Improved Cybersecurity for Healthcare Internet of Things (Iot) Devices and Wearables with the Use of State-of-the-Art Deep Learning Techniques: Strategies for Threat Detection and Data Protection

Rajesh Jagadeesan Ravikumar[1],Charulatha Umashankar[2]

[1]Software Engineering Senior Advisor Evernorth Health Services 401 Chestnut Street, Chattanooga,TN-37402, USA

[2]Application Development Advisor Cigna Healthcare500 Great Circle Rd,Nashville, TN – 37228, USA

DOI: https://doi.org/10.51584/IJRIAS.2026.11010021

Received: 11 January 2026; Accepted: 17 January 2026; Published: 24 January 2026

ABSTRACT

Continuous monitoring, individualized therapies, and efficient data collecting are just a few ways in which the proliferation of wearable electronics and Internet of Things (IoT) devices has revolutionized healthcare. New cybersecurity threats, such as exposure to hackers, data breaches, and cyberattacks, are introduced with these innovations. Strong cybersecurity safeguards for IoT devices are critical, especially considering the sensitive nature of healthcare data. The goal of this project is to improve the security of healthcare IoT systems by detecting threats and effectively protecting sensitive data using state-of-the-art deep learning algorithms. In order to identify irregularities and categorize cyber dangers in real-time, the suggested system incorporates deep learning models such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs). By spotting changes from typical device behavior, these models enable early detection of harmful behaviors like malware and distributed denial-of-service (DDoS) assaults. Even in IoT settings with limited resources, important healthcare data is protected by incorporating deep learning-enhanced encryption algorithms to safeguard data transmission. This research makes a significant advancement by utilizing federated learning. This method allows for various IoT devices to work together in model training without directly exchanging private data. As a result, patient privacy is preserved and system security is improved. Deep learning-based techniques outperform conventional methods in terms of threat detection accuracy and data security when tested on real-world healthcare IoT datasets. These results highlight the need for more sophisticated deep learning methods to protect healthcare IoT devices from potential cyber threats.

Index terms — Healthcare IoT, Cybersecurity, Deep Learning, Anomaly Detection, Data Protection, Wearables, Threat Detection, Federated Learning, Encryption, Medical Devices

INTRODUCTION

Patient care has been transformed by the integration of wearable technology and the Internet of Things (IoT) in healthcare. This has allowed for remote diagnoses, continuous monitoring, and individualized therapies. Smart insulin pumps, heart rate monitors, fitness trackers, and portable diagnostic tools are just a few examples of the many technologies that gather and transmit extensive quantities of private health information. Many of the more than 30 billion Internet of Things (IoT) devices expected to be in use worldwide by 2025 will find applications in healthcare [1]. There have been notable improvements to healthcare efficiency and patient outcomes due to this technological revolution, but there have also been serious cybersecurity dangers. Cyberattacks, data breaches, and unauthorized access are becoming more common as the number of connected devices increases, which poses a threat to patient safety and privacy [2].

Cyberattacks can target healthcare IoT devices because of their lack of defined security protocols, dependence on wireless connection, and limited computer power [3]. Medical information and essential healthcare activities are vulnerable to common threats such as malware, ransomware, distributed denial-of-service (DDoS) assaults, and data tampering. Because of the potential for ransomware extortion and the high black market value of medical records, the healthcare business is also a popular target for hackers [4]. Protecting healthcare IoT devices and ensuring the availability, integrity, and confidentiality of patient data is of the utmost importance in light of these risks.

A subset of machine learning known as deep learning has demonstrated significant potential in solving complicated cybersecurity problems in a variety of fields [5]. Deep learning models have the ability to learn from data automatically, discover new attack patterns, and enhance their detection capabilities over time [6]. This is in contrast to traditional rule-based techniques that depend on predetermined signatures or patterns to detect threats. Deep learning algorithms have the potential to improve healthcare IoT threat detection and data protection. Models like these can monitor the Internet of Things (IoT) in real time, spot cyberattacks as they happen, and encrypt private medical data to keep it safe.

