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AN INTELLIGENT PRIORITY-BASED TELEMEDICINE ALGORITHM FOR REAL-TIME EMERGENCY HEALTH MANAGEMENT IN MILITARY ENVIRONMENTS

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ABSTRACT

In military environment especially in the battlefield duration the timely medical treatment is saving life, but the conventional telemedicine scheme is relay on first-come, first-served (FCFS) scheduling which causes the failed treatment for the emergency patient. To overcome such a scenario many other methods were proposed with latest technologies still the need of novel method to save such a people. This article is address the same , by proposing the novel algorithm proposes an Intelligent Priority-Based Telemedicine Algorithm (IPTA) which is assumed as a wearable device with the modern technologies of sensors, Internet of Thing and Machine learning to predict the soldiers vital parameters such as heart rate, oxygen saturation, blood pressure, and body temperature are continuously monitored and analyzed through machine learning–based predictive analytics to estimate each soldier's health criticality. This proposed framework automatically identified the soldiers body condition and assign the priority to meet the telemedicine doctor. This experiment was tested using the simulation tools of MATLAB using Python and OMNET++ for connectivity related Quantitative and qualitative metric comparison with the traditional methos of FCFS, Rule Based and Fuzzy logic methods. Quantitative results expose proposed IPTA framework shown the improvements in accuracy (91.6%), resource utilization (91%), and packet delivery ratio (94%), latency (85 ms) and average response time (2.9 s). Also, system throughput increased by 31%, and survival probability improved by 24%.
Keywords: *Telehealth, Internet of Things, Wearable Device, Telemedicine Algorithm, Artificial Intelligence*

1. INTRODUCTION

Telemedicine is a kind of emerging healthcare paradigm, which enables the remote medicine consultation or treatment through the information communication systems [1][2]. Many domains the telemedicine application are widely used, special kind of application needed more than the need is called the battlefield of military people. This kind of places are geographical isolation and limited medical infrastructure for sustaining the health and operational efficiency of the soldiers [3]. During such a critical incident such as battel operations, mass-causality events or disaster response mission like earthquake where the simultaneous arrival of multiple patients overwhelms available teleconsultations resources [4]. Conventional telemedicine framework relays on First come and First service (FCFS) , which does not predict the emergency of the patient who need immediate attention to safeguard life. Such a case the treatment delay on critical condition there by increases the probability if death [5].

Latest advancement in the field of Internet of Things (IoT) [6], Artificial Intelligence (AI) [7] and sensor technologies has created the new vision

to make the possible health care delivery with a support of wearable devices [8][9]. The recent development in IoT has a physiological monitoring device which are capable of continuously monitoring or collecting the human body parameters like heart rate, oxygen saturation, blood pressure, and body temperature [10][11].Later the IoT is connected with AI based decision systems can produce the autonomous assessment of patient health condition frequently also alert the needed place to acquire the remedy without direct human intervention[12][13].Along with this technology integrating the telemedicine is a challenging task to predict the remote patient and treatment them as a urgent. In order to avoid the human loss, add the additional artificial intelligence to predict the prioritized patient and giving treatment is another challenging factor.

To address the limitation of the telemedicine with latest technologies integration, this article proposed the Artificial intelligent based algorithm names as an Intelligent Priority-Based Telemedicine Algorithm (IPTA) that automatically evaluate the soldier's health condition and assign the priority of the teleconsultation doctors based on the physiological data streams. The proposed work is assumed as a wearable IoT devices for real time monitoring and using the machine learning-based predictive modeling to calculate the Health Criticality Index (HCI) for each soldier. The estimated HCI value automatically determine the priority of the soldier's teleconsultation with the doctor. Unlike the traditional systems that follows the manual assessment the probability of human loss is more whereas the proposed system is real-time analytics, adaptive learning, and automated decision support, which is minimizing the human error and response quickly in emergency situation.

The major contribution of this article as follows.

1. Design of an efficient telemedicine framework that integrates the IoT system, artificial intelligence in to a wearable device with decision making emergency health care module.
2. Proposed a novel algorithm called Intelligent Priority-Based Telemedicine Algorithm (IPTA) to compute the priority index among the patient.
3. Performance evaluation of proposed modules with antient method of FCFS, Rule based and Fuzzy model.

