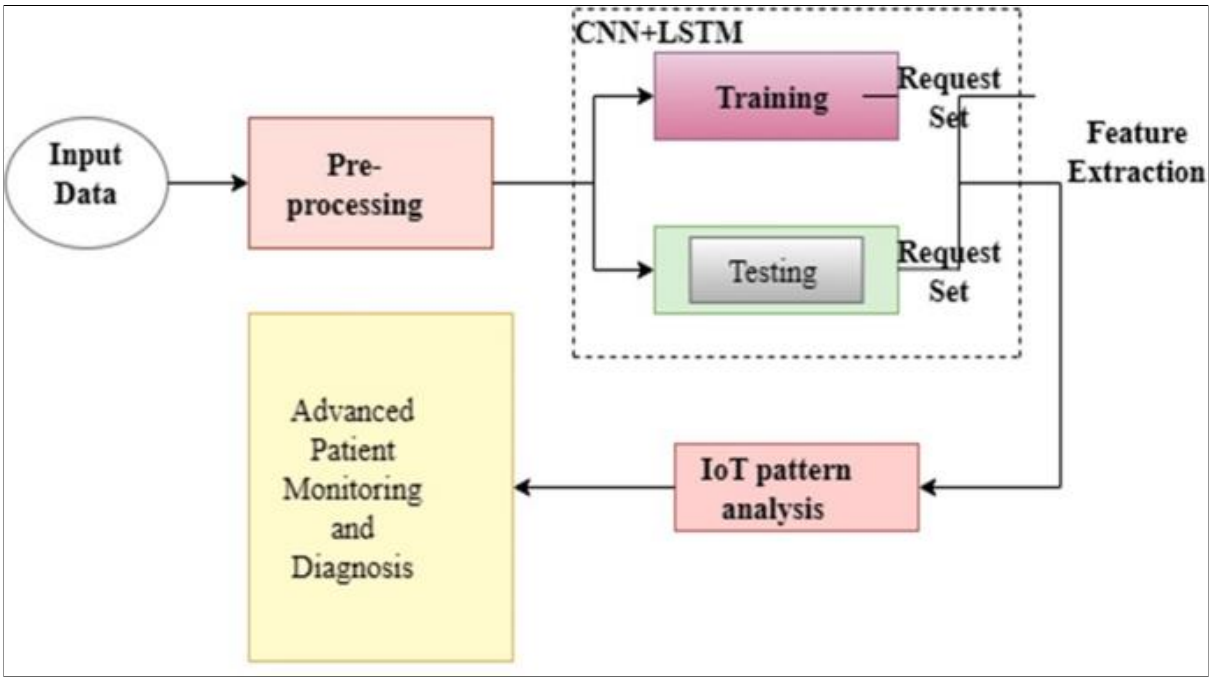

Figure 3 An innovative approach to healthcare data collection and analysis

```
Step 1: Set Up Test and Training Data
do
  Step 2:  load patients' vitals (ECG, images, temperature, pulse rate)
    preprocess data
  Step 3:  while data is not ready
  Step 4:  divide data into training set, test set
  Step 5: CNN input shape = define input shape(data)
  Step 6: Conv layers = []
do
    Step 7:  convlayer = define conv layer (number of filters, kernel size, 'relu', stride)
    Step 8:  Conv layers.append(conv_layer)
    Step 9:  add pooling_layer if necessary
    Step 10: add dropout layer(probability) if necessary
while (more layers needed)

    Step 11 flattened output = flatten (cnn output)
    Step 12 Lstm input shape = define lstm input shape(flattened_output)
    Step 13 lstm layers = []

do
        Step 14 lstm_layer = define_lstm_layer(number_of_units, 'tanh', 'sigmoid')
            Step 15 Lstm layers.append(lstm_layer)
      Step 16   add dropout layer(probability) if necessary
    Step 17 while more lstm layers needed
    Step 18 cnn lstm output = join_cnn_and_lstm(conv_layers, lstm_layers)
    Step 19 output layer = define output layer (number of diagnoses, 'softmax')
    Step 20 compile model (loss='categorical crossentropy', optimizer='adam', metrics=['accuracy'])
    Step 21 while device not ready for use
```

