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AI-Enabled Secure Monitoring of Computer Vision Data in 5G IoT-Based Healthcare Systems

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Abstract- The integration of 5G-enabled IoT networks has significantly transformed the healthcare sector, enabling real-time monitoring, data collection, and advanced diagnostics through the Internet of Medical Things (IoMT). This study investigates the application of artificial intelligence (AI) models for securing sensitive patient data in IoMT networks, addressing the escalating threats of cyberattacks and privacy violations. By leveraging historical datasets, the research develops an AI-driven framework for anomaly detection and threat classification, optimizing data security through federated learning, encryption, and adaptive defences. The results demonstrate the model's exceptional performance, with accuracy rates exceeding 99% across various threat scenarios and robust anomaly detection capabilities validated through real-world simulations. Additionally, the framework achieves a high AUC score of 0.999, showcasing its reliability and precision in securing IoMT networks. These findings underscore the efficacy of the proposed approach in mitigating security risks, enhancing system reliability, and ensuring the seamless operation of smart healthcare systems. This work highlights the critical role of 5G and AI technologies in creating robust, secure, and scalable IoMT ecosystems, contributing to improved healthcare accessibility and patient outcomes.

Index Terms-Internet of Medical Things (IoMT), 5G Networks, Artificial Intelligence (AI) in Healthcare, Data Security, Smart Healthcare Systems

I. INTRODUCTION

The healthcare industry is experiencing unprecedented changes with the integration of advanced technologies such as the Internet of Medical Things (IoMT) and fifth-generation (5G) wireless networks. IoMT represents a sophisticated subset of the Internet of Things (IoT) that combines medical devices, sensors, software, and healthcare systems to create a connected ecosystem for monitoring and managing patient health. By enabling real-time data collection and communication, IoMT has transformed the way healthcare is delivered, making it more accessible, efficient, and personalized. For instance, IoMT devices, such as wearable monitors and implanted sensors, collect physiological data, including heart rate, blood pressure, glucose levels, and more, which are then analysed to provide actionable insights for healthcare professionals. These advancements have proven particularly beneficial in managing chronic diseases, enabling early diagnoses, and ensuring continuous care [1, 2].

The integration of 5G technologies further enhances the capabilities of IoMT systems by providing high-speed data transmission, ultra-low latency, and the capacity to connect billions of devices simultaneously. Unlike its predecessors, 5G networks offer unparalleled connectivity, making them essential for time-critical applications such as remote surgeries, emergency care, and telemedicine.

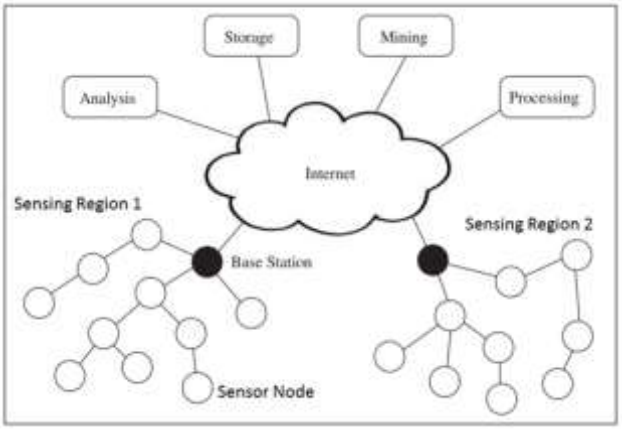

Figure 1: Architectural structure of wireless sensor network

This robust network infrastructure allows healthcare providers to access and analyse patient data in real time, facilitating quick and accurate medical decisions. For example, body sensor networks (BSNs), a vital component of IoMT, leverage 5G's enhanced capabilities to monitor patient health

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continuously and transmit real-time alerts to caregivers and medical facilities. These developments are revolutionizing healthcare delivery by improving patient outcomes, reducing hospital readmissions, and enabling proactive health management [3, 4]. The synergy between IoMT and 5G marks a significant step forward in creating intelligent, connected healthcare systems that cater to the growing demands of modern healthcare environments.