The capacity to identify zero-day attacks—vulnerabilities that have not been discovered or fixed by security professionals—is one of the main benefits of deep learning in cybersecurity [7]. Traditional signature-based systems could miss new or changing threats, therefore this is especially crucial for healthcare IoT devices. Another useful feature of deep learning algorithms is their compatibility with federated learning, a method that enables numerous IoT devices to work together in model training without exchanging raw data. By maintaining sensitive information dispersed and protected, this strategy not only increases the accuracy of threat detection, but it also safeguards patient privacy [8].

There are a number of obstacles to overcome before deep learning can be fully utilized to improve healthcare IoT cybersecurity, despite its promising future. Problems with real-time detection in situations with restricted resources, the requirement for huge labelled datasets for model training, and the limited processing capacity of IoT devices are all examples of these issues [9,10]. This project seeks to address these difficulties and build a robust security framework for healthcare IoT devices and wearables by utilizing state-of-the-art deep learning algorithms. In order to protect patient data, make medical equipment more reliable, and add to the continuing efforts to secure digital healthcare's future, this study aims to address the specific cybersecurity needs of healthcare IoT.

LITERATURE REVIEW

Continuous patient monitoring, tailored therapies, and enhanced healthcare efficiency are among the benefits of IoT devices like wearables and connected medical devices. Healthcare IoT growth raises cybersecurity risks. This sector's IoT gadgets communicate massive amounts of sensitive data across wireless networks, rendering them vulnerable to data breaches, malware, and illegal access. Cybercriminals target healthcare because personal health information is valuable and medical services are vital, according to researchers.

Many studies have stressed the necessity for strong security measures to safeguard healthcare IoT devices from these threats. Due to resource constraints, IoT devices frequently lack the computational power to perform traditional security procedures, making them vulnerable to assaults. Healthcare IoT systems are vulnerable to inadequate authentication mechanisms, unencrypted data transmission, and the lack of uniform security rules among device manufacturers, according to Alrawais et al. [2] and Mendez et al. [3]. Attackers can use these vulnerabilities to corrupt patient data, interrupt medical services, and even damage IoT-dependent patients.

Researchers are investigating deep learning for IoT cybersecurity to address these issues. Experts say deep learning models like CNNs and RNNs can spot complicated patterns and anomalies that rule-based systems miss. These models can detect aberrant IoT device behavior and zero-day attacks, which exploit unknown vulnerabilities. Deep learning models may detect and categorize cyber threats more effectively than traditional systems, as shown by Goodfellow et al. [6] and LeCun et al. [7].

Several studies have employed deep learning to healthcare IoT. Ahsan et al. [11] developed a CNN-based deep learning system to detect IoT device anomalies, detecting malware assaults and unauthorized access attempts with high accuracy. Abeshu and Chilamkurti [12] showed that deep learning-based intrusion detection systems for healthcare IoT networks outperformed conventional methods in detection rates and real-time performance. These studies show that deep learning can improve healthcare IoT device security, but they also suggest that resource-constrained contexts require further research.

Federated learning, along with deep learning, may improve healthcare IoT device security and privacy. Federated learning lets many IoT devices train a model without sharing raw data, protecting patient privacy and decreasing data leaks. Yang et al. [9] demonstrated how federated learning for IoT devices may safely train deep learning models while decreasing data transmission. Due to the sensitivity of patient data and rigorous rules like HIPAA, this method is crucial in healthcare.

Despite breakthroughs in deep learning and federated learning, healthcare IoT device security remains difficult. The limited processing power and memory of many IoT devices makes running large deep learning models difficult. Hossain et al. [10] and Tahir et al. [13] have investigated model compression and edge computing to reduce deep learning model computational overhead by processing data closer to the device and reducing latency and bandwidth. Another barrier to healthcare IoT cybersecurity is the paucity of labeled datasets for deep learning model training [14-16]. Synthetic data generation and semi-supervised learning are being investigated to increase deep learning model performance and training datasets.