Figure 4 Proposed algorithm

The use of the Internet of Things has accelerated the creation of a healthcare monitoring system, as seen in Figure 2. A set of buttons pertaining to health is displayed on the left side of the screen. The user is directed to the "Connection Gateway," a central gateway, when they click on one of these buttons. Icons representing the various Medical Monitoring tools can be found on the screen's left side. Numerous health-related sensors and devices are depicted by these icons, including oxygen saturation meters, blood pressure cuffs, and heart rate monitors. These devices continuously gather vital patient health data. A network of interconnected medical monitoring devices can be established through the Connection Gateway. It collects information from several sources when it talks to other nodes in the network. The unfettered transmission of data from the devices to the following system stages is guaranteed by this hub. Prior to reaching a Cloud Network, this data must pass via the connection gateway. Data generated by DL algorithms is stored and processed in the cloud.

Anyone with the proper authorization can remotely access the patient's data and acquire up-to-the-minute health information, including family members and healthcare providers. One of the symbols represents an operate Panel for Electronic Devices, which implies that patients have the ability to remotely adjust and operate their workout and therapy equipment.

A screen showing a runner on a track, for example, might represent fitness and therapy management equipment. The patient's independence and comfort are both improved by this remote-control capability. In order to forecast a patient's health status, the system's completely linked layers use learnt features for regression or classification. The level of care patients receive can be greatly enhanced by this predictive capability. The use of DL models allows the system to anticipate possible health problems and suggest preventative actions, which improves patient outcomes. The idea of long short-term memory (LSTM) is also crucial to the suggested method. Time series data and patient vitals are two examples of sequential data that LSTMs excel at capturing because they are recurrent neural networks. They are highly beneficial for evaluating oxygen saturation, heart rate, blood pressure, and other vital indicators captured by continuous patient monitoring systems. So, long short-term memories (LSTMs) can enhance patient care by spotting irregularities that could indicate a patient's health problems and enabling quick intervention.

A medical data processing pipeline using deep learning techniques (CNN + LSTM) is shown in Figure 3. This pipeline utilizes data from the Internet of Things (IoT) and includes training, testing, and analytical stages. The LSTM algorithm's memory cells and gating mechanisms control the flow of data in the network. Thanks to these memory cells, the LSTM can remember and recover important data from previous observations, allowing it to hold onto information for long periods of time. The LSTM's gating mechanisms are what allow it to produce correct predictions—they decide which data points to keep and which ones to update. Advanced tracking and diagnostic capabilities are provided by the suggested method, which combines CNN and LSTM features. Figure 4 shows how the suggested method improves patient monitoring and diagnosis in an IoT-enabled healthcare system by using deep learning techniques, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. Preparing the data is the initial step in starting the testing and training processes. This technique includes collecting and processing patient vitals, including ECG data, medical pictures, temperature, and pulse rate. To test how well the model performed on new data, we partitioned the dataset into a training set and a test set. The next step is to configure the convolutional neural network (CNN) part of the method with the input data dimensions.

5. Results analysis

By applying deep learning techniques, the suggested method shows that IoT devices improve patient monitoring and diagnosis. Figure 2 shows a variety of medical monitoring instruments, including electrocardiogram (ECG) monitors, temperature sensors, pulse rate monitors, and medical imaging devices. The algorithm relies on these instruments as its main sources for patient data. The first step is to prepare the system to process these vital indicators by entering them. Data is collected and sent to the cloud by the Connection Gateway, which functions as a central hub for various monitoring equipment. Once finished, the prepared data can be used to train and test deep learning models. The cloud network stores and evaluates data once it has been transmitted over the Connection Gateway (Figure 2). At first, the data is divided into two groups: the training group and the testing group. After that, CNNs and LST are employed to do comprehensive analysis. Figure 3 provides a more detailed overview of the CNN and LSTM integration process for medical data processing. Algorithmically, the method detects diseases in diagnostic images by using CNNs for image processing.

