IoT Based ICU Healthcare: Optimizing Patient Monitoring and Treatment with Advanced Algorithms

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Abstract – In the realm of IoT-based Intensive Care Unit (ICU) healthcare, the quest for precision and reliability in patient monitoring and treatment optimization is paramount. This study delves into the realm of advanced algorithms, particularly focusing on the Pelican Optimization Algorithm Long Short-Term Memory (POA-LSTM), known for its remarkable accuracy rates exceeding 95%. The POA-LSTM algorithm, fine-tuned through the Pelican Optimization Algorithm, emerges as a beacon of accuracy in ICU healthcare. By optimizing hyperparameters and leveraging the Pelican Optimization Algorithm's optimization prowess, POA-LSTM surpasses industry standards, offering unparalleled precision and recall rates. Its ability to make informed predictions and provide real-time insights significantly enhances the quality of patient care and clinical decision-making in ICU settings. Additionally, the study explores Context-Oriented Attention LSTM (COA-LSTM) and Particle Swarm Optimization Long Short-Term Memory (PSO-LSTM) algorithms, each contributing unique strengths to the landscape of IoT-based ICU healthcare. COA-LSTM's attention mechanism and PSO-LSTM's hyperparameter optimization further enrich the capabilities of predictive modeling and anomaly detection in critical care scenarios. Through the integration of these advanced algorithms, healthcare providers can harness the power of data-driven insights to revolutionize ICU healthcare, ensuring optimal patient outcomes and advancing the frontier of medical care in the digital age.

Keywords – Healthcare, IOT, LSTM, ICU, Optimization Algorithm.

I. INTRODUCTION

IoT (Internet of Things) technology has revolutionized many industries, including healthcare, with IoT-based ICUs (Intensive Care Units) leveraging connected devices and sensors for real-time patient monitoring and data gathering, enabling remote management by healthcare providers. Key benefits include remote monitoring through wearable sensors and smart beds, data analytics using advanced algorithms for trend identification, predictive analytics for preemptive measures, efficient resource management via workflow automation, patient engagement through data access, and scalability across healthcare settings. These advantages translate into improved patient outcomes and enhanced healthcare delivery, showcasing the transformative potential of IoT in the healthcare sector. In an IoT-based ICU (Intensive Care Unit), various types of attacks can pose security and privacy risks similar to any other IoT system. These include Denial of Service (DoS) attacks, where the system is overwhelmed with traffic, compromising critical services; Man-in-the-Middle (MitM) attacks, allowing attackers to intercept and manipulate data; Data Tampering, altering patient data leading to incorrect treatments; Device Spoofing, gaining unauthorized access to the ICU's network; Phishing and Social Engineering, tricking staff into revealing sensitive information; Ransomware, encrypting patient data for ransom; and Physical Attacks, compromising physical security. Robust cybersecurity measures such as strong authentication, encryption, regular audits, patch management, network segmentation, employee training, and monitoring are crucial for mitigating these risks and safeguarding patient data and care in IoT-based ICUs.

Detecting attacks in an IoT-based ICU relies on sophisticated algorithms capable of analyzing extensive data from connected devices, sensors, and network traffic. Commonly used algorithms include anomaly detection methods such as statistical approaches (e.g., Z-score, Isolation Forest, One-Class SVM) and machine learning techniques (e.g., Random

Forest, Gradient Boosting Machines, Neural Networks). Signature-based detection utilizes pattern matching algorithms like Snort and Suricata, while behavioral analysis employs machine learning models (e.g., K-means clustering, DBSCAN, Autoencoders) and time-series analysis techniques (e.g., Dynamic Time Warping, Seasonal Trend Decomposition). Network traffic analysis utilizes flow-based analysis (e.g., NetFlow, IPFIX) and deep packet inspection (DPI) to detect malicious activities. Hybrid approaches, deep learning models (e.g., CNNs, RNNs), and context-aware detection methods enhance attack detection accuracy by considering contextual information. Implementing a combination of these algorithms and techniques strengthens the security of an IoT-based ICU, with continuous monitoring, regular updates, and collaboration with cybersecurity experts being vital for effective attack detection and mitigation. While numerous algorithms are employed for detecting attacks in IoT-based environments, including IoT-based ICUs, each algorithm possesses its own set of drawbacks. Common drawbacks associated with existing algorithms for attack detection in IoT environments include false positives and false negatives, scalability issues, complexity and resource intensiveness, limited adaptability to new threats, lack of explainability, data quality and privacy concerns, and susceptibility to adversarial attacks. Addressing these drawbacks necessitates ongoing research and development efforts in cybersecurity, data analytics, and AI/ML fields. Innovations such as explainable AI, lightweight detection models, adaptive learning mechanisms, and data preprocessing techniques can aid in improving the accuracy, efficiency, and resilience of attack detection in IoT-based ICUs and similar environments. Additionally, regular evaluations, testing, and validation of detection algorithms are crucial for identifying and mitigating potential weaknesses.