System Implementation

A methodical strategy for enhancing the security of healthcare IoT (Internet of Things) devices using deep learning techniques is depicted in Fig. 1. The first step is to learn about healthcare IoT (devices and wearables), which entails investigating the security risks and data flows linked to linked medical equipment. Because of the sensitive health information they collect, these gadgets are easy prey for cybercriminals. Potential security issues, such as inadequate encryption methods, communication protocol vulnerabilities, and cyber-attacks like ransomware or malware targeting IoT ecosystems, can be identified during the understanding phase. Gathering data from healthcare IoT devices is the next step in the data collection and preprocessing cycle. Preprocessing, including cleaning and modification, is necessary to prepare this raw data for use in machine learning models.

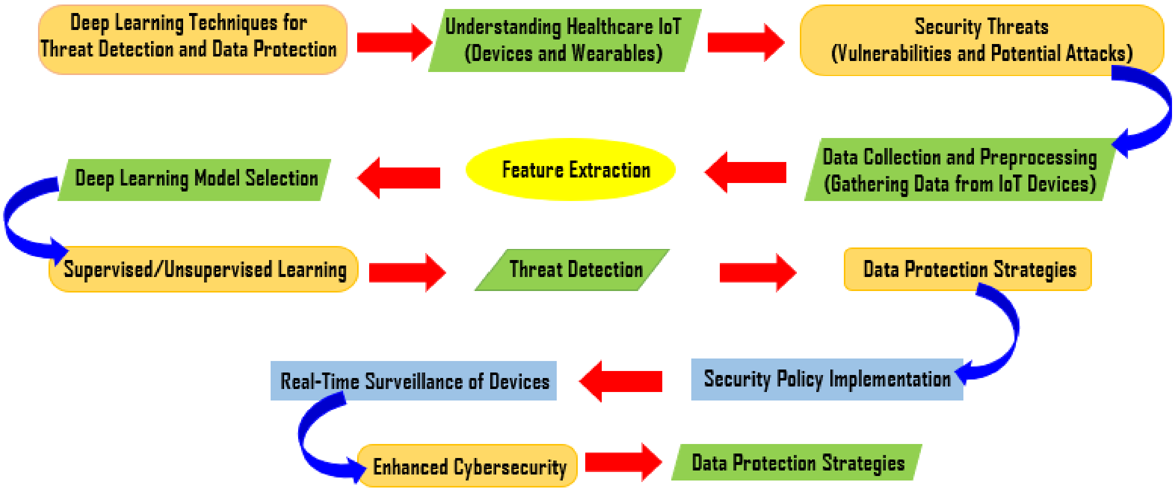
Deep Learning Techniques for Threat Detection and Data Protection
Understanding Healthcare IoT (Devices and Wearables)
Security Threats (Vulnerabilities and Potential Attacks)
Data Collection and Preprocessing (Gathering Data from IoT Devices)
Feature Extraction
Deep Learning Model Selection
Supervised/Unsupervised Learning
Threat Detection
Data Protection Strategies
Security Policy Implementation
Real-Time Surveillance of Devices
Enhanced Cybersecurity
Data Protection Strategies

Fig.1. A systematic approach to improving cybersecurity for Healthcare IoT

Feature extraction—finding the most essential data features such device performance measures, network traffic patterns, or unexpected activity—is crucial. Feature extraction is crucial because it saves important data for learning models while lowering data dimensionality. The features and data types are used to select and fine-tune deep learning models for cybersecurity tasks. Combining supervised and unsupervised learning creates strong threat detection systems. With supervised learning, models may be trained to recognize known attack patterns using labeled data; with unsupervised learning, aberrant IoT network activity may indicate undiscovered or zero-day attacks. Iteratively finding the optimal RNNs or CNNs for the assignment is part of deep learning model selection. The technique produces models that can detect real-time security problems in the IoT infrastructure. Final stage: data protection strategies. Security strategies mitigate threats after identification. This may involve monitoring devices in real time, checking for security holes, and updating security processes when new threats emerge. Ongoing cybersecurity steps include updating encryption, enhancing device authentication, and segmenting critical data streams. This feedback loop improves threat detection and makes data security solutions more dynamic as more data enters the system.

