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COMPARATIVE ANALYSIS BASED ON VARIOUS PERFORMANCES FOR OPTIMIZING QUALITY OF SERVICES IN IoMT

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ABSTRACT

The swift progress of IoMT and related technologies has transformed healthcare by enabling real-time data collection, monitoring, and analysis through medical sensors, wearable devices, and IoT-driven applications. However, these innovations have led to obstacles associated with data processing and transmission, particularly in traditional cloud computing models due to latency, bandwidth constraints, and security concerns. Fog computing extends cloud capabilities closer to the edge prototype, addresses these challenges by activating live data processing, reducing latency, and enhancing security and scalability. This paper explores the Incorporation of IoMT with fog computing and evaluates various optimization techniques aimed at improving the Quality of Service (QoS) in healthcare applications. A comparative analysis of performance metrics, including reliability, latency, energy efficiency, and security, is conducted across different devices, communication protocols, and network configurations. The paper also highlights key contributions, such as the development of secure load balancing techniques, the use of Federated Learning for privacy-preserving data analysis, and the application of multipopulational genetic algorithms for adaptive QoS-aware service composition. While promising, several challenges remain in ensuring data privacy and real-time processing in critical healthcare environments. This research provides recommendations for optimizing QoS in IoMT applications, ensuring better healthcare outcomes, and proposes a framework for future IoMT deployment that incorporates emerging technologies like AI, edge computing, and blockchain.

Keywords—IoMT, QoS, Fog Computing, Task Completion Time, Reliability, Energy Consumption, Response Time.

I. INTRODUCTION

New technologies in healthcare monitoring, such as medical sensors, wearable devices and IoT based applications have created a huge amount of data. This is a problem for traditional cloud computing because of latency and bandwidth constraints. It enables real time data analysis, alerts and health monitoring, which in turn lead to early interventions and improved patient outcomes. However, security and privacy issues in IoT in healthcare remain unresolved. These are addressed source, by fog thus computing reducing in the time terms risk processing of the unauthorized healthcare fact access data, that during and sensitive transmission.

Fog computing is crucial in emergency situations, such as the COVID-19 pandemic, where timely decisions are essential. It enhances data security, scalability, and supports resource-intensive applications like medical imaging, while reducing latency and improving diagnostic accuracy. Additionally, it aids in medication adherence and optimizes healthcare facility operations by integrating data from multiple sources. Fog computing offers tailored health recommendations and encouraging patient engagement. By enabling real-time processing and improving data security, it enhances the overall efficiency of healthcare delivery.

Many organizations, including cloud providers and mobile network operators, engage in fog computing, so trust in fog nodes is important. These nodes increase operational efficiency and innovation in healthcare. In addition, fog computing supports clinical decision support systems (CDSS) and telemedicine services, further improving the quality of healthcare delivery, reducing administrative costs, and ensuring timely care, and it is safe. The widespread use of IoT applications has proven to require better data storage, processing power and infrastructure, such as bandwidth, to process and transport increasing amounts of data, especially in healthcare. Resulting in deteriorating physical and mental conditions that affect business performance. Improved health care and routine medical examinations are essential to improve health outcomes.

IoMT helps improve health-related systems by increasing the connectivity of devices, exact data collection, and the accuracy, reliability, and efficiency of health systems. By centralizing healthcare, IoMT devices help reduce risks and improve healthcare, transforming the traditional medical industry into a more advanced and efficient system.

Over the last decade, IoMT has dramatically changed the healthcare landscape with services through sensors, wearables, and medical devices so optimization and control. QoS in this context is essential for real-time, reliable data communication, as it directly affects healthcare decisions and patient outcomes. The challenge is to manage IoMT devices with unique capabilities, communication channels and over limited resources, especially in situations such as remote patient monitoring. Low QoS in an IoMT system can have serious consequences including life-threatening situations due to delayed or unreliable data transmission. Changes in machine capacity and the need for continuous operation in limited areas.