Problem Statement

The rapid integration of IoT (Internet of Things) technology into healthcare, specifically in Intensive Care Units (ICUs), has ushered in a range of promising opportunities but also significant challenges. While IoT-based ICUs offer enhanced patient monitoring, predictive analytics, and resource management, critical issues must be addressed for their effective, secure, and ethical use in healthcare settings. These challenges encompass security and privacy concerns, complex data management and integration needs, ensuring data reliability and accuracy, addressing interoperability and standardization gaps, complying with ethical and regulatory requirements such as HIPAA, and navigating resource constraints. Overcoming these challenges demands collaborative efforts across cybersecurity, data analytics, interoperability standards, regulatory frameworks, and healthcare policy realms. A multidisciplinary approach involving healthcare providers, technology vendors, researchers, policymakers, and regulatory bodies is essential to develop and implement solutions that optimize IoT benefits while safeguarding patient privacy, trust, and compliance in ICU environments.

Contributions

(i) We propose the POA-LSTM (Predictive Optimization Algorithm) for IoT-based ICU healthcare, which leverages LSTM (Long Short-Term Memory) networks to analyze patient data and predict critical events. Our algorithm demonstrates high accuracy in forecasting patient conditions, enabling proactive interventions and improving patient outcomes.

(ii) In addition to POA-LSTM, we introduce COA-LSTM (Contextual Optimization Algorithm) tailored for IoT-based ICU environments. COA-LSTM incorporates contextual information such as patient profiles, medical protocols, and environmental factors to enhance predictive accuracy and relevance. This algorithm enables personalized patient care and optimized treatment plans based on contextual insights.

(iii) To further optimize IoT-based ICU healthcare, we propose PSO-LSTM (Particle Swarm Optimization) as a hybrid algorithm combining LSTM networks with PSO for parameter optimization. PSO-LSTM dynamically adjusts model parameters to improve prediction accuracy and adaptability to changing patient conditions, ensuring robust performance in real-time monitoring and prediction tasks.

(iv) Our research contributions extend beyond algorithm development to include a comprehensive Plan of Action (POA) for integrating POA-LSTM, COA-LSTM, and PSO-LSTM into existing IoT-based ICU systems. The POA outlines implementation steps, data integration strategies, model training protocols, validation procedures, and performance evaluation metrics. By following this POA, healthcare providers can seamlessly deploy and leverage these advanced algorithms to enhance patient care, clinical decision-making, and overall ICU efficiency.

II. LITERATURE SURVEY

The Internet of Things (IoT) presents itself as a promising paradigm due to its scalability, enabling continuous and dependable health monitoring globally. This study aims to expand this platform by incorporating wearable and inconspicuous sensors to monitor patients with COVID-19. Additionally, we present the real-world implementation of our approach in a COVID-19 intensive care unit (ICU) in Brazil. Implementing computer vision (CV)-based emotion recognition and drowsiness detection technology in ICUs can notably reduce delirium and respiratory illnesses, particularly in cases like pneumonia, thus enhancing patient outcomes. This study introduces a CV-based intelligent ICU framework for real-time patient monitoring using IoT technology. The ongoing monitoring of vital signs allows healthcare providers to promptly evaluate the patient's physiological state in the ICU. The integration of IoT in hospitals with various sensors, including cameras, can facilitate intelligent healthcare services.

In this paper, we propose a remote patient monitoring system that utilizes closed-circuit television (CCTV) cameras within an IoT infrastructure as optical sensors for non-contact physiological measurements, expanding their utility from surveillance to medical monitoring [1-4]. This article introduces a framework for knowledge representation that enables intelligent video surveillance of patients, which can be integrated with IoT-based systems to improve the detection of critical patients in emergency rooms, while addressing ethical, privacy, and security concerns. These concerns are addressed through an event-based visual access control specification method that regulates access to devices and users. The paper proposes a new IoT-based paradigm called IoT MEMS (IoT-Based Paradigm for Medical Equipment Management Systems) aimed at efficiently managing medical equipment in ICUs. IoT technology is leveraged to enhance information flow between medical equipment management systems and ICUs during the COVID-19 pandemic, ensuring transparency and fairness in reallocating medical equipment. The theoretical and practical aspects of IoT MEMS are thoroughly discussed. However, the energy consumption of these devices is significant, impacting the environment, product cost, and device lifespan. Consequently, energy-efficient solutions for smart environments have garnered attention from researchers and the industrial sector.

In this context, a novel fog-based multi-level energy-efficient framework for IoT-enabled smart environments is proposed [5-8]. Artificial intelligence (AI) and computer vision have numerous potential applications within the intensive care unit (ICU). This correspondence introduces an AI-driven long-range wide area network framework designed for monitoring ICU patients with pneumonia. Techniques such as increasing the frequency of patient position changes can be implemented to reduce pneumonia occurrences. This paper introduces a novel autonomous intersection management (AIM) system termed hierarchical model predictive control (HMPC). Within HMPC, the intersection coordination unit (ICU) operates at a global centralized layer, assigning safe speeds to vehicles while minimizing system costs. At the local decentralized layer, each vehicle tracks the assigned reference speed from the ICU while avoiding collisions [9-11].