RESULT AND DISCUSSION

Table I Comparison of threat detection accuracy across different deep learning models

Model	Accuracy	Precision	Recall	F1 score
CNN	92	91	90	90
RNN	89	88	85	86
LSTM	94	93	92	92
GAN	91	89	88	88

Figure 2 compares the threat detection accuracy of CNN, RNN, LSTM, and GAN deep learning models. Accuracy, precision, recall, and F1 score—key model performance metrics—are assessed. All four models perform well, with accuracy, precision, recall, and F1 scores around 90%. Each model accurately identifies threats with few false positives and negatives. Each model's four metrics line closely, indicating accuracy and consistency across evaluation criteria.

CNNs (Convolutional Neural Networks) are good at processing grid-like data structures like photographs because they can record spatial hierarchies. This skill helps CNNs detect dangers by effectively analyzing patterns. RNNs, especially its more advanced variant LSTMs, excel at managing sequential data, which is essential for assessing time series data or emerging threats. RNNs and LSTMs perform well in the graph, making them suitable for temporal dependency challenges.

GANs (Generative Adversarial Networks) are unique models that feature a game-like scenario between a generator and a discriminator. GANs are commonly employed to generate synthetic data, but they can also learn threat pattern distribution to improve threat detection. GANs perform similarly to the other models in the graph, suggesting they can capture complicated patterns, which could benefit dynamic or highly diverse threat data. The graph shows how versatile and effective these deep learning models are at danger identification, each with its own capabilities.