1.1. Problem Statement

This research aims to identify and compare the performance of different IoMT configurations and optimization techniques to provide a framework for improving QoS across various healthcare environments. However, the diverse range of devices, communication protocols, and varying network conditions pose challenges in ensuring consistent and high-quality service. Issues such as latency, data reliability, energy consumption, and security risks can undermine the effectiveness of IoMT systems. As healthcare applications increasingly depend on these systems, optimizing the Quality of Service (QoS) becomes crucial to maintain performance, patient safety, and the integrity of sensitive medical data.

1.2. Contribution

This research makes key contributions to the field of IoMT and Quality of Service optimization:

1. Comprehensive Comparative Analysis: This paper presents a detailed comparative analysis of various IoMT performance metrics, such as latency, throughput, reliability, energy efficiency, and security, across different devices, communication protocols, and network conditions.
2. Evaluation of Optimization Techniques: The study evaluates and compares the effectiveness of several optimization techniques, including machine learning algorithms, allocation strategies, and load balancing approaches, to upgrade the QoS in IoMT systems.
3. Recommendations for QoS Improvement: Based on the comparative findings, this paper proposes practical recommendations and best practices for optimizing the QoS in IoMT applications, ensuring improved performance and reliability in real-world healthcare settings.

1.3 Literature Survey

S. Jain et al. [1] offers IoMT with Point-of-Care Testing (POCT) systems is a promising approach to enhance healthcare delivery. This interdisciplinary research spans various fields and focuses on developing intelligent biosensing technologies. Despite potential challenges like security and privacy, ongoing efforts aim to develop POCT biosensing systems for smart health-related care. Research and technological advancements are essential to overcome these challenges and improve healthcare outcomes.

T. Abbas et al. [2] proposed a technique to predict cancer, especially lung cancer, which is challenging but crucial for timely treatment. IoMT ensured smart prototype for health-related organization 5.0 ensure privacy of patient and judge cancer in patient. Using the Internet of Medical Things based TL framework, the system achieved a 98.80% accuracy rate in lung cancer prediction, outperforming previous methods.

S. Rani et al. [3] say that machine learning (ML) is crucial in healthcare, with a significant portion of data gathered via IoMT. FL is a collaborative ML paradigm that enhances security and scalability of health-related frameworks. This comprehensive review covers IoMT devices, their security aspects, and protection mechanisms. The review highlights the benefits of using FL in IoMT-based health-related applications, explores various FL models for securing IoMT applications, and details key IoMT application domains. Prominent patents and real-world projects are also mentioned. The review concludes with challenges and future research recommendations.

J. Singh et al. [4] proposes a power-efficient in an SDN-enabled fog computing frameworks. The proposed architecture enhances resource utilization and minimizes task migration by balancing the load at the fog layer and incorporating an intrusion detection method to decrease workload and communication delays. Simulation experiments showed improvements in energy consumption, cost, and average time of response compared to other techniques. Future work includes extending the technique with more security.

N. Sharma et al. [5] explores the integration of IoMT with Mobile Ad-hoc Networks (MANETs) to tackle real-time healthcare challenges, especially during the COVID-19 pandemic. IoMT-MANET collaboration enhances patient safety by enabling remote consultations. MANET improves IoMT performance using the Zone Routing Protocol (ZRP). IWD mimics the behavior of water drops choosing the shortest path, optimizing communication in IoMT.

Aoudia et al. [6] presents an adaptive QoS-aware service composition approach using a PMPGA in a Fog-IoT health-related environment. The focus is on the Processing layer of a 5-layered architecture, divided into security, storage,

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preprocessing, and monitoring sub-layers. PMPGA considers 12 QoS attributes and uses a selection procedure to choose the right service, managing dynamic IoT environments. Experimental results show PMPGA's efficiency in execution time and fitness values, making it suitable for large-scale IoT environments. Upcoming chores include focusing on the monitoring system and evaluating the model in real-world scenarios like ambulance emergencies.