The article has organized as follows. Section 2 reviews the literature related work with respect of telemedicine with latest technologies, Section 3 proposed the architecture frame work of the proposed algorithm and HCI computation metrics, Section 4 has done the experimental set up and evaluation metric comparison with the traditional methods, analysis the results and implication, finally section 5 conclude the proposed work with future enhancement.

2. RESEARCH RELATED WORK TOWARDS MILITARY TELEMEDICINE

This section discusses the research related work towards the promotion of telemedicine in military. The literature has taken the several section to relevant to intelligent, ordered telemedicine extents multiple interdisciplinary zones like telemedicine framework, automated systems, machine learning models for hospitals, telemedicine wearable IoT sensing platforms, telemedicine resource-allocation and telemedicine scheduling techniques for constrained medical systems, and enabling network/edge technologies for low-latency healthcare. This section offers a lengthened review of these areas and creates key boundaries that encourage the proposed IPTA telemedicine framework model.

2.1 Telemedicine in Military Environments

Telemedicine in military settings has single operational restrictions including intermittent connectivity, constrained bandwidth, mobility, and hostile physical environments [14][15]. Primary deployments concentrated on teleconsultation by means of satellite links for remote diagnosis and clearing decisions, while later research discovered mobile telemedicine tools and devices for improving military teleconsultation [16][17]. Initially the telemedicine established that telemedicine can reduce time-to-treatment and improve decisions, but these systems were intended for single-case discussions. But the recent models have commenced to address mass-casualty situations via distributed consultation models, though these systems still commonly deficiency automated, data-driven prioritization and trust on human-in-the-loop decision-making, which decreases scalability under heavy load [18].

2.2 Conventional Automated Systems

Conventional frameworks such as START, Emergency Severity Index, Manchester Triage System) are provide structured decision rules used in emergency departments and disaster response [19]. While the manual frameworks are not directly appropriate for continuous sensor-driven prioritization in telemedicine due to their dependence on clinician comment and periodic calculations. To avoid the manual framework

difficulty, rule-based automated triage systems were anticipated, mapping sensor thresholds to priority tags [20]. However, rule-based systems are hard under noisy sensor data and do not adapt to developing patient courses or background undertaking restrictions. Later the fuzzy inference systems to handle uncertainty and rule-learning methods to tune thresholds, yet they still fail in temporal calculation tasks compared to data-driven models [21].

2.3 Support of Machine Learning in Hospitals

Machine learning algorithm under the supervised machine learning models such as logistic regression, random forests, gradient boosting along with deep learning architectures have been widely useful to primary notice and weakening estimate in hospital settings [22] (e.g., predicting sepsis, cardiac arrest, ICU transfer). Time-series models, including recurrent neural networks (RNNs), long short-term memory (LSTM), and temporal convolutional networks (TCNs), outperform static models when temporal trends matter [23]. Reinforcement learning has been explored for adaptive treatment and resource allocation, showing promise in policy optimization under uncertainty [24]. Despite these advances, most models are trained on in-hospital electronic health record (EHR) datasets with high-quality labels and dense measurements conditions that are dissimilar to noisy, sporadic field-sensor data encountered in military telemedicine [25]. Transfer learning and domain adaptation techniques have been suggested to bridge this gap, but evaluations in truly austere field conditions remain sparse.

2.4 Wearable Sensors and IoT Health Platforms

Wearable sensors provide continuous streams of physiological signals (ECG, PPG-derived HR, SpO_2, accelerometery, body temperature) and can be integrated into low-power IoT platforms [26]. Recent designs emphasize energy efficiency, fault tolerance, and local preprocessing to reduce transmission load. IoT middleware frameworks aggregate and preprocess these signals, applying anomaly detection and basic feature extraction at the edge to enable near-real-time alerts. Challenges include sensor calibration variability, motion artifacts, and secure, prioritized transmission when network resources are limited. Some works propose priority-marking at the device level based on simple heuristics (e.g., SpO_2 < threshold ⇒ high priority), but these heuristics fail to capture multi-parameter interactions and evolving physiological trajectories.