5.1. Accuracy Graph

Description: This bar graph displays the accuracy of different algorithms was shown in figure 5 and table 1. With an accuracy of 0.85, the suggested approach outperformed the LSTM model, which had an accuracy of 0.87. The SVM and KNN algorithms had the lowest accuracy, indicating a potential area for improvement.

Table 1 Accuracy Simulation and Results Analysis

Algorithm	Dataset	Accuracy
Proposed	MIMIC-III	0.85
CNN	PhysioNet	0.82
SVM	eICU Collaborative	0.78
LSTM	MIMIC-CXR	0.87
KNN	PTB Diagnostic ECG	0.75
Random Forest	eICU Clinical Database	0.81

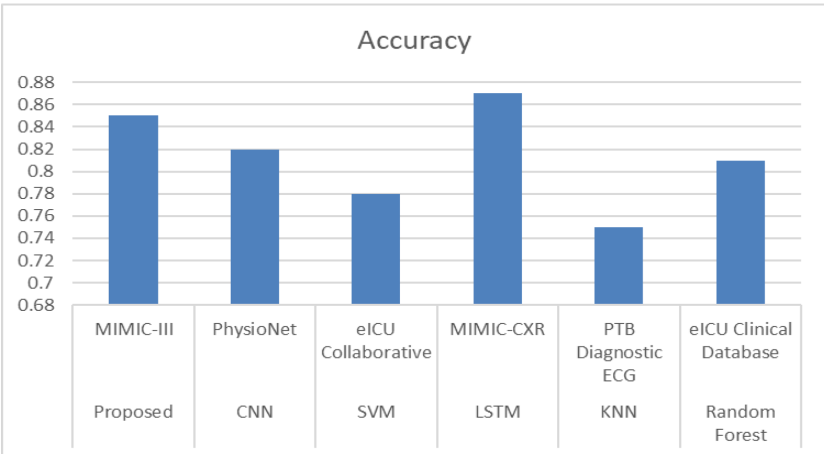

Figure 5 Accuracy Simulation and Results Analysis

5.2. Precision Graph

Description: This bar graph illustrates the precision of each algorithm was shown in figure 6 and table 2. The proposed algorithm and the LSTM model both had high precision scores (0.86 and 0.88, respectively), indicating that when they predict a positive outcome, they are highly likely to be correct. The KNN algorithm had the lowest precision.

Table 2 Precision Simulation and Results Analysis

Algorithm	Dataset	Precision
Proposed	MIMIC-III	0.86
CNN	PhysioNet	0.81
SVM	eICU Collaborative	0.79
LSTM	MIMIC-CXR	0.88
KNN	PTB Diagnostic ECG	0.76
Random Forest	eICU Clinical Database	0.80

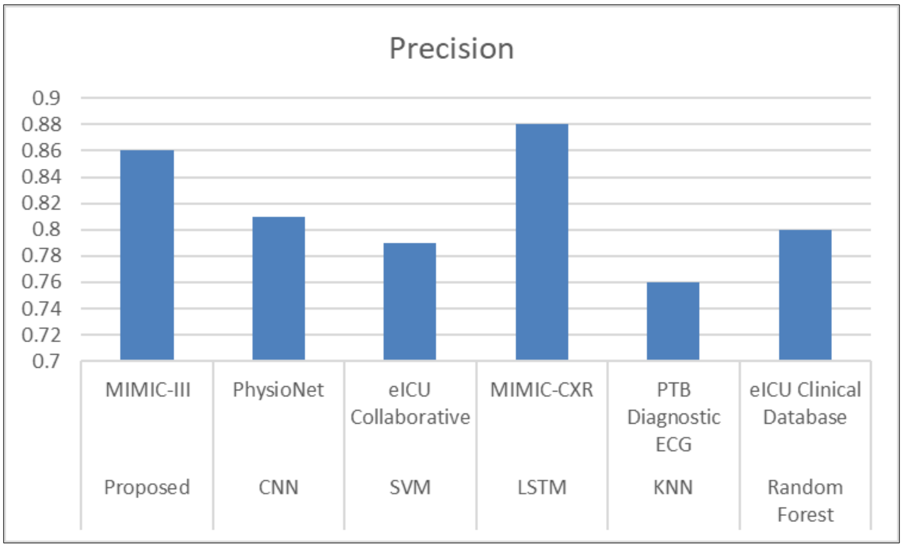

Figure 6 Precision Simulation and Results Analysis

5.3. Recall Graph

Description: This graph shows the recall scores for each algorithm was shown in figure 7 and table 3. The proposed algorithm and the LSTM model performed well, with recall values of 0.84 and 0.86, respectively. The SVM algorithm had the lowest recall, suggesting it missed a significant number of positive instances.