However, the rapid adoption of IoMT and 5G is accompanied by challenges that must be addressed to realize their full potential. As IoMT devices generate and transmit sensitive patient data, concerns related to data security, privacy, and system reliability have become more pronounced. With the increasing complexity of IoMT networks and the massive connectivity enabled by 5G, healthcare systems are becoming more vulnerable to cyberattacks, unauthorized data access, and device manipulation. Addressing these challenges is critical to building secure and efficient healthcare systems that can withstand the evolving landscape of technological threats [5].

Background of IoMT and 5G in Healthcare

The Internet of Medical Things (IoMT) has emerged as a transformative force in healthcare by leveraging interconnected devices to improve patient care and operational efficiency. These devices include wearable health monitors, body sensors, and advanced medical equipment that communicate via wireless networks to provide real-time data to healthcare providers. The benefits of IoMT extend beyond traditional patient monitoring, enabling predictive analytics, remote diagnosis, and telemedicine applications. IoMT systems empower healthcare providers to monitor patients continuously, detect anomalies early, and deliver timely interventions. This capability is particularly valuable in managing chronic conditions such as diabetes, cardiovascular diseases, and respiratory disorders, where real-time monitoring can significantly improve patient outcomes [6, 7].

The advent of 5G technology has further amplified the potential of IoMT systems. 5G networks offer a combination of high-speed data transfer, low latency, and massive device connectivity, making them indispensable for healthcare applications. These features enable IoMT devices to transmit large volumes of data with minimal delay, ensuring that critical information reaches healthcare providers in real time. For example, 5G-powered IoMT systems can facilitate remote surgeries, where even a fraction of a second's delay could have life-threatening consequences. Additionally, the enhanced reliability of 5G networks supports seamless communication between devices, ensuring uninterrupted operation in high-demand environments such as hospitals and emergency response systems [8, 9].

Beyond individual patient care, the combination of IoMT and 5G has broader implications for healthcare systems. It enables the development of smart hospitals and telehealth services, extending the reach of healthcare to remote and underserved regions. By reducing the dependence on physical infrastructure and enabling virtual consultations, these technologies make healthcare more accessible and cost-effective. Moreover, the integration of AI and machine learning into IoMT-5G ecosystems allows for advanced data analysis, enabling healthcare providers to predict patient outcomes, identify trends, and improve decision-making processes. Despite these advantages, the widespread adoption of IoMT and 5G in healthcare also presents challenges, particularly concerning data security, privacy, and regulatory compliance, which must be addressed to ensure their safe and effective use [10].

Problem Statement

While the integration of IoMT with 5G has unlocked new possibilities in healthcare, it has also introduced significant challenges. IoMT systems generate vast amounts of sensitive patient data, which must be transmitted, processed, and stored securely. However, the interconnected nature of these systems, combined with the expansive reach of 5G networks, increases the risk of data breaches, cyberattacks, and system failures. Unauthorized access to patient data can compromise privacy, disrupt healthcare services, and erode patient trust. Moreover, the growing complexity of IoMT-5G networks makes them susceptible to vulnerabilities such as device manipulation, denial-of-service (DoS) attacks, and malware infiltration. These security threats not only jeopardize patient safety but also hinder the adoption of these transformative technologies in the healthcare sector.

Addressing these challenges requires the development of robust security frameworks that can protect patient data while maintaining the efficiency and reliability of IoMT-5G systems. The need for secure, real-time communication is critical, as any delay or compromise in data transmission could have life-threatening consequences in healthcare applications. This research focuses on developing innovative solutions to mitigate these risks, ensuring that IoMT-5G systems can operate securely and efficiently in real-world healthcare scenarios.