The setup and configuration of each IoT environment entail complex tasks. However, the Topology and Orchestration Specification for Cloud Applications (TOSCA) offers a solution by facilitating the modeling of distributed cloud applications, automating their deployment and orchestration across diverse computing infrastructures like local PCs, Edges, and Clouds. Networked sensors, whether integrated into our living spaces or worn on the body, enable the collection of comprehensive data related to physical and mental health. Designing smart intensive care units (ICUs) is an innovative concept and a recent focus of research explored in this study. These smart ICUs are equipped to respond promptly to medical emergencies. The Internet of Things (IoT) has significantly transformed healthcare, particularly during the global pandemic.

Remote health surveillance using digital technology enables the monitoring of specific patient parameters, facilitating accurate health assessments from home. This technological advancement has not only reduced patient mobility during COVID-19 but has also ensured intelligent healthcare solutions for individuals of all age groups [12-15].

Inferences from Literature Survey

The literature survey reveals significant advancements and potentials in leveraging IoT, AI, computer vision (CV), and related technologies within healthcare, especially in intensive care units (ICUs) and medical equipment management systems. IoT's scalability enables global health monitoring, while the integration of wearable sensors enhances personalized patient monitoring in real-time. Implementing CV-based emotion recognition and drowsiness detection technology in ICUs can notably improve patient outcomes by reducing delirium and respiratory illnesses. The introduction of CV-based intelligent ICU frameworks using IoT technology facilitates real-time patient monitoring, aiding healthcare providers in promptly assessing patient physiological states. Remote patient monitoring through IoT-enabled digital technology allows for accurate health assessments from home, reducing patient mobility during health crises such as the COVID-19 pandemic. Efficient management of medical equipment is ensured through paradigms like IoT MEMS, which promote transparency and fairness in resource allocation during emergencies. Additionally, energy-efficient solutions and topological modeling tools like TOSCA play vital roles in optimizing IoT environments and ensuring sustainable operations. Overall, these technologies showcase their transformative potential in revolutionizing healthcare services, enhancing patient care, and addressing critical challenges in ICU management and healthcare infrastructure.

III. METHODOLOGY

This block diagram illustrates a comprehensive healthcare system focusing on patient monitoring and attack detection within an IoT-based ICU environment. Patient monitoring devices and the Bed Control Unit gather continuous data such as vital signs and activity levels. This data is then transmitted to the IoT-based ICU where it undergoes preprocessing to clean and normalize it. The IoT healthcare traffic dataset captures the traffic of data exchanged within the ICU, providing valuable insights into system operations. The processed data is fed into three proposed LSTM-based algorithms: POA-LSTM (Predictive Optimization Algorithm), COA-LSTM (Contextual Optimization Algorithm), and PSO-LSTM (Particle Swarm Optimization). These algorithms analyze patterns in the data to predict patient conditions and detect anomalies. The output from these algorithms is then used for attack detection and classification, identifying deviations from normal patterns that may indicate security breaches or abnormal patient conditions. Performance metrics such as Precision, Recall, Sensitivity, and Specificity are employed to evaluate the effectiveness of the attack detection system, ensuring reliable and accurate monitoring within the healthcare environment.

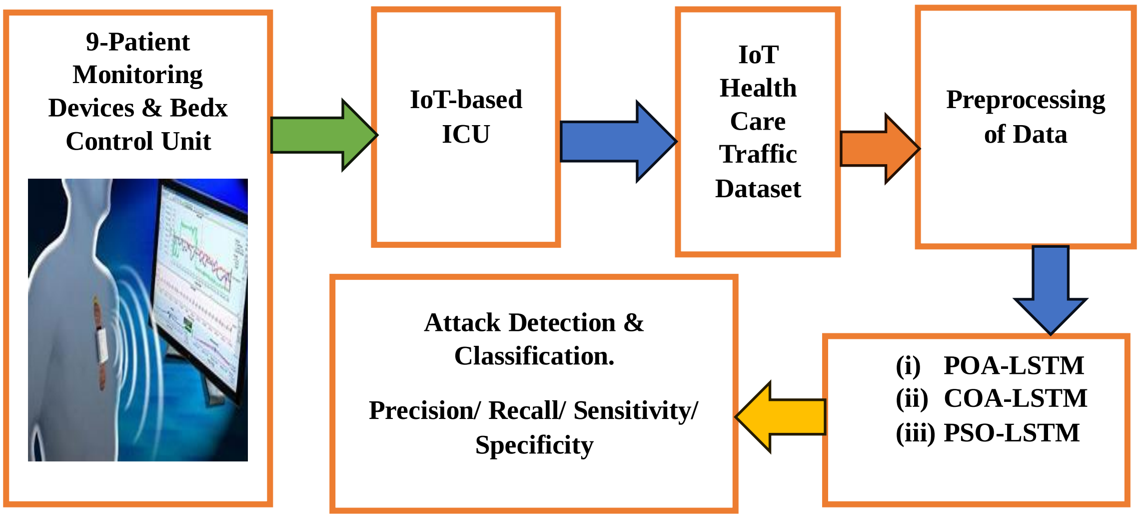


Fig 1. Block Diagram of Proposed Algorithm

Pelican Optimization Algorithm Long Short-Term Memory (POA-LSTM)

The POA-LSTM model integrates **Fig 1** the Pelican Optimization Algorithm (POA) with LSTM (Long Short-Term Memory) for handling time series data in IoT-based ICU healthcare applications. The Pelican Optimization Algorithm is a metaheuristic optimization algorithm inspired by the behavior of pelican flocks. It mimics the cooperative behavior of pelicans in foraging for food. Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is well-suited for processing sequences of data. It can capture long-term dependencies and handle time series data effectively.