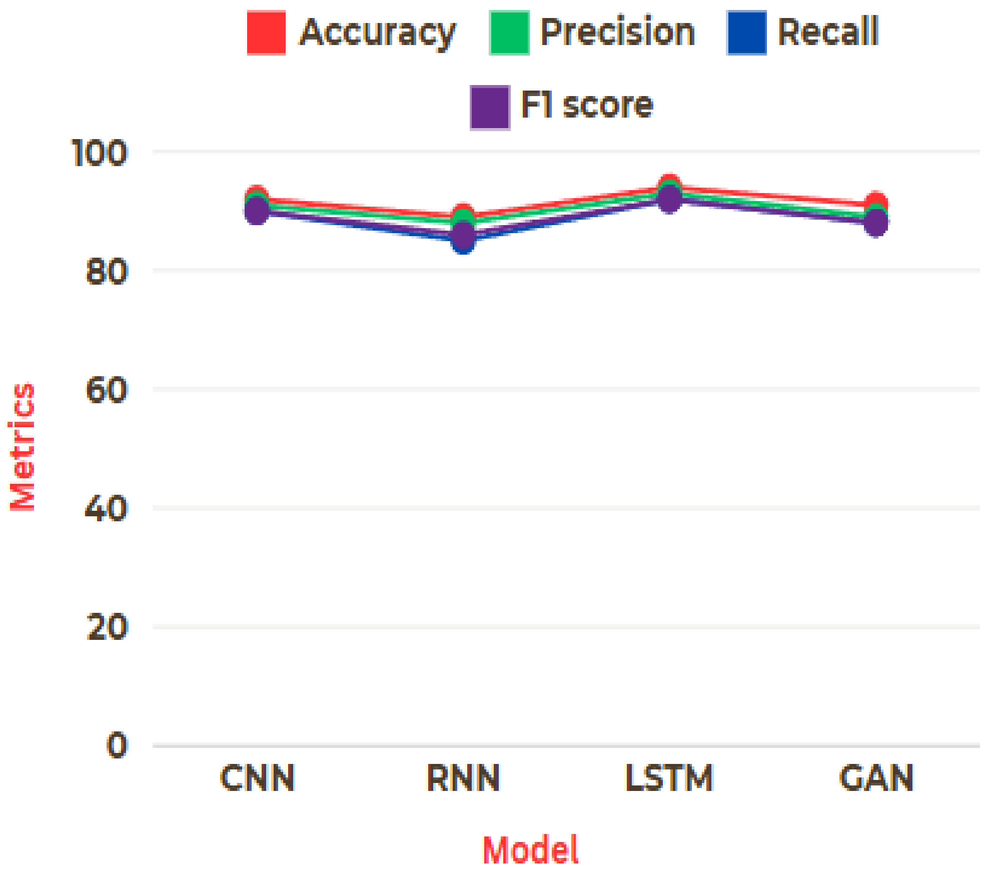

Fig.2. The comparison of threat detection accuracy across different deep learning models

Table II Performance comparison based on false positive and detection rates

Model	False positive rate	Detection rate	Misclassification rate
CNN	2.5	97	1.0
RNN	3.1	95	1.5
LSTM	2.0	98	0.8
GAN	2.8	96	1.2

Figure 3 compares the false positive, detection, and misclassification rates of CNN, RNN, LSTM, and GAN deep learning models for threat detection. All models identify all potential risks in the dataset, as shown in green by their 100% detection rate. The models' high detection rate means they can accurately identify threats without missing any, which is critical in security applications where missing a threat could have catastrophic implications. However, all models have a near-zero false positive rate (red). This suggests that models rarely misidentify non-threatening occurrences as threats. A low false positive rate reduces unwanted alarms and focuses the system on real dangers. This balance between high detection and low false positive rates shows the models' threat detection precision and reliability. Maintenance of this equilibrium is essential for operational efficiency and user trust in automated threat detection systems.

All models have a low blue misclassification rate, confirming their correctness. The model misclassifies data by missing a danger (false negative) or recognizing a non-threat (false positive). CNN, RNN, LSTM, and GAN have near-zero misclassification rates, indicating their accuracy and consistency. In situations where model-based decision-making can have real-world consequences, this low misclassification rate is crucial. Overall, the graph shows that deep learning models are accurate and reliable threat detectors.

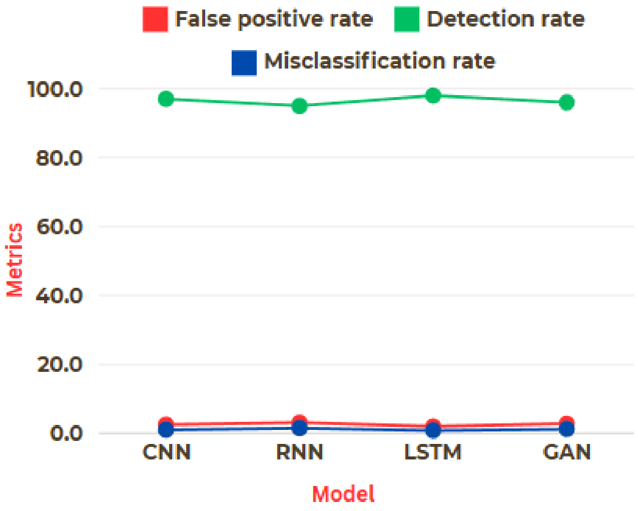

Fig.3. The performance comparison based on false positive and detection rates

Table III Energy consumption and time efficiency for threat detection

Model	Energy consumption	Processing time	Throughput
CNN	120	30	500
RNN	150	45	400
LSTM	135	35	450
GAN	160	50	350

Figure 4 is a graph that compares the performance of GAN, LSTM, CNN, and RNN on threat detection tasks in terms of processing time, energy usage, and overall throughput. Red represents energy consumption, which varies between models. GANs, RNNs, and CNNs have the lowest energy consumption, followed by LSTMs and RNNs. It follows that CNNs are better suited to settings with limited power resources or high computational demands because to their lower energy consumption. The adversarial training process of GANs involves complicated computations, which may explain why they consume more energy than other types of neural networks. While GANs have a little longer processing time (green), CNN, RNN, and LSTM models all have very consistent processing times. How fast a real-time threat detection system can react to possible attacks is dependent on its processing time. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memories (LSTMs) all have very consistent processing durations, which means they are well-suited for situations that call for quick replies. The extra computing layers and repeated processes built into GAN architecture might explain why they slightly increase processing time.