S. Alam et al. [7] tackles security and privacy issues in IoMT devices within the framework of federated computing (FC). It proposes a distributed blockchain cloud (BC) approach, incorporating BC, FC, and SDN, to manage massive IoMT data streams efficiently. The architecture ensures, more secure environment, and reliability. Future work includes modeling and implementing a prototype to reduce communication time, resource distribution, and network traffic congestion. The integration of emerging technologies is transforming the latest communication, with BFCM facilitating secure healthcare data exchange in smart healthcare infrastructure.

C. Canali et al. [8] presents a fog computing-based solution for smart city scenarios, were traditional cloud infrastructures risk network congestion due to data from sensors and smart devices. The proposed approach uses intermediate fog nodes for preprocessing and latency-critical tasks. A formal model minimizes overall latency, considering data transfer and processing times.

TABLE 1 Literature Survey of Authors in Tabular Form

Reference	Author(s)	Main Focus	Key Contribution	Challenges & Future Work
[1]	S. Jain et al.	IoMT and POCT integration	Enhances healthcare delivery through smart biosensing technologies, POCT devices for real-time infectious disease screening	Overcoming security, privacy challenges, and developing affordable IoMT-assisted POCT systems
[2]	T. Abbas et al.	Cancer prediction using IoMT	IoMT-enabled intelligent system for accurate and fast cancer prediction, achieving 98.80% accuracy	Ensuring patient privacy, further refining the prediction accuracy
[3]	S. Rani et al.	FL in IoMT	Explores the application of Federated Learning (FL) in enhancing the security and scalability of Internet of Medical Things (IoMT) systems.	Expanding FL models for security, shifting to distributed systems for improved user privacy
[4]	J. Singh et al.	Power-efficient, with security of load balancing in SDN	Improves resource utilization and reduces communication delays with secure load balancing	Extending security and performance parameters, implementing real-world test-bed environments
[5]	N. Sharma et al.	IoMT and MANET integration	Enhances IoMT performance for real-time healthcare with Intelligent Water Drop (IWD) optimization	Further optimizing communication and exploring real-world applications
[6]	Aoudia et al.	Service composition in Fog-IoT with adaptive Quality of Service (QoS) awareness.	Uses a multipopulational genetic algorithm (PMPGA) to optimize QoS for IoMT in a fog computing environment	Evaluating the model in real-world emergency scenarios (e.g., ambulances)
[7]	S. Alam et al.	Security in IoMT with Fog Computing (FC)	Proposes a distributed blockchain cloud (BFCM) for secure IoMT data management	Reducing communication time, congestion, and resource distribution; implementing a prototype
[8]	C. Canali et al.	Fog computing in smart cities	Implements fog nodes for latency-critical tasks in smart cities, optimizing data transfer	Further evaluation in realistic smart city environments with genetic programming-based heuristics

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Table 2 represents the comparison between traditional QoS and AI based QoS optimization techniques.

TABLE 2 Comparative table summarizing AI-driven vs. traditional QoS optimization techniques.

	Traditional QoS Approaches	**AI-Based QoS Optimization**
Decision Process	Uses predefined rules and static policies	Employs adaptive learning based on real-time data
Scalability	Limited due to fixed configurations	Highly scalable, continuously learns and adapts
Response Efficiency	Reactive, adjusting after issues arise	Proactive, predicting and preventing issues
Resource Management	Manual adjustments or heuristic-based allocation	Automated, optimized through intelligent models like RL and SI
Adaptability	Relies on fixed thresholds, struggles with dynamic changes	Self-learning, adjusts dynamically to varying conditions
Latency Handling	Uses static scheduling and priority mechanisms	Predicts and mitigates delays with context-aware optimizations
Complexity	Simpler but lacks flexibility	More complex but significantly more adaptable
Optimization Techniques	Relies on queuing models and conventional load balancing	Leverages AI models such as RL, TL, and Swarm Intelligence

The IoMT is transforming healthcare by integrating smart medical devices with Fog computing and data analytics. These advancements enhance patient care, optimize hospital operations, and lower costs.