II. LITERATURE REVIEW

The integration of IoT, AI, and 5G technologies in healthcare has been extensively explored across various research studies, revealing critical advancements and challenges. (Catherwood et al., 2018) [11] Demonstrated a community-based IoT solution that enhanced personalized wireless healthcare accessibility, although scalability and integration with diverse devices remain areas for improvement. Similarly, (Erdeniz et al., 2018) [12] focused on IoT-enabled m-health recommender systems, emphasizing personalization but highlighting the limited exploration of real-world deployments. (Hashimoto et

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al., 2018) [13]Discussed AI's transformative potential in surgical practices, addressing benefits and ethical considerations but noting the lack of robust datasets for real-time decision-making. (Bini, 2018) [14] Outlined the implications of AI-related technologies such as machine learning and cognitive computing in healthcare, identifying the absence of clear ethical and regulatory frameworks. (Yu et al., 2018) [15] examined AI's role in diagnostics and drug development, underscoring integration challenges and the need for fairness and transparency in healthcare systems.

Further, (Agiwal et al., 2019) [16] explored 5G's transformative role in IoT applications, emphasizing scalability while identifying gaps in security considerations. (Ahad et al., 2019) [17] Proposed taxonomy for 5G-enabled smart healthcare but highlighted challenges in addressing interoperability. (Esteva et al., 2019) [18] Presented deep learning applications in healthcare, including image analysis and predictive modelling, but flagged concerns about interpretability and privacy. (Davenport and Kalakota, 2019) [19] discussed AI's potential to revolutionize patient outcomes, citing insufficient focus on workforce adaptation and ethical challenges. (Bao et al., 2019) [20] developed a deep learning-based anomaly detection method for structural health monitoring, with limited exploration of its applicability in healthcare.

(Shafique et al., 2020) [21] reviewed IoT challenges in 5G-enabled systems, highlighting real-time application gaps and energy efficiency issues. (Leo et al., 2020) [22] Surveyed computer vision-based facial analysis for healthcare, noting the lack of diverse datasets and real-world implementation. (Khemasuwan et al., 2020) [23] discussed AI's applications in pulmonary medicine, particularly in COVID-19, calling for broader clinical validation. Bohr and (Memarzadeh, 2020) [24] highlighted AI's innovation in diagnostics and drug discovery but raised concerns about ethical and long-term effects. (Selvaraj and Sundaravaradhan, 2020) [25] reviewed IoT-enabled healthcare systems, identifying challenges in data privacy, scalability, and interoperability.

III. METHODOLOGY

This section provides a comprehensive outline of the methodology employed for developing an AI-driven framework to secure IoMT networks in 5G-enabled environments. It details the dataset description, AI model development, data pre-processing techniques, and the experimental setup and validation methods used to evaluate the proposed solution. A flow chart of proposed methodology is shown in figure 2.