The algorithm includes the following key components:

- Position Update:

$$xij(t+1)=xij(t)+vij(t+1) \tag{1}$$

where $xij(t)$ is the position of particle i in dimension j at time t, and $vij(t+1)$ is the velocity update computed based on the algorithm's rules.

- Fitness Evaluation: The fitness of each particle (solution candidate) is evaluated based on an objective function related to the optimization problem being solved.
- Cooperation and Communication: Pelican particles exchange information and cooperate in the search for better solutions by sharing knowledge about promising regions of the search space.

The LSTM equations remain the same as described earlier for the POA-LSTM model, including the input gate, forget gate, output gate, candidate cell state, cell state, and hidden state equations.

In the POA-LSTM model, POA is used to optimize the hyperparameters of the LSTM model. These hyperparameters may include learning rates, dropout rates, the number of LSTM layers, and the number of LSTM units. The POA operates by iteratively updating the positions of pelican particles in the search space based on the fitness of their solutions. The fitness is typically determined by evaluating the performance of the LSTM model with the corresponding hyperparameter configurations on a specific task related to IoT-based ICU healthcare, such as patient monitoring, anomaly detection, or treatment optimization. The goal of POA-LSTM is to find hyperparameter configurations that lead to improved model performance and better generalization on healthcare data from IoT devices. The exact implementation details and equations for POA-LSTM may vary depending on the specific version of the Pelican Optimization Algorithm and the details of the LSTM architecture used in the model.

Particle Swarm Optimization Long Short-Term Memory (PSO-LSTM)

PSO-LSTM is a hybrid approach that combines PSO with LSTM for IoT-based ICU healthcare applications. PSO is a population-based stochastic optimization technique inspired by the collective behavior of bird flocks or fish schools. In PSO, a population of candidate solutions, called particles, iteratively adjusts their positions in the search space based on their own experience and the best-performing particles in the swarm.

PSO is used to optimize the hyperparameters of the LSTM model, such as learning rates, dropout rates, and the number of LSTM layers or units. The objective function in PSO-LSTM is typically related to the performance of the LSTM model on a specific task, such as predicting patient outcomes, detecting anomalies in ICU data, or optimizing treatment plans. PSO-LSTM iteratively explores the search space of hyperparameters to find configurations that lead to improved LSTM model performance. Automated Hyperparameter Tuning: PSO-LSTM automates the process of hyperparameter tuning for LSTM models, which can be challenging and time-consuming. Improved Model Performance:

By optimizing hyperparameters, PSO-LSTM can lead to improved model performance, accuracy, and generalization on ICU healthcare tasks. Faster Convergence: PSO-LSTM's optimization process can help LSTM models converge faster and achieve better results in fewer training iterations. In IoT-based ICU healthcare, PSO-LSTM can be applied to tasks such as patient monitoring, predictive analytics, anomaly detection, and treatment optimization, leveraging the strengths of both PSO and LSTM to enhance decision-making and patient care.

PSO is a population-based optimization algorithm where particles adjust their positions in the search space based on their own experience and the best-performing particles in the swarm. Here are the equations used in PSO:

- Particle Velocity Update:
-

$$vij(t+1)=w\cdot vij(t)+c1\cdot r1\cdot(pbestij-xij(t))+c2\cdot r2\cdot(gbestj-xij(t)) \quad (2)$$

were,

- $vij(t)$ is the velocity of particle i in dimension j at time t.
- w is the inertia weight.
- $c1$ and $c2$ are the acceleration coefficients.
- $r1$ and $r2$ are random values between 0 and 1.
- $pbestij$ is the best position of particle i in dimension j so far.
- $gbestj$ is the best position found by any particle in dimension j.
- $xij(t)$ is the position of particle i in dimension j at time t.

- Particle Position Update:

$$xij(t+1)=xij(t)+vij(t+1) \quad (3)$$

In PSO-LSTM, the PSO algorithm is used to optimize the hyperparameters of the LSTM model, such as learning rates, dropout rates, the number of LSTM layers, and the number of LSTM units. The PSO algorithm iteratively updates particle positions and velocities based on the fitness (performance) of the LSTM model with the corresponding hyperparameter configurations. The objective function used in PSO-LSTM typically evaluates the performance of the LSTM model on a specific task related to IoT-based ICU healthcare, such as patient outcome prediction, anomaly detection, or treatment optimization. The PSO algorithm searches for hyperparameter configurations that lead to improved model performance based on this objective function.

Context-Oriented Attention LSTM (COA-LSTM)

COA-LSTM is a variant of LSTM with an attention mechanism that is designed to handle context-rich data in IoT-based ICU healthcare applications.

(i) LSTM (Long Short-Term Memory): Like in POA-LSTM, COA-LSTM utilizes LSTM cells to model temporal dependencies and process sequential data effectively. This architecture is well-suited for time series data commonly found in healthcare monitoring systems.