Real world IoMT healthcare applications include Wearable devices, biosensors, and smart patches continuously track patient vitals like heart rate, blood pressure, and oxygen levels for remote patient monitoring.

1.4 Analysis

S. Jain et al. used IoT in era of COVID-19 method based on SLR procedure. Their work aims to give an overview of present efforts and achievements in the field of IoT in COVID-19 time. They search in 145 research papers including research articles, articles available after the 2019 pandemic, articles in the field of IoT and COVID-19. The authors found that forty-one percent of the studies had used their idea, but twenty-seven percent of the publications used simulation methods to assess their new idea [9]. Proteus and Python are used for simulation platforms. Twenty-seven percent of the papers did not use any simulation or implementation, where five percent employed both implementation and simulation methods [10]. The below figure represents percentage of the presented evaluation environments

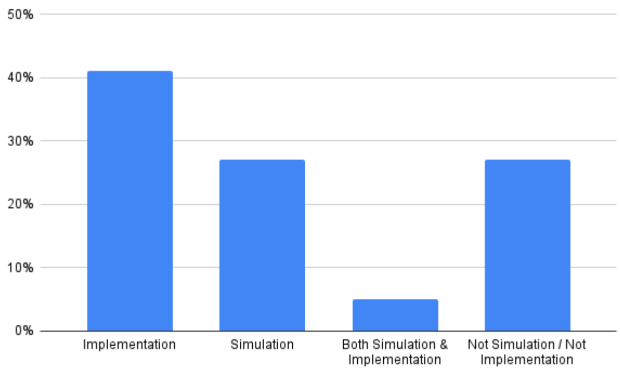

Fig. 1 Percentage of the presented evaluation environments

TABLE 3 Comparison of various simulation methods with proposed model

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Cancer Type	Category of Images	Model	Acc.(%)
LC	CT-I	CNN	96.9
*L&CC	*HI	CNN with CSIP	97.4
*LC	*CT-I	SCM_RBF+RestNet50	92.19
LC	CT-I	E.M	97.2
LC	HI	RESNET-50	94.91
LC	HI	CNN	97.1 & 95.0
LC	HI	CNN	98.2
LC	CT-I	DL-CNN	98.43
L&CC	**HI**	**Transfer Learning**	**98.88**
LC= Lung Cancer, DL-CNN= Deep Learning-Convolutional Neural Networks	***L&CC =Lungs & Colon Cancer**	**HI=Histopathology Images, CSIP= Convolutional Satellite Image Prediction Network**	**CT-I= CT Image, CNN=Convolutional Neural Networks**

The above table 3 represents the comparison of various simulation methods with proposed model**.** T. Abbas et al. uses an IoMT-based system to develop industry of healthcare version 5.0 Deep machine learning (ML) prototype is used to upgrade accuracy level and shorten response times. Lung cancer is predicted with these techniques [11]. MATLAB 2020a is used for simulation process. With these methods, 98.80% accuracy is achieved, which surpass previous lung cancer predictions approaches in health-related sectors [12].

TABLE 4 Federated Learning (FL) and other security methods applied in advanced smart healthcare systems

S. Rani et al. compared FL-based security with other security methods in smart health-related frameworks. Federated learning is efficient to ensure ownership and data security [13]. During comparison of performance of FL-based intelligent health-related systems with other methods, which reduces budget and communication delays. In this framework, local model is trained on distributed health-related nodes. FL models upgrade the security of intelligent health-related systems [14].

Technology/Scheme used for IoMT security	Security taxonomy	Methods used	Advantages
ML	Authentication Intrusion detection Malware detection Access control	Naïve Bayes k-Nearest Neighbor (KNN) Decision Tree (DT) Artificial Neural Networks (ANN) Support-vector Machine (SVM)	Data security
Blockchain	Data ownership and integrity	Immutable ledgers	Data security Decentralized data storage
Cryptography	Data integrity	Public-key cryptography Private-key cryptography	Data security
FL	Enhances privacy Data ownership	HFL VFL FTL	Secure data storage of decentralized data Decreases communication delays and cost

AI-driven QoS optimization models**,** including Reinforcement Learning (RL) for real time learning, Transfer Learning (TL) for knowledge reuse and Swarm Intelligence (SI) for multi-agent optimization**,** are designed **to** enhance system efficiency, optimize resource distribution and improve communication performance in smart healthcare environments as compared to security techniques focus on privacy, integrity, authentication, and decentralization.