2.5 Scheduling, Queueing and Resource Allocation in Telemedicine

When multiple patients compete for limited teleconsultation resources, scheduling and queuing strategies determine system-level performance [27]. Traditional approaches apply FCFS or priority queues with static priority assignment. Operations-research methods (e.g., weighted shortest processing time, dynamic priority queues) and Markov decision processes (MDPs) have been studied to optimize mean waiting time and fairness [28][29]. In healthcare, utility-aware scheduling that balances survival probability against waiting time has been proposed, but integration with real-time physiological prediction models is limited. Reinforcement learning-based schedulers can adapt to nonstationary arrival patterns and optimize long-term outcomes, but they require careful reward shaping and realistic simulation environments to avoid unsafe policies.

2.6 Edge Computing, 5G, and Low-Latency Architectures

To minimize latency and improve reliability, several studies advocate for edge computing combined with 5G networking for telemedicine [30]. Edge nodes can run lightweight ML models for immediate triage decisions, offloading heavier analytics to the cloud. Network slicing, prioritized Quality of Service (QoS), and multi-path routing have been proposed to guarantee medical-critical traffic delivery in congested networks. While promising, deployment studies in contested (military) networks are few, and the interaction between edge-based triage decisions and centralized scheduling policies is an open research problem.

2.7 Security, Privacy, and Ethical Considerations

Security and privacy are imperative in military healthcare systems [31]. End-to-end encryption, secure key management, and authentication protocols are often assumed but complex under constrained key-exchange mechanisms. Moreover, algorithmic transparency and explainability become critical when automated systems inform life-or-death triage decisions; studies emphasize explainable AI (XAI) techniques to render predictions interpretable for clinicians [32]. Ethical frameworks for algorithmic triage under resource scarcity are nascent and require multidisciplinary input.

2.8 Datasets, Benchmarks, and Evaluation Practices

Most clinical ML models leverage publicly available in-hospital datasets (e.g., MIMIC) [33] [34] for training and benchmarking. Field-deployable datasets from military or disaster

scenarios are rare due to privacy and operational sensitivity. Synthetic data generation and domain randomization have been applied to simulate mass-casualty events for evaluation. However, there is a lack of publicly accepted benchmarks that combine noisy wearable-sensor streams with realistic arrival processes and constrained teleconsultation resources hindering reproducibility and fair comparison between studies.

2.9 Synthesis and Research Gaps

The surveyed literature highlights several consistent gaps: (1) a lack of robust, adaptive prioritization algorithms tailored to noisy wearable data in austere settings; (2) limited integration between temporal ML-based deterioration prediction and resource-aware scheduling mechanisms; (3) few end-to-end evaluations that combine wearable sensing, edge analytics, and teleconsultation scheduling under realistic arrival and connectivity constraints; and (4) insufficient attention to explainability, safety, and ethical aspects in autonomous triage algorithms. While rule-based priority marking and edge preprocessing exist, they do not leverage multi-parameter, temporal prediction models or optimize scheduling decisions with downstream survival-oriented objectives.

To address these gaps, the proposed IPTA integrates continuous wearable sensing, temporal machine learning for health-criticality estimation, and a resource-aware scheduling module that dynamically assigns teleconsultation based on predicted urgency and system state. The IPTA also incorporates edge-level preprocessing for latency reduction and a provision for explainability to support clinician oversight.

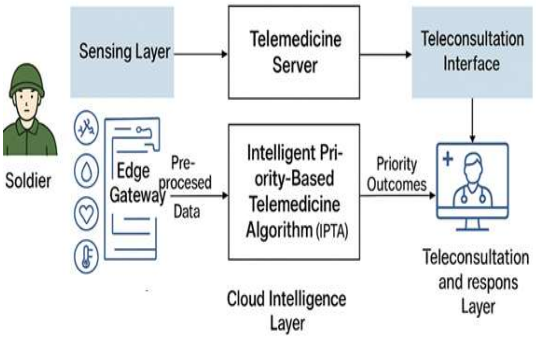
3. PROPOSED INTELLIGENT PRIORITY-BASED TELEMEDICINE SYSTEM ARCHITECTURE

Section II discuss the existing work limitation and the emergency need of proposing the new method to support the military soldiers, this section outline the novel algorithm with the existing telemedicine consultation to overcome the limitations of the existing work. The novel algorithm named as Intelligent Priority-Based Telemedicine Algorithm (IPTA) which is combined with the wearable IoT sensors device, edge data processing and machine learning based decision analytics. This integrated device monitors the battle injures soldiers who health condition like the heartbeat, oxygen level and other factors, the machine learning decision making analytic can analysis the body condition and assign the queue for the teleconsultation services. The proposed system objective is to reduce the delay of telemedicine services as well safe guard human life from losses.