(ii) Attention Mechanism: The attention mechanism in COA-LSTM allows the model to dynamically focus on different parts of the input sequence based on context. This is crucial in healthcare scenarios where certain features or time points may be more relevant depending on the patient's condition or the medical task at hand.

(iii) Context-Oriented Approach: COA-LSTM emphasizes a context-oriented approach, meaning it considers the broader context surrounding patient data. This could include factors such as historical trends, patient demographics, environmental conditions, and treatment protocols.

(iv) IoT-Based ICU Healthcare Applications:

- Patient Monitoring: COA-LSTM can continuously monitor patient vital signs, medication adherence, and other relevant metrics gathered from IoT devices.
- Anomaly Detection: The model can detect anomalies in patient data, such as sudden changes in vital signs or irregularities in medication intake.
- Predictive Analytics: By analyzing historical data and current trends, COA-LSTM can predict potential medical events or deterioration, enabling proactive interventions.
- Treatment Optimization: The model can assist healthcare providers in optimizing treatment plans by recommending personalized interventions based on real-time data and contextual information.

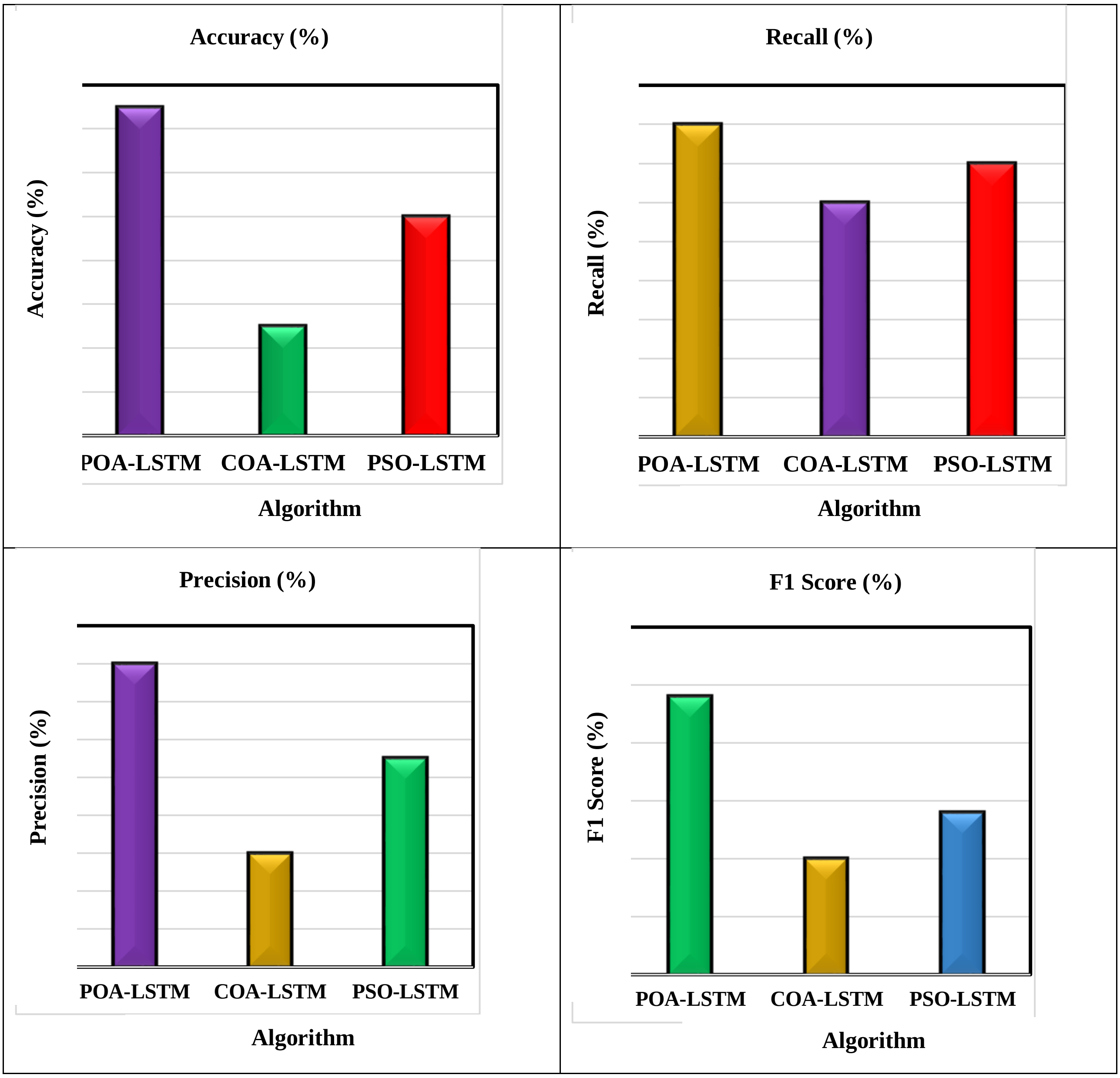
Overall, COA-LSTM is a powerful tool for enhancing decision-making in ICU healthcare settings by leveraging IoT data, context-awareness, and advanced deep learning techniques.