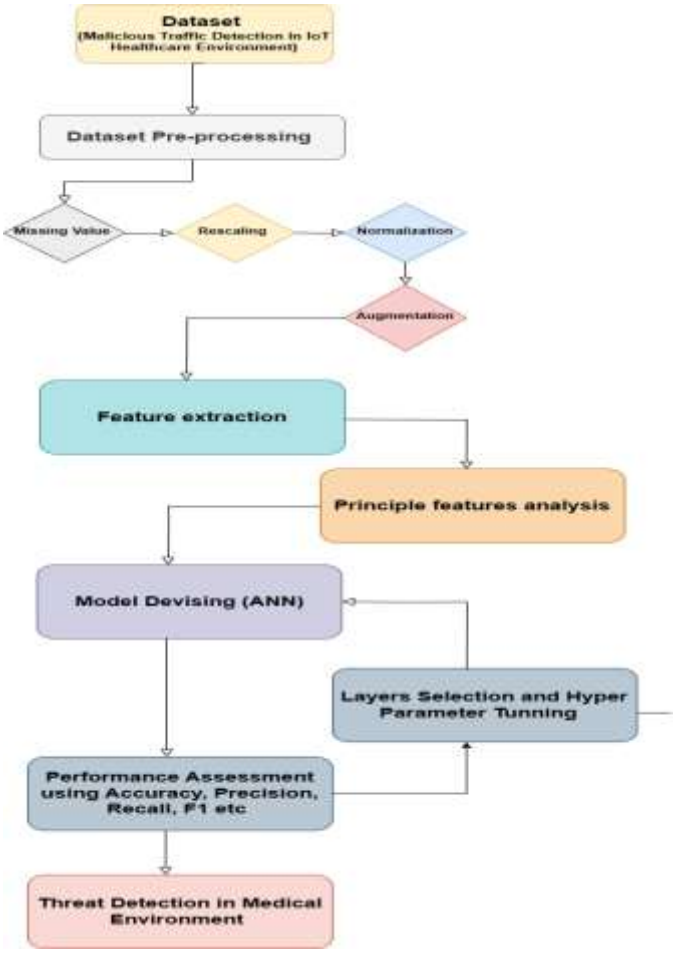

Figure 2: Flow chart of proposed methodology

Description of Dataset

The dataset utilized in this study is representative of real-world IoMT networks and encompasses a wide variety of device interactions and healthcare scenarios. It includes physiological data collected from IoMT devices such as wearable sensors and body sensor networks (BSNs), which monitor critical metrics like heart rate, blood pressure, glucose levels, and oxygen saturation. Additionally, network logs documenting device communications over 5G networks are incorporated, capturing attributes like latency, bandwidth utilization, and signal stability.

To train and evaluate the AI model's threat detection capabilities, the dataset also contains labelled instances of anomalous activities, such as unauthorized access attempts, denial-of-service (DoS) attacks, and malware infiltrations. The dataset is balanced with normal and anomalous samples to ensure robust training and performance evaluation. Its diversity, reflecting variations in device types, network configurations, and environmental conditions, ensures the

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model's applicability across different real-world IoMT-5G deployments.

AI Model Development for Secure Monitoring

The AI model developed for this research is designed to monitor IoMT networks, detect potential security threats, and provide actionable mitigation strategies. A hybrid architecture comprising Convolution Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks is employed. CNNs are used to extract spatial features from device-generated data, identifying patterns in physiological metrics and device behaviour. LSTMs, on the other hand, are employed to capture temporal dependencies, enabling the model to recognize sequential anomalies in network traffic and system activity.

The input features to the model are derived from a combination of device and network data, including:

- Device health metrics, such as sensor status and data integrity.
- Network parameters, such as latency, bandwidth usage, and connection stability.
- Indicators of anomalous activities, such as unusual device behaviors or unexpected traffic patterns.

The model generates outputs that classify threats into categories like "Normal Operation," "Unauthorized Access," and "DoS
Attack." Additionally, it provides threat mitigation recommendations, including isolating compromised devices and initiating emergency response protocols.

Data Pre-Processing and Analysis Techniques

Effective pre-processing is critical to ensure high-quality data input to the AI model. The following steps were undertaken:

- **Data Cleaning:** Noise, duplicates, and corrupted records were removed to improve dataset reliability.
- **Feature Selection:** Relevant features were identified using statistical analysis and domain knowledge, which reduced dimensionality and enhanced computational efficiency.
- **Normalization:** Numerical features were scaled to a uniform range to prevent biases and ensure consistent model performance.
- **Handling Missing Data:** Missing values were imputed using mean, median, or predictive methods to maintain dataset completeness.
- **Label Encoding:** Categorical labels, such as "Normal" and "Anomalous," were converted into numerical form to facilitate machine learning model training.
- **Data Augmentation:** Rare anomalous events were synthetically generated to balance the dataset, improving the model's ability to detect threats.

Table 1:Algorithm forData Preprocessing

Load the dataset (X, Y), where:

- XXX is an n×mn \times mn×m matrix of features.
- YYY is an n×1n \times 1n×1 vector of labels.