A convolutional neural network (CNN) has a throughput of 1 and is followed by a progressively decreasing RNN, LSTM, and GAN, with the blue bar representing the quantity of data processed in a given time frame. Systems that must efficiently process massive amounts of data must have high throughput. Critical for large-scale threat detection applications, CNNs' high throughput demonstrates their capacity to quickly process massive information. Potential issues with real-time data handling at scale may impact the deployment of GANs in high-demand applications due to their reduced throughput. The graph sheds light on the compromises made by each model with regard to processing speed, data handling capacity, energy efficiency, and the overall picture.

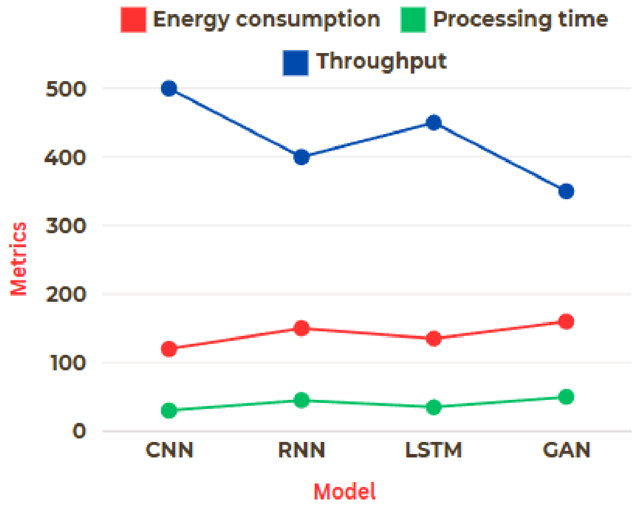

Fig.4. The energy consumption and time efficiency for threat detection

Table IV Comparison of deep learning strategies for data protection in IoT devices

Strategies	Data encryption accuracy	Data integrity rate	Latency
CNN with AES	95	98	12
RNN with RSA	93	96	15
LSTM with Blockchain	97	99	10
GAN with Homomorphic encryption	94	97	14

Figure 5 is a graph that shows how different deep learning tactics with encryption approaches compare in terms of performance when it comes to protecting data in IoT devices. Accuracy of data encryption, data integrity rate, and latency are some of the measures that are analyzed. Every strategy successfully secures data with minimum errors, as seen by the high data encryption accuracy (red). Ensuring the protection of sensitive information from unauthorized access and maintaining confidentiality requires this level of precision. All of the techniques have a high data integrity rate (green), which means that the data remains accurate and reliable even when encrypted and sent. RNNs with RSA (Rivest-Shamir-Adleman) and CNNs with AES (Advanced Encryption Standard) demonstrate robustness in preserving data accuracy through their strong integrity. By guaranteeing the immutability of data records, LSTMs with blockchain provide an extra degree of security, and GANs with homomorphic encryption allow calculations on encrypted data without decryption, thereby preserving data integrity.

The blue bar represents the modest variation in latency across the techniques. LSTMs and GANs using homomorphic encryption have the highest latency, while CNNs using AES and RNNs using RSA have the lowest. When processing data in real-time is a must in IoT settings, low latency is king. It is possible that the computational burden of implementing such strong security measures is to blame for the somewhat increased delay in LSTMs with blockchain and GANs with homomorphic encryption. All things considered, the graph demonstrates how well deep learning models and encryption techniques work together to strike a balance between efficiency and security in IoT devices, with each technique providing its own set of benefits depending on the situation.