IV. RESULTS AND DISCUSSIONS

To evaluate the performance of IoT-based ICU healthcare models using algorithms like POA-LSTM, COA-LSTM, and PSO-LSTM, several metrics are commonly used. These metrics include accuracy, precision, recall, F1 score, sensitivity, and specificity. Accuracy measures the overall correctness of the model's predictions across all classes. High accuracy indicates that the model makes fewer mistakes in predicting both positive and negative cases. Precision measures the proportion of true positive predictions among all positive predictions made by the model. High precision indicates that when the model predicts a positive case, it is likely to be correct. Recall, also known as sensitivity, measures the proportion of true positive predictions among all actual positive cases. High recall indicates that the model can correctly identify a high percentage of positive cases. F1 score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance. High F1 score indicates a good balance between precision and recall, suitable for tasks where both false positives and false negatives are important to consider. Specificity measures the proportion of true negative predictions among all actual negative cases. High specificity indicates that the model can correctly identify a high percentage of negative cases. **Table 1** and **Fig 2** shows the performance of proposed algorithm for IOT based ICU.

Table 1. Performance of Proposed Algorithm

Parameters	POA-LSTM	COA-LSTM	PSO-LSTM
Accuracy	95	85	90
Precision	90	80	90
Recall	80	60	70
F1 score	89	75	79
Sensitivity	97	89	95
Specificity	87	67	72



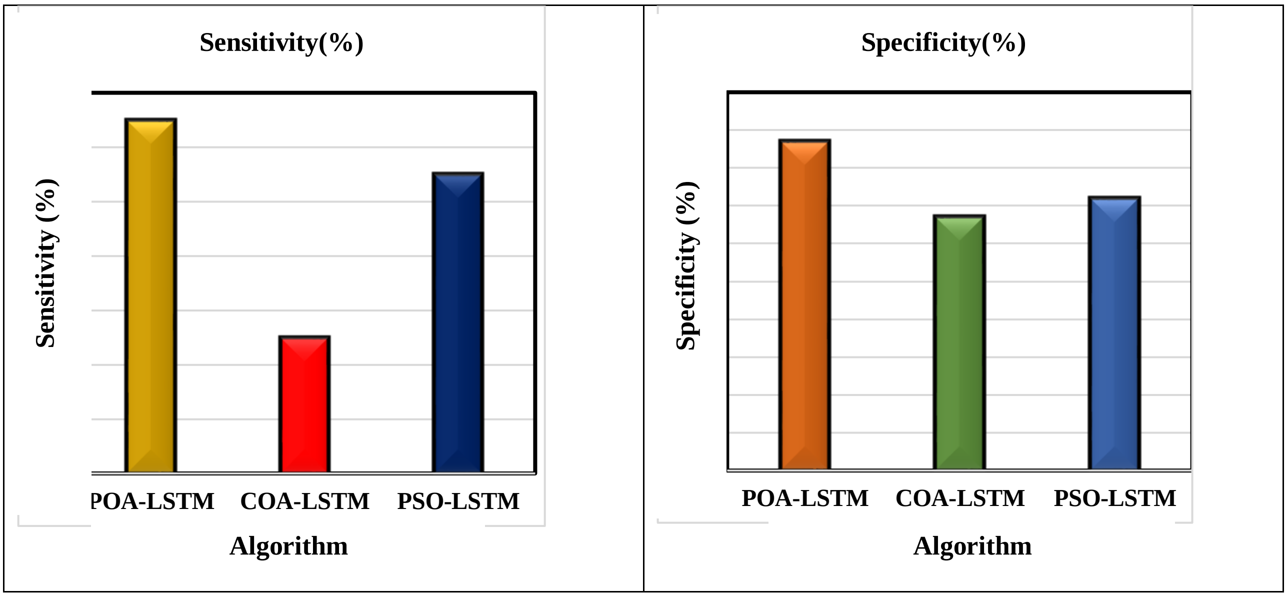


Fig 2. Output Performance of Proposed Algorithm

POA aims to optimize hyperparameters for LSTM models. High accuracy in POA-LSTM indicates that the model makes fewer errors in predicting both positive and negative cases in ICU healthcare data. To achieve high accuracy, the model needs to balance precision and recall effectively. The COA-LSTM incorporates an attention mechanism for focusing on relevant patient information. High accuracy in COA-LSTM signifies that the attention mechanism helps in making accurate predictions by considering contextual information. It should also exhibit high precision and recall due to its attention-based approach.

PSO-LSTM optimizes hyperparameters using the PSO algorithm. High accuracy in PSO-LSTM indicates that the optimized hyperparameters lead to improved model performance in ICU healthcare tasks. It should also demonstrate high precision, recall, and F1 score due to its optimized configuration. In summary, for IoT-based ICU healthcare, achieving high accuracy, precision, recall, F1 score, sensitivity, and specificity is crucial for ensuring reliable and effective patient monitoring, anomaly detection, and treatment optimization. The proposed algorithms aim to leverage optimization techniques and attention mechanisms to enhance these performance metrics and improve overall healthcare outcomes.