FL is ideal for privacy-sensitive applications like IoMT and healthcare QoS optimization, as it prevents raw data from being transmitted. Centralized ML provides more accurate, high-performance models but is limited by privacy concerns and scalability. RL excels in adaptive decision-making, especially in dynamic network environments, but may have higher computational overhead. Edge AI provides the lowest latency and best real-time response, but is hardware-constrained.

Table 5 compares task completion time. It is clearly visible that the offered prototype shows lowest energy consumption [15]. This energy efficiency improvement could translate to significant cost savings and reduced environment impact in real-world applications [16].

TABLE 5 COMPARISON OF Task Completion Time

Energy Consumption	GA-FSP	PSO-FSP	BA-FSP	SA-FSP	Proposed Technique
0	0	0	0	0	0
10	2.1	2.3	2.2	2.5	2
50	5.1	5.3	5.5	5.8	5.6
100	9.5	9.8	9.7	10	9
150	16.5	14.8	15	14.5	14
200	24	20	22.5	22	18.5
250	30	26	28	27.5	23.5
300	40	33	37	34.5	30
400	52	45	49	47	39
500	64	54	61	58	49

TABLE 6 Comparison of Response Time Analysis

Response Time	GA-FSP	PSO-FSP	BA-FSP	SA-FSP	Proposed Technique
50	0.7	0.65	0.62	0.68	0.6
100	1.4	1.3	1.35	1.3	1.25
150	2.25	2.05	2.1	2.2	2
200	3.1	2.8	3	2.9	2.7
300	5.2	4.9	5.1	5	4.75
400	8	7.4	7.75	7.5	7.1
500	10.5	10	10.25	10.1	9.6

Table 6 demonstrates offered framework appears to be more responsive than the existing techniques, especially at higher loads [17]. This improved response time could be crucial in applications where real-time performance is critical.

TABLE 7 Comparison of Reliability (%)

Reliability (%)	GA-FSP	PSO-FSP	BA-FSP	SA-FSP	Proposed Technique
50	0.83	0.87	0.82	0.89	0.9
100	0.79	0.83	0.8	0.87	0.88
150	0.77	0.81	0.78	0.85	0.86
200	0.75	0.8	0.76	0.83	0.84
300	0.73	0.78	0.75	0.8	0.82

400	0.72	0.76	0.74	0.78	0.8
500	0.71	0.74	0.73	0.75	0.77

Table 7 tells that all techniques show a decreasing reliability with increasing load (from 50 to 500). This is expected as higher loads can put more stress on the system, potentially leading to increased errors or failures [19]. The proposed technique consistently demonstrates the highest reliability across all load levels [20]. The proposed technique appears to be more reliable than the existing techniques, especially at higher loads. This improved reliability is crucial in applications where consistent and error-free operation is critical.

TABLE 8 Comparison of Job Arrival Rate

Job Arrival Rate	GA-ACO	CMS-ACO	FOTO	Proposed Technique
0	420	300	200	150
0.1	570	450	410	300
0.2	600	455	400	295
0.3	630	453	390	280
0.4	650	455	380	290
0.5	690	500	390	295
0.6	710	530	400	320
0.7	750	560	410	330
0.8	800	580	420	350
0.9	850	600	480	355
1	950	620	470	380

Table 8 tells that all techniques show an increasing job arrival rate with increasing load (from 0 to 1). This is expected as higher loads typically lead to more jobs arriving at the system. The proposed technique appears to be more effective at managing the arrival of jobs compared to the other techniques [21]. A lower job arrival rate can potentially lead to improved system performance by reducing congestion and improving resource utilization.