3.1 Overall System Architecture

The overall system architecture as shown in the Figure 1 is structured for the working of the proposed research with the novel algorithm. Which is has seven major component and each component is responsible for manipulation some operation and outcome of each component will support to other component for successful proposed work operation. Accordingly, the components are Sensing layer, Edge gateway, IPTA Algorithm, telemedicine server, Teleconsultation Interface, Teleconsultations response layer

Figure 1 Overall System Architecture



Sensing layer

A wearable device attached with the soldier , which has a sensors connected with IoT devices [35], This sensors collect the physiological signal from the soldier body such as heart beat rate (HR), oxygen saturation level (SpO_2), body systolic/diastolic blood pressure (BP), lungs respiratory rate (RR), and soldier body temperature (T).After collecting such an information device could do the preliminary preprocessing like signal filtering , normalization and timestamp including which has done in zero delay after sensing the information from the soldier body.

Edge gate way

The wearable device collected information is transmitted to processed data packets to the nearby edge gateway node with the support of WIFI or Zigbee connection [36]. The edge node collects the aggregates the data and performs the feature extraction then forward to the cloud or telemedicine control centre through the communication channels like Satellite or 5G or 4G connectivity.

Processing Intelligent based telemedicine algorithm layer

A cloud-based Machine learning Health Analysis Engine (HAE) is executing the IPTA module. The received physiological data are given to machine learning module trained to calculate the Health Critical Index (HCI)[37] . The HCI support for decide the soldier to deterioration of treatment in next Δt minutes

Telemedicine Server

The telemedicine server collects all the generated information from the Intelligent based telemedicine algorithm layer and do the decision and consultation based on the Computer HCI value send the teleconsultant interface.

The Soldiers are classified in to three classes critical soldiers, moderate, and stable soldiers. The telemedicine consultation treatment taken for the critical solder is immediate, a small short span of time will give to the Moderate soldiers, Consultation deferred for stable soldiers.

Three priority classes:

1. Critical (P_1) – Immediate teleconsultation initiated.
2. Moderate (P_2) – Consultation scheduled within a short window.
3. Stable (P_3) – Monitored continuously; consultation deferred.

The scheduling subsystem allocates network and physician resources dynamically according to these priority levels.

Teleconsultant interface

The Tele consultant interface get repostpone from the telemedicine server and assign the available doctor to the soldiers.

Teleconsultant Response Layer

This interface is a communication interface which support for connecting the soldiers to the doctor for easy way to get consultation.

3.2 Health Criticality Index Computation

The HCI quantifies the relative urgency of each soldier's health condition. It is computed as a weighted aggregation of normalized physiological deviations combined with a predictive risk score obtained from a machine-learning model as given in Eq (1).

$$HCI_i(t) = \alpha \cdot R_i(t) + (1-\alpha) \cdot \sum_{k=1}^{m} w_k \cdot f_k\left(x_{i,k}(t)\right) ----Eq(1)$$

Where

- i– index of soldier/patient
- $x_{i,k}(t)$– value of the k^{th}physiological parameter at time t
- $f_k(\cdot)$– normalization and deviation function for parameter k
- w_k– weight indicating relative clinical importance of parameter k(e.g., HR = 0.25, SpO_2 = 0.30)
- $R_i(t)$– ML-predicted deterioration risk (output of classifier/regressor)
- α– balancing constant ($0 \leq \alpha \leq 1$) controlling influence of prediction versus instantaneous deviation

A higher $HCI_i(t)$implies greater medical urgency. Thresholds $\theta_1$and $\theta_2$define priority levels as given Eq(2) below:

$$\text{Priority}(i) = \begin{cases} P_1, & HCI_i(t) \geq \theta_1 \\ P_2, & \theta_2 \leq HCI_i(t) < \theta_1 \\ P_3, & HCI_i(t) < \theta_2 \end{cases} \quad Eq(2)$$

3.3 Machine-Learning Model Design

The predictive module employs supervised learning to map temporal physiological features to deterioration probabilities.