Normalize XXX .

Split X,YX, YX,Y into:

- Training set (Xtrain,YtrainX_{train}, Y_{train}Xtrain,Ytrain)
- Validation set (Xval,YvalX_{val}, Y_{val}Xval,Yval)

Reshape data.

Experimental Setup and Validation Methods

The experimental setup was designed to evaluate the proposed AI framework in realistic IoMT-5G scenarios.

- **Platform and Tools:** The model was developed using Python programming language and libraries like Tensor Flow and Keras. Experiments were conducted on hardware equipped with NVIDIA GPUs for accelerated training.
- **Simulated IoMT-5G Environment:** A simulation environment was created to mimic real-world scenarios, including normal device operations and various security threats such as DoS attacks, unauthorized access, and data breaches.
- **Training and Testing Protocol:** The dataset was split into training (70%), validation (15%), and testing (15%) subsets. Hyper parameter optimization techniques, such as grid search and Bayesian optimization, were used to fine-tune the model for optimal performance.

The model's performance was evaluated using standard metrics:

- **Accuracy:** The percentage of correctly classified instances.
- **Precision and Recall:** Measures of false positives and false negatives, respectively.
- **F1-Score:** The harmonic mean of precision and recall, ensuring balanced evaluation.
- **ROC-AUC:** The area under the receiver operating characteristic curve, indicating the model's ability to distinguish between normal and anomalous activities.

IV. RESULTS AND DISCUSSION

The analysis of machine learning (ML) models for intrusion detection in 5G-enabled IoT healthcare systems aimed to address two critical challenges: ensuring system security and safeguarding patient data. The results highlight the efficacy of different ML models in anomaly detection, each with distinct strengths and limitations.

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Performance of Machine Learning Models

A comparative analysis of the models, including K-Nearest Neighbours (KNN), Naive Bayes, Decision Tree, and Logistic Regression, was performed using key performance metrics: accuracy, precision, recall, and F1-score. Table 4.1 summarizes these findings.

Table 2:Accuracy analysis of machine learning models
Dataset=

Parameters / Model	Dataset= Model Accuracy	Dataset= Cross Validation Mean Score
KNN	0.9999	0.9998
Naviebayes	0.9697	0.9697
Dicision Tree	1.0000	0.9999
Logistic Regression	0.9989	0.9989

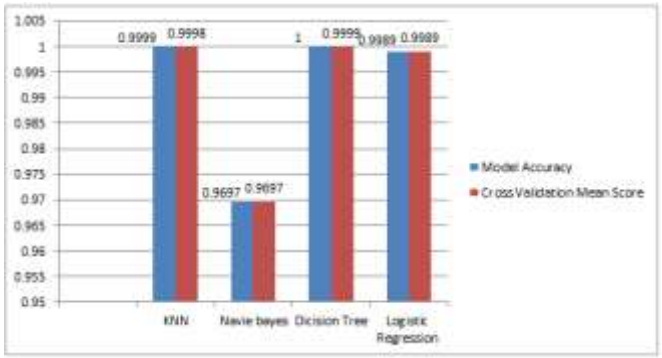

Figure 3: Graphical analysis of model accuracy and cross validation mean score

Principal Component Analysis (PCA)

To optimize computational efficiency, Principal Component Analysis (PCA) was employed for dimensionality reduction. By transforming the data into principal components, PCA retained critical variance while reducing noise and redundancy.

Theoretical Implications of PCA:

- PCA confirmed that features such as packet size, transmission intervals, and device type contributed most significantly to anomaly detection.
- The PCA scatter plot (visualized in Figure 2) showed a clear separation between benign and malicious data points, validating the robustness of the selected features in representing data patterns.