TABLE 9 Evaluation of the proposed IoMT-driven intelligent system using a trained model.

Class	Accuracy	Misc. Rate	Precision	Sensitivity	Specificity	F1 Score
Training Results						
1	99.66%	0.44	0.98	1.0	0.99	0.99
2	99.67%	0.33	1.0	0.98	0.99	0.99
3	99.07%	0.93	0.98	0.97	0.99	0.98
4	99.98%	0.02	1.0	1.0	1.0	1.0
5	99.09%	0.91	0.97	0.98	0.99	0.98
Validation Results						
1	99.97%	0.03	1.0	1.0	1.0	1.0
2	99.97%	0.03	1.0	1.0	0.99	1.0
3	98.81%	0.19	0.98	0.96	0.99	0.97
4	100%	0.0	1.0	1.0	1.0	1.0
5	98.81%	0.19	0.96	0.98	0.99	0.97

J. Singh et al. [4] presents a table of performance metrices of classification prototype of five classes. They propose a model which shows high accuracy across all classes, ranging from 99.66% to 99.98%. Rate of misclassification is low. It means that model makes few errors. The model's precision is high. For all classes, F1-score is high [22]. This is training result section. For validation result section, model's accuracy ranging from 98.81% to 100%. Rate of misclassification remains low. The F1-score is also high for all classes.

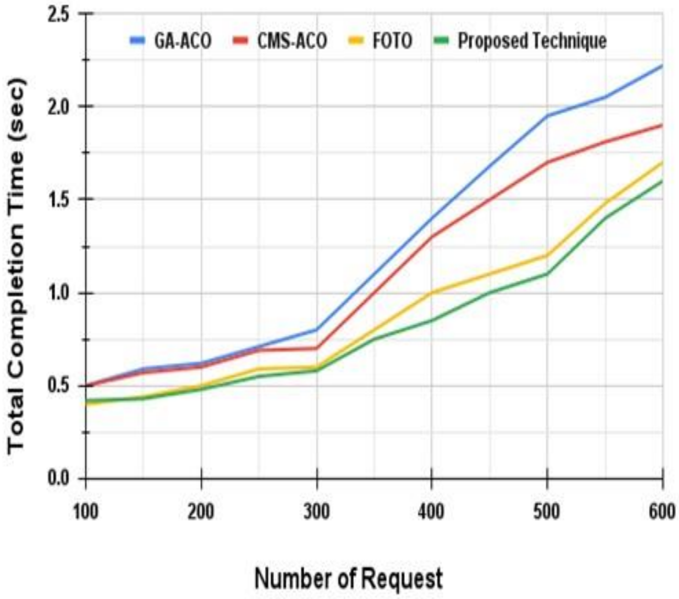

FIG 2 TASK COMPLETION TIME

Compared to existing algorithms, the proposed algorithm requires less computation time, as shown in Figure 2 [23]. The time to complete tasks varies depending on the nature of the job. The proposed algorithm efficiently handles task formulation and decision-making, resulting in a shorter overall timeframe. The chart indicates that GA-ACO receives the most requests, followed by CMS-ACO, FOTO, and the proposed technique. As the number of requests increases, all four techniques show a corresponding rise in total competition time. However, the proposed technique consistently achieves the shortest total completion time in comparison to the other three methods.