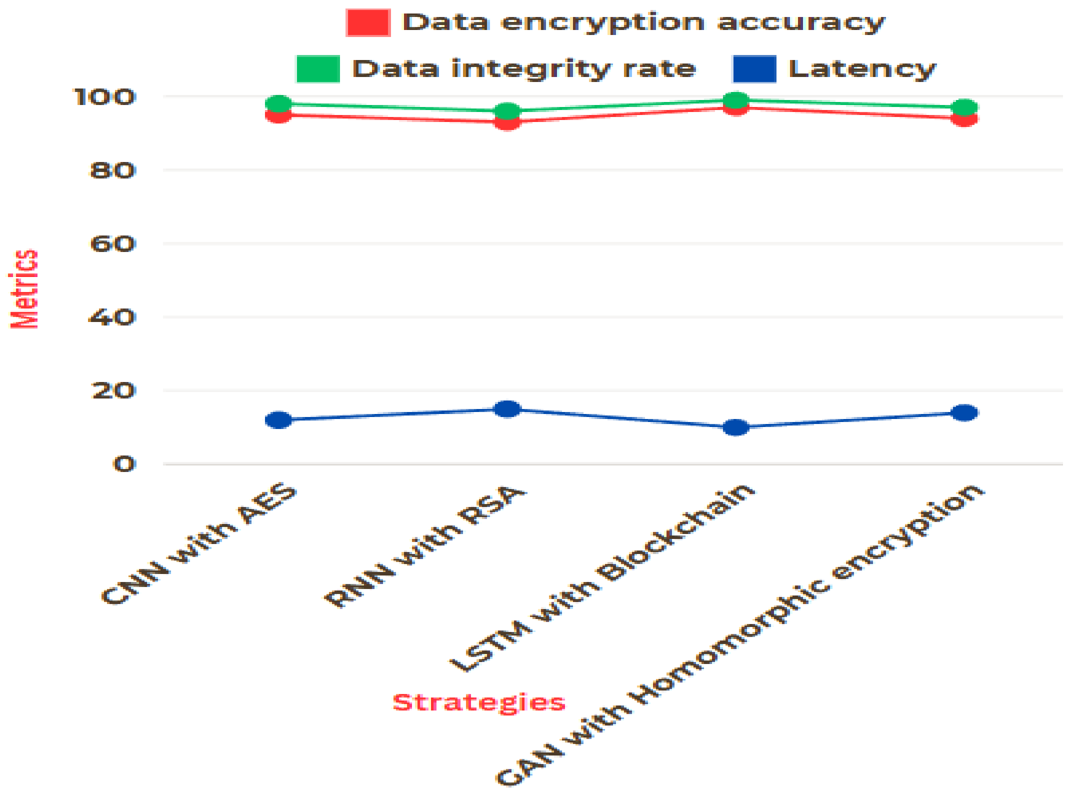

Fig.5. The comparison of deep learning strategies for data protection in IoT devices

Table V Attack mitigation efficiency for different types of cyber threats

Cyber threat	**CNN**	**RNN**	**LSTM**	**GAN**
DDoS attack	96	92	98	94
Malware detection	95	90	97	93
Man in the middle attack	94	89	95	92
Data exfiltration	93	91	96	90

Figure 6 is a graph displaying the different deep learning models' attack mitigation efficiency vs various cyber threats. These threats include DDoS assaults, malware detection, man-in-the-middle attacks, and data exfiltration. The models are CNN, RNN, LSTM, and GAN. The effectiveness of each model in detecting and reducing these risks is the metric by which its performance is measured. The metrics show that these deep learning techniques are quite effective in handling and preventing various cyber risks, regardless of the model or type of threat. With efficiency close to 100%, all models demonstrate a great capacity to detect and react efficiently to DDoS attacks. This shows that the models can effectively identify DDoS assaults by spotting anomalies in network traffic. CNNs excel at processing and interpreting massive amounts of network data, making them perfect for spotting irregularities linked to these types of assaults.