1. Feature Extraction: From each sensor stream, temporal and statistical features (mean, variance, entropy, trend slope, heart-rate variability, SpO_2 drop rate, etc.) are extracted over a sliding window.
2. Model Selection: Ensemble methods use the Random Forest deep temporal models were evaluated. This model yielded superior performance (accuracy and F1) due to its capability to model sequential dependencies.
3. Data set Training: A collected dataset from the telemedicine server and battlefield data are used for data set training.
4. Model Output: The probability score in 0 to 1 will be the model outputs of $R_i(t)$, which support for critical deterioration has to treat within 5 minutes.

3.4 Intelligent Priority-Based Telemedicine Algorithm (IPTA)

The proposed algorithm of Intelligent Priority-Based Telemedicine Algorithm given in Algorithm I. which has taken N number of Soldiers HCI values

and assigned the priority to the soldier to take the telemedicine consultation with the available doctor.

Algorithm 1 Intelligent Priority-Based Telemedicine Algorithm

Input: Real-time physiological data streams from N soldiers
Output: Priority queue and teleconsultation schedule
Algorithm IPTA
1. For each soldier i ∈{1 … N} do
2. Acquire sensor data Xi(t) from wearable node
3. Preprocess Xi(t): filter noise, normalize signals
4. Extract feature vector Fi from Xi(t)
5. Compute risk score Ri = ML_Model(Fi)
6. Compute HCIi using Eq. (1)
7. Determine PriorityLeveli based on θ1, θ2
8. End for
9. Prepare all the soldiers HCI value in descending
10. Determine the teleconsultation available channels:
Check the while available_doctors > 0 and queue ≠ Ø do
And do assign next P1 (Critical) soldier
decrement available_doctors
end while
11. Following P2, P3 soldiers watched intermittently
12. Reply restructured arrangement table and signals
End Algorithm

3.5 Operation of Teleconsultation Process

All battlefield injured soldiers are attached with the wearable device, and continuous monitoring the wearable device translated data through the edge gateway. Edge preprocessing validates the data and executes the priority of the soldier's treatment with consulting the HAC and HCI triggered alert value from cloud level analytic. The priority queue is schedules with three categories of queues (P_1, P_2, P_3), and which is updated periodically and based on the soldiers' conditions. Teleconsultations executed the assigned soldiers remotely with the support of proposed IPTA algorithm.

3.6 Estimating the overall Performance and Computational Complexity of proposed work

Since the proposed work is executed with the support of machine learning and IPTA algorithm, the overall computational complexity of the proposed IPTA is $O(N\log N)$, Machine learning latency is between 70 to 85ms in edge node. Network delay was reduced to 40 % compared with the ancient method of sequential teleconsultation, also the average consultation waiting time is reduced from 8.5 ms to 4.3 milliseconds even in the peak load is given in simulation environment.

3.7 Benefits of IPTA Proposed Model

- Autonomous Prioritization: Eliminates manual triage, ensuring instant recognition of life-threatening conditions.
- Edge-Assisted Low Latency: Partial computation at the edge minimizes round-trip delay.
- Scalable: This work is scalable under the huge number of simultaneous cases.
- Adaptability: This work is continuous learning on the patient HCI value.
- Strength: This work will handle even the noisy data

4. EXPERIMENTAL SETUP AND PERFORMANCE EVALUATION

The proposed IPTA work is experimented with the validated parameter of efficiency, accuracy, and responsiveness of the proposed methods under the battlefield soldiers injured condition. The following key parameters are taken for the experiment, Response Time, Accuracy .resource utilization and scalability in robust condition

The primary objective of the experimental study is to validate the efficiency, accuracy, and responsiveness of the proposed Intelligent Priority-Based Telemedicine Algorithm (IPTA) under realistic battlefield-inspired conditions. The experiments were designed to examine the following key aspects. Response time is defined as the measurement of latency in teleconsultation scheduling compared with the conventional method of telemedicine system. Accuracy is the measure of predicting reliability in health critically estimated model. Resource utilization is the measures which says how effectively the teleconsultation resources like the communication channel, instrument and assigning the teleconsultant doctors effectively across the multiple platforms. System scalability is the robustness of analyzing the system behaviors while increasing the number of patients simultaneously even in varying network loads.