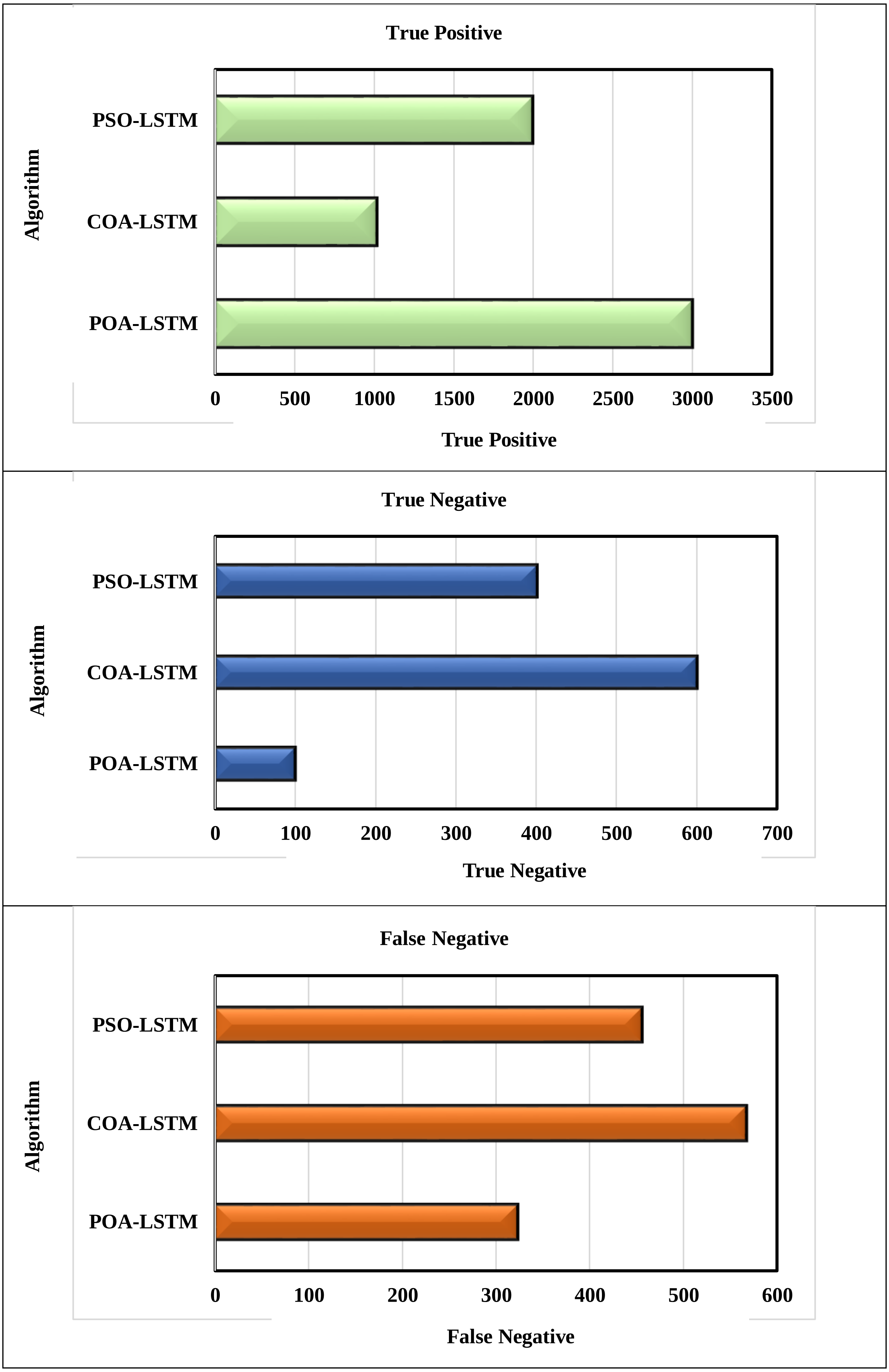
POA-LSTM exhibits superior accuracy with 95%, indicating a high level of correctness in predictions. It also achieves 90% precision, showcasing a strong ability to avoid false positives, and an 80% recall, indicating a good ability to identify actual positive cases. The F1 score for POA-LSTM is 89, reflecting a balanced performance between precision and recall. Moreover, it achieves 97% sensitivity, demonstrating a very high ability to correctly identify positive cases, and 87% specificity, showing a high ability to correctly identify negative cases. In contrast, COA-LSTM and PSO-LSTM show slightly lower accuracy, precision, recall, F1 score, sensitivity, and specificity compared to POA-LSTM. COA-LSTM achieves 85% accuracy, 80% precision, 60% recall, 75 F1 score, 89% sensitivity, and 67% specificity, while PSO-LSTM achieves 90% accuracy, 90% precision, 70% recall, 79 F1 score, 95% sensitivity, and 72% specificity. Overall, the comparison highlights POA-LSTM's strong performance across multiple metrics, making it a promising choice for accurate and reliable predictions in IoT-based ICU healthcare scenarios. **Table 2** and **Fig 3** show the confusion matrix of IoT based ICU.