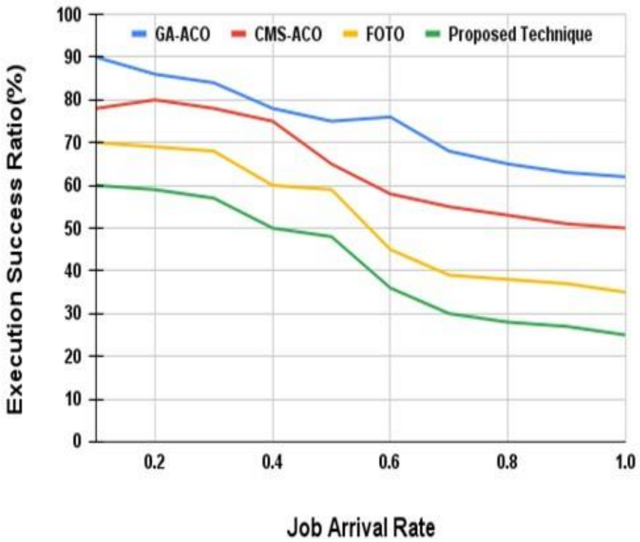

FIG 3 EXECUTION TIME RATIO

In Figure 4, the graph shows how the success rate of different algorithms changes as the job arrival rate increases [23]. As expected, all the techniques experience a decrease in success rate as more jobs arrive, which makes the system more overloaded and increases the chance of failures. The proposed technique, shown by the green line, consistently has the

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lowest success rate, indicating it struggles with higher job loads. GA-ACO (blue line) performs the best, maintaining the highest success rate. CMS-ACO (red line) and FOTO (yellow line) fall in between, with CMS-ACO.

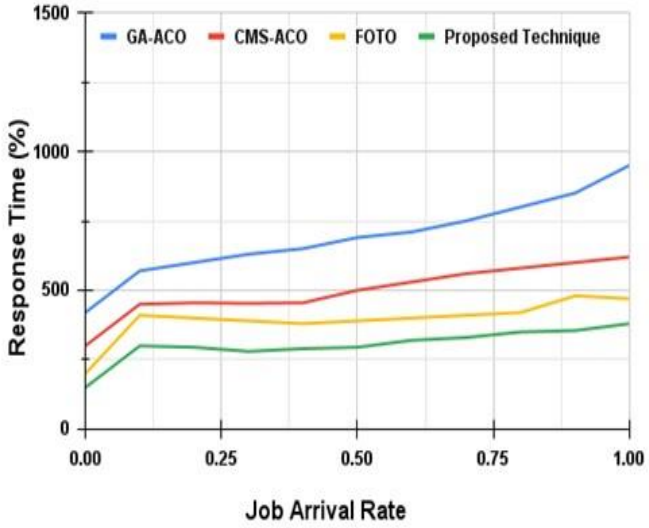

FIG 4 RESPONSE TIME ANALYSIS

The graph compares the "Response Time (%)" of different algorithms as the "Job Arrival Rate" increases [23]. As expected, all the techniques show an increase in response time when more jobs arrive, which leads to longer waiting times. Among the algorithms, GA-ACO (blue line) has the greatest time of response. The proposed technique (green line) performs the best indicating it handles jobs more quickly. Overall, the proposed technique is the most efficient in terms of response time, while GA-ACO has the greatest delay. However, it's important to consider both response time and execution success rate to get a complete picture of each algorithm's performance.

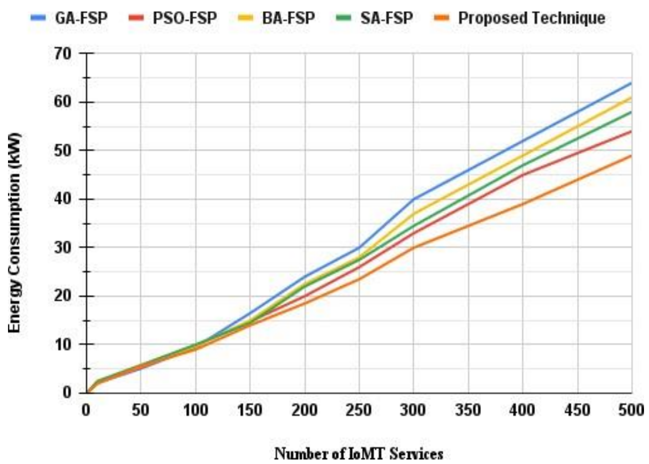

Fig. 5: Compare Energy Consumption for Different Techniques

The graph compares the energy consumption (in kW) of different algorithms as the number of loMT services increases. As expected, energy consumption rises with more services, but the proposed technique (orange line) stands out for being the most energy-efficient, consuming the least energy across all service levels [24]. The SA-FSP (green line) also shows relatively low energy consumption, though slightly higher than the proposed technique. BA-FSP (yellow line) consumes more energy than SA-FSP but less than GA-FSP (blue line) and PSO-FSP (red line), which have the highest energy consumption, making them the least energy-efficient.