Table 3 Recall Simulation and Results Analysis

Algorithm	Dataset	Recall
Proposed	MIMIC-III	0.84
CNN	PhysioNet	0.83
SVM	eICU Collaborative	0.77
LSTM	MIMIC-CXR	0.86
KNN	OTB Diagnostic ECG	0.74

Random Forest	eICU Clinical Database	0.82

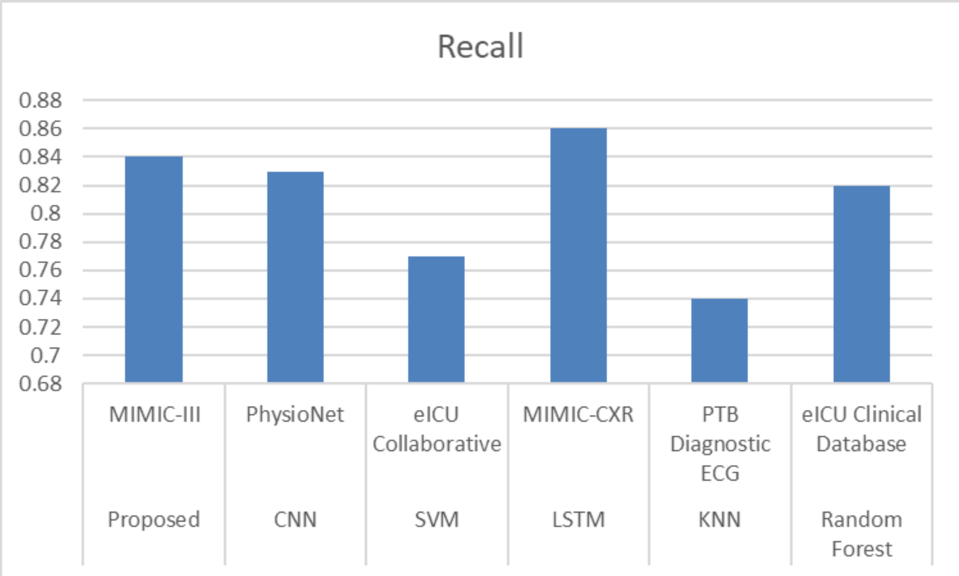

Figure 7 Recall Simulation and Results Analysis

5.4. F1-Score Graph

Description: In figures 8 and 4, you can see the F1-score graph, which shows the harmonic mean of recall and precision for all of the algorithms. High F1-scores (0.85 and 0.87, respectively) for the suggested method and the LSTM model show that the two performed similarly in terms of recall and precision. Once more, the KNN algorithm demonstrated the worst performance.

Table 4 F1-Score Simulation and Results Analysis

Algorithm	**Dataset**	**F1-Score**
Proposed	MIMIC-III	0.85
CNN	PhysioNet	0.82
SVM	eICU Collaborative	0.78
LSTM	MIMIC-CXR	0.87
KNN	PTB Diagnostic ECG	0.75
Random Forest	eICU Clinical Database	0.81