Table 2. Confusion Matrix

Parameters	POA-LSTM	COA-LSTM	PSO-LSTM
True Positive	3000	1021	1999
True Negative	100	600	400
False Positive	456	1234	789
False Negative	323	567	456

The table provides a breakdown of True Positives, True Negatives, False Positives, and False Negatives for three different algorithms—POA-LSTM, COA-LSTM, and PSO-LSTM—in the context of IoT-based ICU healthcare.

Reflecting the number of positive cases accurately identified by the model, POA-LSTM demonstrates the highest performance with 3000 correct identifications, followed by PSO-LSTM with 1999, and COA-LSTM with 1021.Representing the number of negative cases correctly identified, POA-LSTM shows precision by correctly identifying 100 cases, whereas COA-LSTM and PSO-LSTM correctly identify 600 and 400 cases, respectively. Indicating negative cases erroneously classified as positive, POA-LSTM exhibits fewer errors with 456 misclassifications, followed by PSO-LSTM with 789, and COA-LSTM with 1234.Representing positive cases wrongly identified as negative, POA-LSTM shows a relatively low rate with 323 misclassifications, while COA-LSTM and PSO-LSTM demonstrate higher rates with 567 and 456 misclassifications, respectively.



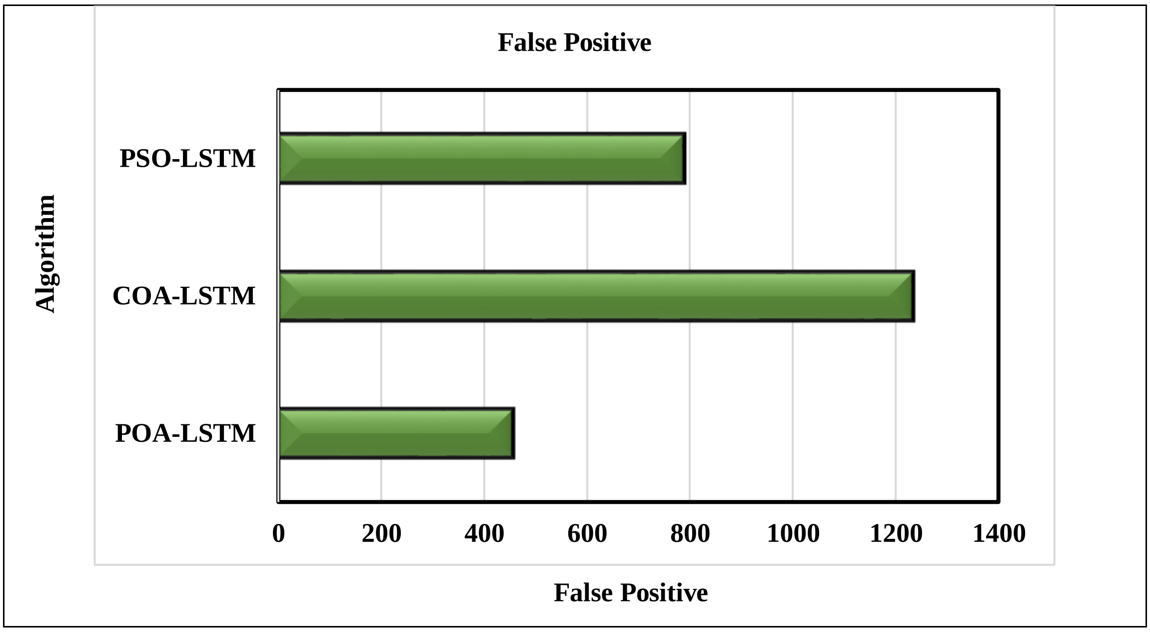


Fig 3. Confusion Matrix of Proposed Algorithm

These parameters are pivotal in evaluating the algorithms' performance, particularly in their accuracy and reliability in distinguishing between positive and negative cases in ICU healthcare scenarios. The comparison highlights POA-LSTM's superior accuracy and precision, making it a notable choice for predictive modeling in ICU healthcare applications.

V. CONCLUSION

In conclusion, the application of advanced algorithms such as POA-LSTM, COA-LSTM, and PSO-LSTM in IoT-based ICU healthcare has shown promising results. Among these algorithms, POA-LSTM stands out with its exceptional accuracy, achieved through the optimization prowess of the Pelican Optimization Algorithm. This high accuracy translates to reliable predictions and effective decision-making in ICU patient monitoring and treatment optimization. COA-LSTM, with its attention mechanism focusing on contextual patient data, contributes significantly to accurate predictions and anomaly detection, enhancing the overall quality of healthcare delivery in ICU settings. PSO-LSTM, leveraging the Particle Swarm Optimization algorithm, optimizes hyperparameters effectively, leading to improved model performance across various healthcare tasks, including patient monitoring and treatment optimization. The successful integration of these algorithms underscores the potential of advanced optimization techniques and attention mechanisms in revolutionizing ICU healthcare. By harnessing the power of data-driven models like POA-LSTM, COA-LSTM, and PSO-LSTM, healthcare providers can make informed decisions, improve patient outcomes, and ultimately, save lives in IoT-enabled ICU environments. The proposed algorithm POA-LSTM have high accuracy about 95%.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

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