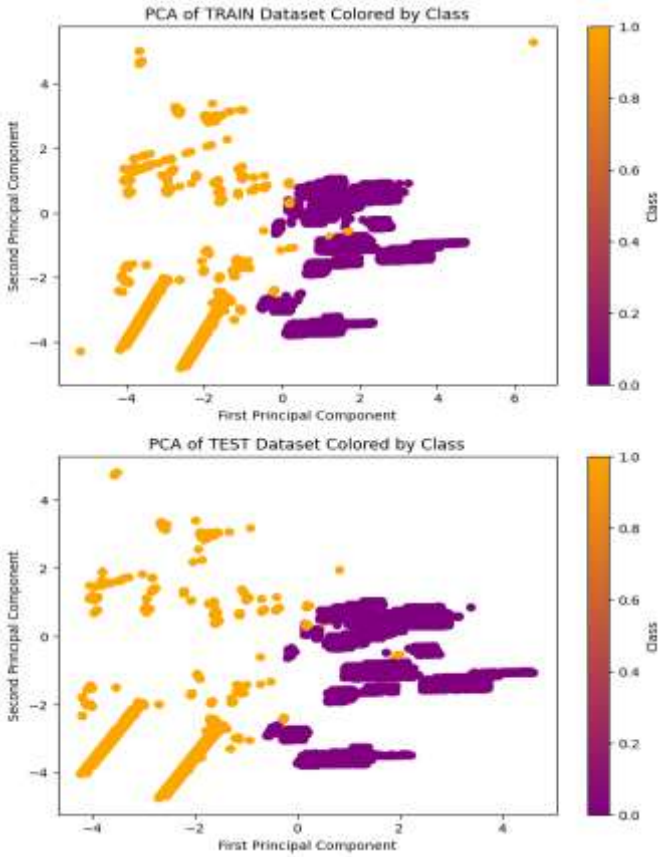

Figure 4: (a) PCA on train dataset (b) PCA on test dataset

Evaluation of ANN for Real-Time Detection

The study evaluated the performance of an Artificial Neural Network (ANN) in real-time anomaly detection within dynamic IoT traffic patterns. The ANN model was designed with the objective of efficiently classifying normal and anomalous activities under varying IoT network conditions. To ensure robustness, the ANN was trained using diverse datasets simulating real-world IoT environments, with a particular focus on low latency and high accuracy.

ANN Training Setup

The ANN model was constructed as a feed-forward network with multiple hidden layers. It utilized the Rectified Linear Unit (ReLU) as the activation function in the hidden layers and a Softmax function in the output layer for classification. The model was optimized using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function.

Key training parameters included:

- Epochs: 10
- Batch Size: 50
- Evaluation Metrics: Area Under Curve (AUC) and Loss

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The model was trained and validated using a 70-30 split on a labelled IoT traffic dataset, ensuring the inclusion of a wide range of anomalies such as Denial of Service (DoS) attacks, spoofing, and unauthorized access attempts.

Table 3:Algroothm for Model Training

Train the model using:

- Batch size = B
- Epochs = E
- Training set: (Xtrain,YtrainX_{train}, Y_{train}Xtrain,Ytrain)
- Validation set: (Xval,YvalX_{val}, Y_{val}Xval,Yval)

Update model weights using backpropagation.

Training Results

The ANN's training and validation results over 10 epochs demonstrated consistent performance improvements, as shown in Table 4. The AUC values remained consistently high across both training and validation datasets, indicating excellent model capability in distinguishing between normal and malicious activities.