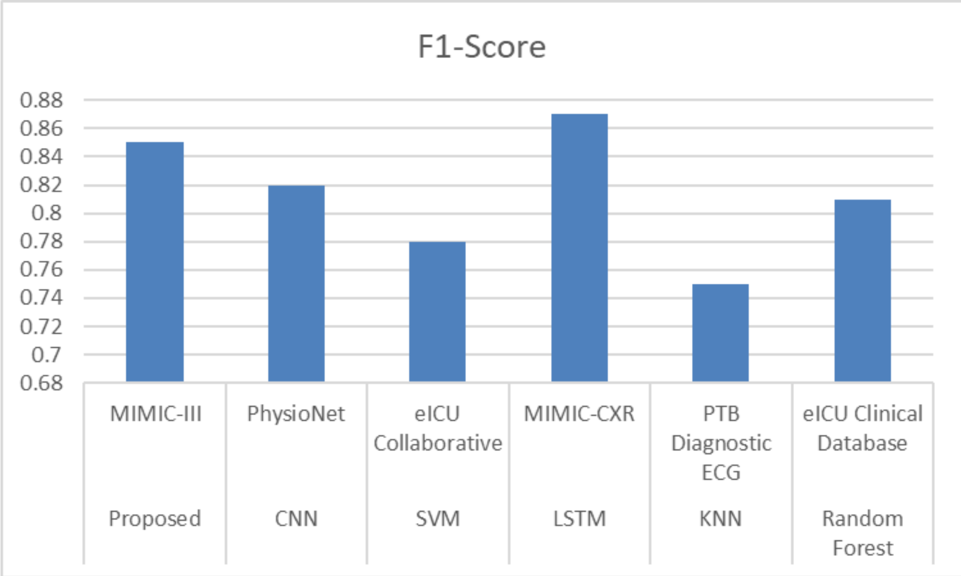

Figure 8 F1-Score Simulation and Results Analysis

6. Conclusions

Due to the high stakes and stringent restrictions, the healthcare industry is one of the most complicated, making it a crucial and critical area for innovation. The healthcare industry now has access to a wealth of new opportunities made possible by the Internet of Things (IoT), which has the potential to address numerous issues. Many new possibilities, including telemedicine and remote patient condition monitoring, will open up as a result of the medical IoT's implementation. Using ML models could make this a reality. We compiled a list of healthcare-related ML applications, summarized the most effective ML algorithms, and examined the role of the internet of things (IoT) and machine learning in healthcare to foretell future trends. We investigated the possibility of improving patient monitoring and diagnosis through the integration of IoT with deep learning techniques, particularly CNNs and LSTMs, in this article. The suggested technique allows for precise diagnostics and real-time monitoring by combining CNNs for picture interpretation with LSTMs for time-series data analysis. By utilizing medical technologies connected to the Internet of Things for optimal data analysis, this integration greatly enhances patient care and outcomes. Streamlining patient tracking and diagnosis, enabling remote monitoring, early disease identification, and individualized treatment regimens are all ways the IoT improves healthcare efficiency. Critical health insights are continuously provided by wearable technology and sensors, which aid in the treatment of chronic diseases. One way to make the healthcare supply chain even more secure and transparent is to use blockchain technology.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] T. T. Chhowa, M. A. Rahman, A. K. Paul and R. Ahmmed, "A Narrative Analysis on Deep Learning in IoT based Medical Big Data Analysis with Future Perspectives," 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE), Cox'sBazar, Bangladesh, 2019, pp. 1–6, https://doi.org/10.1109/ECACE.2019.8679200.

[2] V. Veeraiah, A. Pankajam, E. Vashishtha, D. Dhabliya, P. Karthikeyan and R. R. Chandan, "Efficient COVID-19 Identification Using Deep Learning for IoT," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 128–133, https://doi.org/10.1109/IC3I56241.2022.10073443.

[3] Sarmah SS (2020) An Efficient IoT-Based Patient Monitoring and Heart Disease Prediction System Using Deep Learning Modified Neural Network. IEEE Access 8:135784–135797. https://doi.org/10.1109/ACCESS.2020.3007561

[4] S. R, S. R, R. Rajeshwari, B. Thyla and S. K. M, "Patient health monitoring system using smart IoT devices for medical emergency services," 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), Chennai, India, 2022, pp. 1–10, https://doi.org/10.1109/ICSES55317.2022.9914385.

[5] T. Deepa, S. Hariprasad, N. Bharathiraja and A. Chokkalingam, "A Real Time Face Mask Detection and Health Status Monitoring using Deep Learning after Pandemic," 2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), Trichy, India, 2022, pp. 430–435, https://doi.org/10.1109/ICAISS55157.2022.10010823.