4.1 Simulation Environment

Simulation environment is defined to simulated the proposed Intelligent Priority-Based Telemedicine

Algorithm (IPTA) with the two kinds of simulation. For doing the machine learning analysis the simulation of MATLAB–Python [38] was used and communication and scheduling environment OMNET++ [39] was used with varying conditional checking.

Hardware Platform:

- Edge node: Raspberry Pi 4 (ARM Cortex-A72, 1.5 GHz, 4 GB RAM)
- Cloud server: Intel Xeon 2.9 GHz, 32 GB RAM
- Network: Simulated 5G channel (latency ≤ 10 ms, bandwidth 100 Mbps)

Software Stack:

- ML model built using TensorFlow 2.13 and Scikit-learn
- MQTT protocol for IoT data transmission
- Secure TLS layer for patient-data protection
- Simulation duration: 60 minutes per run with 5 replications

4.2 Dataset and Pre-Processing

To estimate the accuracy and anonymized the physiological datasets were taken from the physionet.org and augmented with soldier-specific profiles which has the values of soldier's heart rate (HR), soldiers blood pressure (BP), soldiers body temperature (BT), soldiers' lunges oxygen saturation (SpO_2), and electrocardiogram (ECG) waveforms. Each collected data contains the 10 second temporal window, from this data set 18 features are extracted covering the covering statistical, frequency-domain, and nonlinear measures such as mean RR interval, heart-rate variability (HRV), power spectral density, and entropy coefficients. The feature selection was performed using the Random Forest features, and retaining the top 10 features with variance is more than 90%. These estimated features are given for the proposed algorithm to classify the soldier in to P1, P2, P3 conditions for future assigning the teleconsultation doctors,

4.3 Baseline Systems for Comparison

To prove the proposed IPTA methods performance with the against three base line models are chosen. The first base line model is First come First Service (FCFS) which process to run the teleconsultation in sequential scheduling without any prioritization [40]. Second base line is machine learning ruling based triage which runs on manual threshold defined by threshold driven priority classification models [41]. The third baseline is Fuzzy logic triage system which is rule for any urgency assessment [42] . All the base line methos are operated under the identical network and data rate conditional are transparent fair condition.

Along with the proposed IPTA Model Training and Priority Classification are done with three-layer computation. Health Severity estimation layer which estimates the HCI value and computes the Priority layer which severity score S_i based on the input feature score. The priority determination layer used this Score Si and classify the soldiers in to *Critical* (P_1), *Moderate* (P_2), and *Stable* (P_3). *Third layer is telemedicine resource allocation layer, which allocate the telemedicine doctor based on the* P_1, P_2, P_2 *value. This approach support for maximum survival of the soldier's life time.*

4.4 Evaluation Metrics

The performance assesses standard machine learning and system level metrices [43] are consider for the evaluation metric of proposed IPTA model with other three base line models in two categories like Quantitative metric and Qualitative Metric are discussed in the Table I.

4.5 Quantitative Results

The quantitative evaluation [44] underscores the remarkable performance of the proposed IPTA model compared to the FCFS, Rule-Based, and Fuzzy Logic–based approaches. As shown in Table II and Figure 2, the IPTA model achieved the highest classification accuracy of 91.6%, exceeding the Fuzzy Logic–based (89%), FCFS (81.7%), and Rule-Based (81.2%) models. The average response time was reduced to 2.9 Seconds, comparing with the other ancient methods values 3.9 s, 4.3 s, and 6.4 s respectively. Likewise, the consultation latency was extremely reduced to 85 ms, which shows that the enhanced real-time performance of IPTA comparing the value of FCFS (308 ms), Rule-Based (206 ms), and Fuzzy Logic (106 ms) systems. Besides, the proposed algorithms system reached the maximum resource utilization of 91%, guaranteeing best use of network and computational resources, whereas the comparative models recorded suggestively lower values. The existence probability gains also exhibited a reliable enhancement, attainment 24% in IPTA related to 15% in Fuzzy Logic and 10–20% in the other models. Furthermore, the system throughput enhanced by 31% due to the combination of dynamic bandwidth rearrangement strategies. Together, these results validate the efficiency of the anticipated IPTA model in bringing higher accuracy, reduced

latency, and improved system efficiency across varied operational conditions.