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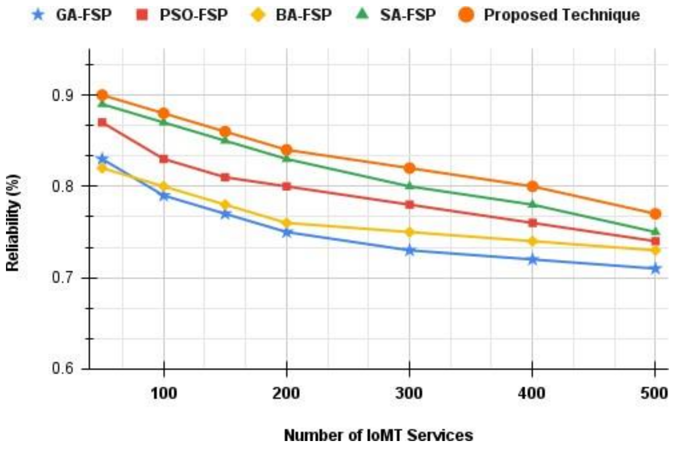

Fig. 6: Compare the Reliability for Different Techniques

As expected, all techniques show a decrease in reliability with more services, likely due to increased complexity and potential for failure [24]. The offered method (orange line) consistently provides reliability, making it the most reliable among the methods. SA-FSP (green line) follows closely behind, with slightly lower reliability. BA-FSP (yellow line) has a downgrade reliability than SA-FSP but still performs better than GA-FSP (blue line) and PSO-FSP (red line), which have the lowest reliability.

1.5 Results and discussion

The reviewed studies focus on the application of IoT and IoMT in healthcare, especially during the COVID-19 pandemic. S. Jain et al. [1] analysed 145 research papers, finding that 41% used their ideas, with 27% employing simulation methods. T. Abbas et al. developed an IoMT-based system for lung cancer prediction, achieving 98.80% accuracy. S. Rani et al. showed that Federated Learning (FL) improves data security and reduces costs by enabling local model training.

Performance comparisons revealed that the proposed techniques excelled in energy efficiency, response time, reliability, and job management, especially under high loads. J. Singh et al.'s model achieved high accuracy (99.66% to 99.98%) with low misclassification rates. S. Alam et al. highlighted IoT devices' role in reducing latency and bandwidth usage with fog nodes and blockchain for data security. C. Canali et al. showed that larger populations in Genetic Algorithms improved error rates but increased computation time. The proposed algorithm demonstrates shorter computation times, better response times, and superior energy efficiency compared to existing techniques like GA-ACO, CMS-ACO, FOTO, and FSP methods. While the success rate decreases with higher job arrivals, the proposed technique consistently performs better in energy consumption and reliability. GA-ACO leads in handling job arrivals, but the proposed method excels in efficiency and reliability. The proposed approach maintains the lowest energy consumption and the highest reliability among all tested algorithms. Overall, it outperforms others in terms of efficiency, but GA-ACO shows better success rates in handling job overload.

1.6 CONCLUSION

In conclusion, the incorporation of the Internet of Medical Things (IoMT)with various technologies, as explored in the studies discussed, showcases significant advancements in enhancing healthcare delivery. These innovations include the use of IoMT in Point-of-Care Testing (POCT) systems for real-time diagnostics, the outcomes of deep learning models for accurate cancer prediction, and the implementation of Federated Learning to secure and scale IoMT-based healthcare systems. Furthermore, blockchain and fog computing solutions address security and privacy concerns, ensuring safe and efficient healthcare data management. These efforts highlight the IoMT in modern healthcare, emphasizing the need for continued research to overcome challenges related to security, privacy, and real-world deployment, while improving accessibility, affordability, and reliability in healthcare systems.

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