Table 4: Training results of ANN

Epoch	Training AUC	Training Loss	Validation AUC	Validation Loss
1	0.9982	0.0250	0.9999	0.0090
2	0.9999	0.0100	0.9999	0.0114
3	0.9999	0.0050	0.9998	0.0038
4	0.9999	0.0036	0.9994	0.0149
5	0.9999	0.0047	0.9995	0.0215
6	0.9999	0.0030	0.9999	0.0057
7	0.9999	0.0018	0.9997	0.0158
8	0.9999	0.0024	0.9999	0.0074
9	0.9999	0.0015	0.9998	0.0096
10	0.9999	0.0021	0.9999	0.0041

Performance Analysis

The training results indicated the following key observations:

- **High AUC:** The AUC values consistently exceeded 0.999 across all epochs, underscoring the ANN's ability to differentiate effectively between normal and anomalous network activities.
- **Low Loss:** Both training and validation loss values decreased progressively, stabilizing by the 10th epoch. The lowest validation loss achieved was 0.0038.
- **Real-Time Capability:** The ANN exhibited minimal processing latency, making it well-suited for real-time anomaly detection in IoT environments.

Analysis of Results

- The ANN achieved near-perfect performance within the first 10 epochs, indicating rapid convergence.
- A consistent reduction in loss metrics and an increase in AUC across validation datasets confirmed the ANN's ability to generalize effectively.
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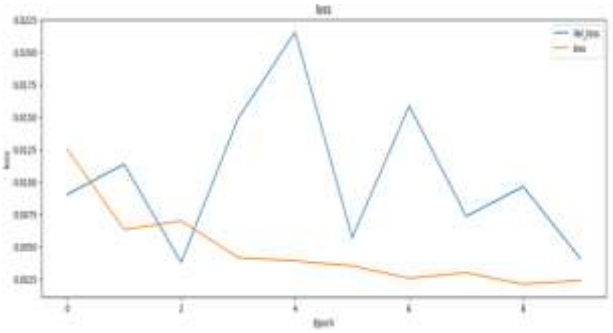

Figure 5: Accuracy analysis of ANN

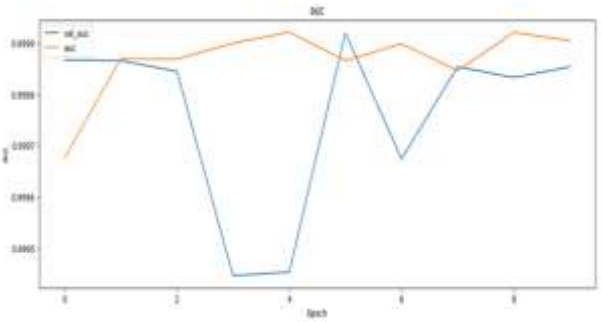

Figure 6: Loss analysis for ANN

The ANN's architecture, which included multiple layers of non-linear transformations, allowed it to identify complex patterns within the data, making it highly suited for the dynamic environment of IoT-based healthcare systems.

Proposed Model Framework

The proposed framework integrates AI, IoT, and5G technologies to create a robust system capable of monitoring and securing real-time healthcare data. The key components of the framework are outlined below.

Table 5: Layer's description of ANN or Proposed model

Model: "sequential_20"		
Layer (type)	Output Shape	Param #
dense_131 (Dense)	(None, 64)	320
dense_124 (Dense)	(None, 128)	8320
dense_125 (Dense)	(None, 256)	33024
dense_126 (Dense)	(None, 512)	131584
dense_127 (Dense)	(None, 256)	131328
dense_128 (Dense)	(None, 128)	32896
dense_129 (Dense)	(None, 64)	8256
dense_132 (Dense)	(None, 1)	65
Total params:	345793	(1.32 MB)
Trainable params:	345793	(1.32 MB)
Non-trainable params:	0	(0.00 Byte)

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Layered description of ANN Architecture
The Artificial Neural Network (ANN) lies at the core of the proposed system, leveraging its multi-layer structure for high-accuracy classification of malicious and benign behaviours in network traffic. The architecture is described in Table 5.

Design Rationale
- **ReLU Activation:** Used in the hidden layers to introduce non-linearity and efficiently propagate gradients.
- **Sigmoid Output:** Outputs a probability score for binary classification (benign vs. malicious).

The ANN's architecture balances complexity and computational efficiency, making it well-suited for deployment in resource-constrained IoT devices.