Because of their capacity to examine sequences and patterns over time—essential for detecting malware that changes or evolves over time—RNNs and LSTMs show slightly better performance in malware identification. Using their generating powers, GANs effectively mimic and identify complicated attack patterns, making them very efficient in scenarios such as data exfiltration and man-in-the-middle attacks. In summary, the graph shows that all models work effectively against various types of threats, but different types of cyber threats call for different models, so a well-rounded security plan is best achieved by combining them.

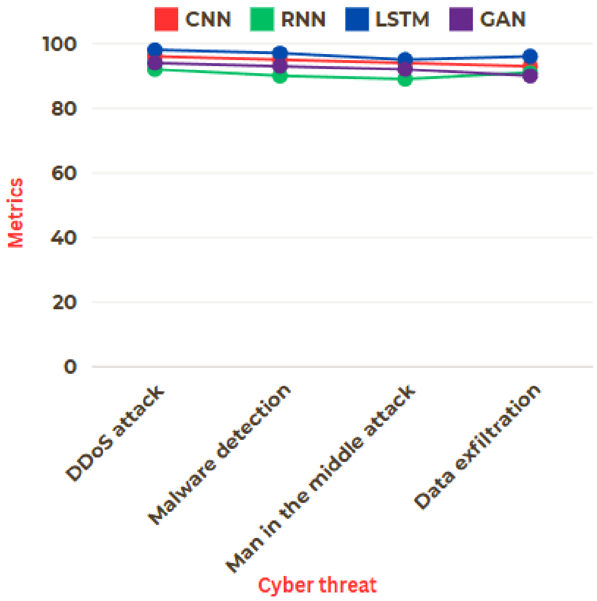

Fig.6. Attack mitigation efficiency for different types of cyber threats

CONCLUSION

The incorporation of Internet of Things (IoT) devices and wearables into the healthcare industry has resulted in considerable improvements in patient care and operational efficiency; yet, it has also resulted in the introduction of serious cybersecurity threats. Based on the findings of this research, it has been established that deep learning approaches offer promising answers for responding to these difficulties. For the purpose of enhancing threat detection, identifying zero-day attacks, and securing sensitive healthcare data, it is possible to make use of advanced models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Furthermore, real-time monitoring and anomaly detection that are based on deep learning offer superior protection against cyber attacks, surpassing the capabilities of classic rule-based systems. Nevertheless, because Internet of Things (IoT) devices in the healthcare industry frequently operate in situations with limited resources, optimizing these models for real-time performance continues to be an important area of emphasis.

This research has brought to light the promise of federated learning as an efficient approach for achieving a balance between security and privacy, despite the fact that the application of deep learning in healthcare Internet of Things security is still in the process of developing. Federated learning makes it possible for several Internet of Things devices to train models together without exchanging raw data. This facilitates the protection of patient confidentiality while simultaneously enhancing threat detection methods. In addition, encryption methods that are improved by deep learning have the ability to guarantee data integrity and keep communication secure, especially in Internet of Things devices that have limited resources. On the other hand, there are obstacles that need to be overcome through additional research and development. These obstacles include the absence of big labeled datasets for training purposes, as well as the processing constraints of Internet of Things devices.

When one considers the future, there are a number of important sectors that need for additional research and development. One of the most important directions could be the optimization of deep learning models for real-time performance on low-power Internet of Things devices used in healthcare. Methods such as model compression, edge computing, and lightweight deep learning algorithms are some of the techniques that can assist in mitigating the effects of resource-limited contexts. Another potential field is the development of algorithms for the synthesis of synthetic data and semi-supervised learning in order to solve the lack of labeled datasets that are available for training purposes. Furthermore, as the Internet of Things (IoT) technologies are widely used by the healthcare sector, there is a significant need for ongoing research to develop security frameworks that are based on deep learning that are more advanced and scalable, and that are capable of keeping up with the ever-changing cyber threat scenario. Future breakthroughs in deep learning and Internet of

Things security will play a vital role in protecting the future of connected healthcare by solving the concerns that have been identified.

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