[6] Thamilarasu, Geethapriya, and Shiven Chawla. "Towards Deep-Learning-Driven Intrusion Detection for the Internet of Things." Sensors, vol. 19, no. 9, 27 Apr. 2019, p. 1977, www.mdpi.com/1424-8220/19/9/1977/pdf, https://doi.org/10.3390/s19091977. Accessed 16 Jan. 2020.

[7] Zhou, Ji, et al. "Toward New-Generation Intelligent Manufacturing." Engineering, vol. 4, no. 1, Feb. 2018, pp. 11–20, www.sciencedirect.com/science/article/pii/S2095809917308652, https://doi.org/10.1016/j.eng.2018.01.002. Accessed 9 Nov. 2019.

[8] Lau, Billy Pik Lik, et al. "A Survey of Data Fusion in Smart City Applications." Information Fusion, vol. 52, Dec. 2019, pp. 357–374, https://doi.org/10.1016/j.inffus.2019.05.004. Accessed 12 Aug. 2019.

[9] B. M. Elbagoury, M. Zaghow, A. -B. M. Salem and T. Schrader, "Mobile AI Stroke Health App: A Novel Mobile Intelligent Edge Computing Engine based on Deep Learning models for Stroke Prediction – Research and Industry Perspective," 2021 IEEE 20th International Conference on Cognitive Informatics & Cognitive Computing (ICCI*CC), Banff, AB, Canada, 2021, pp. 39–52, https://doi.org/10.1109/ICCICC53683.2021.9811307.

[10] R. Singh, P. A. Mishra, A. Prakash, K. Tongkachok, M. Upadhyaya and M. Kalyan Chakravarthi, "Smart Device for Effective Communication in the Healthcare System," 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), Chennai, India, 2022, pp. 1–6, https://doi.org/10.1109/ICSES55317.2022.9914093.

[11] B. S. Yelure, N. S. Deokule, S. S. Mane, M. V. Bhosale, A. B. Chavan and V. C. Satpute, "Remote monitoring of Covid-19 patients using IoT and AI," 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS), Coimbatore, India, 2022, pp. 73–80, https://doi.org/10.1109/ICAIS53314.2022.9742750.

[12] Bianchi V, Bassoli M, Lombardo G, Fornacciari P, Mordonini M, De Munari I (2019) IoT Wearable Sensor and Deep Learning: An Integrated Approach for Personalized Human Activity Recognition in a Smart Home Environment. IEEE Internet Things J 6(5):8553–8562. https://doi.org/10.1109/JIOT.2019.2920283

[13] M. H. Islam Chowdhuryy, M. Sultana, R. Ghosh, J. U. Ahamed and M. Mahmood, "AI Assisted Portable ECG for Fast and Patient Specific Diagnosis," 2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2), Rajshahi, Bangladesh, 2018, pp. 1–4, https://doi.org/10.1109/IC4ME2.2018.8465483.

[14] I. Pavan Kumar, R. Mahaveerakannan, K. Praveen Kumar, I. Basu, T. C. Anil Kumar and M. Choche, "A Design of Disease Diagnosis based Smart Healthcare Model using Deep Learning Technique," 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2022, pp. 1444–1449, https://doi.org/10.1109/ICEARS53579.2022.9752063.

[15] S. M. N. Arosha Senanayake and P. Wulandari, "Soft Real Time Data Driven IoT for Knee Rehabilitation," 2020 5th International Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA), Sydney, Australia, 2020, pp. 1–7, https://doi.org/10.1109/CITISIA50690.2020.9371780.

[16] Liu L, Xu J, Huan Y, Zou Z, Yeh S-C, Zheng L-R (2020) A Smart Dental Health-IoT Platform Based on Intelligent Hardware, Deep Learning, and Mobile Terminal. IEEE J Biomed Health Inform 24(3):898–906. https://doi.org/10.1109/JBHI.2019.2919916

[17] Yu HQ, Reiff-Marganiec S (2021) Targeted Ensemble Machine Classification Approach for Supporting IoT Enabled Skin Disease Detection. IEEE Access 9:50244–50252. https://doi.org/10.1109/ACCESS.2021.3069024