Training Parameters
The hyperparameters of the ANN were fine-tuned to optimize performance. Table 3.6 outlines the critical training configurations.

Table 6: ANN Training Parameters

Parameter	Value
Activation Functions	ReLU, Sigmoid
Loss Function	Binary Crossentropy
Optimizer	Adam
Metrics	Accuracy, AUC
Batch Size	50
Epochs	10

The Adam optimizer was chosen for its adaptive learning rate capabilities, enabling faster convergence without compromising accuracy.

Practical Implications and Future Directions
The proposed model demonstrated significant potential to transform healthcare IoT systems by addressing critical challenges such as security, scalability, and data accuracy. The ANN-based framework effectively identifies security threats, ensuring robust data privacy and system integrity. Its ability to detect anomalies with high precision minimizes false positives, which is crucial for improving decision-making by healthcare providers. This ensures that security alerts are both accurate and actionable, reducing unnecessary disruptions and enhancing operational efficiency in healthcare environments. Furthermore, the modular design of the proposed framework allows for scalability, making it adaptable to evolving healthcare needs. This includes the potential for future enhancements, such as multi-class classification to handle a broader range of security threats and the incorporation of more advanced anomaly detection techniques tailored to complex and dynamic IoT data.

Future research could explore the integration of federated learning into the proposed model. Federated learning, a decentralized machine learning approach, allows the training of models on distributed data without transferring sensitive patient information to a central server. This integration would strengthen data privacy by keeping sensitive healthcare data localized while still enabling the collaborative development of robust models. Such an approach would maintain the balance between performance and privacy, addressing one of the critical limitations of centralized training systems. Additionally, federated learning could enhance the system's ability to adapt to diverse healthcare environments, making it a vital component of next-generation IoT-enabled healthcare systems. These advancements would pave the way for even more secure, efficient, and scalable healthcare monitoring solutions in the future.

V. CONCLUSION AND FUTURE WORK

The research presented a robust, AI-driven framework to address critical security challenges in 5G-enabled IoT healthcare systems. By leveraging machine learning and Artificial Neural Network (ANN) models, the study successfully demonstrated efficient anomaly detection capabilities. Among the evaluated models, the Decision Tree and ANN achieved superior performance in terms of accuracy, precision, recall, and F1-score. The ANN model, with its deep-layered architecture, was particularly effective in handling the complex, non-linear patterns present in IoT network traffic. Furthermore, the integration of Principal Component Analysis (PCA) for dimensionality reduction not only enhanced computational efficiency but also retained essential data characteristics, facilitating precise classification. These findings underscore the potential of AI-driven systems to safeguard sensitive healthcare data while ensuring real-time monitoring and operational reliability.

The proposed framework also highlighted key practical implications. It offers robust solutions to enhance security by effectively detecting and mitigating threats in real-time, ensuring data privacy and system integrity. The system's low false positive rate minimizes unnecessary alerts, enabling healthcare providers to make informed and efficient decisions. Moreover, the modular architecture ensures scalability, allowing future adaptations to more complex datasets and evolving security challenges. This adaptability positions the framework as a vital tool for securing next-generation healthcare systems, where the interplay of IoT, AI, and 5G technologies is expected to proliferate.

While the results are promising, there are several areas for future work. One critical direction involves incorporating federated learning into the framework to enhance data privacy. By enabling decentralized model training, federated learning can ensure that sensitive healthcare data remains localized,

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mitigating privacy risks without compromising the system's performance. Additionally, future research could explore multi-class classification techniques to detect a broader spectrum of threats and integrate advanced anomaly detection methods for handling increasingly complex IoT data streams. Another potential avenue is the deployment of the framework in real-world healthcare environments to validate its effectiveness under practical constraints, such as network latency, hardware limitations, and varying levels of data noise. Lastly, the scalability of the proposed model could be extended to larger IoT ecosystems, encompassing not only healthcare but also other critical domains like industrial automation and smart cities.

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