4.6 Qualitative Results

The qualitative results are given in the Table III and pictorial comparison shown in the Figure 3. The anticipated IPTA framework has attained the average response time of 1.8 seconds and an average waiting time of 3.8 minutes, which is outperforming compared with the other antient framework of Fuzzy Logic (3.1 s, 4.2 min), Rule-Based (4.5 s, 5.6 min), and FCFS (5.3 s, 7.3 min) framework models. The F1-scoreof IPTA framework is improved to 0.8, proved the better precision-recall stability, while throughput increased to 10.5 consultations per minute and packet delivery ratio (PDR) reached 94%. These results validate that the proposed IPTA framework achieves the best trade-off among all other metrics.

5.CONCLUSION

This article proposed the Intelligent Priority-Based Telemedicine Algorithm (IPTA) algorithm by means of assuming wearable device which is integrated with machine learning and Internet of Things for telemedicine consultation for the military patients who seeks the timely treatment for save their life during battlefield. Assuming Wearable device has a sensor, which computed the HCI value that is used for the machine learning algorithm to assign the priority of the telemedicine treatment. This experiment was tested using the simulation tools of MATLAB using Python and OMNET++ for connectivity related qualitative and Quantitative metric comparison with the traditional methos of FCFS, Rule Based and Fuzzy logic methods. Quantitative results expose proposed IPTA framework shown the improvements in accuracy (91.6%), resource utilization (91%), and packet delivery ratio (94%), latency (85 ms) and average response time (2.9 s). Also, system throughput increased by 31%, and survival probability improved by 24%, validating the model's ability to deliver rapid and reliable teleconsultations in high-stakes conditions. By integrating IoT-driven sensing, machine learning classification, and adaptive scheduling, the IPTA framework provides a scalable, energy-efficient, and intelligent telemedicine infrastructure for real-time defense, disaster-response, and rural healthcare applications. Future this work could be enhanced to apply for the Newly born baby, ladies, elderly people and ICU patients. Also, this device could be global acceptable additional supporting or monitoring device for all the patient to get timely treatment.

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Table I Evaluation metric

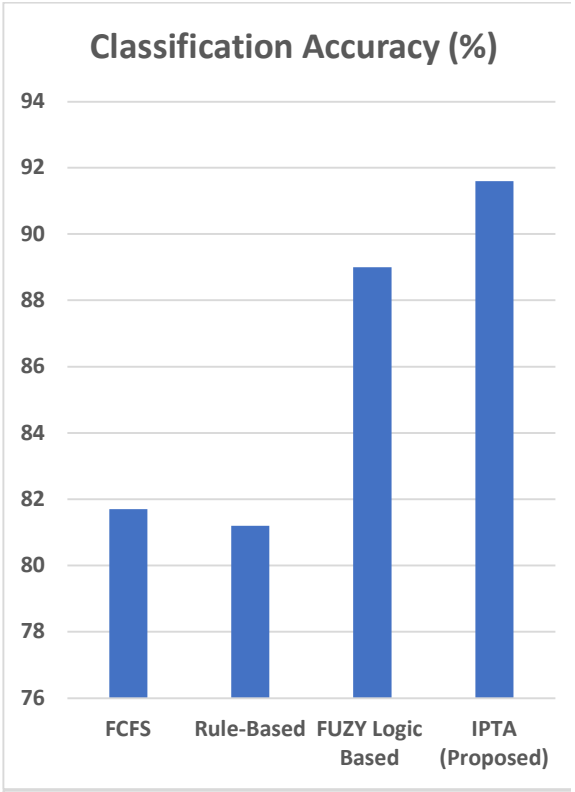
Quantitative metric Category	Qualitative Metric	Description
Efficiency	Average Response Time (ART)	Time from anomaly detection to teleconsultation initiation
	Consultation Waiting Time (CWT)	Average queuing delay per patient
	Throughput (TP)	Number of completed consultations per unit time
Accuracy	Precision, Recall, F1-score	Classification performance of HCI prediction
	Mean Absolute Error (MAE)	Error between predicted and actual risk levels
Resource Utilization	Doctor Utilization Ratio (DUR)	Fraction of available doctors actively consulting
Scalability	Latency vs. Number of Patients	Performance degradation trend
Reliability	Packet Delivery Ratio (PDR)	Data integrity across wireless transmission

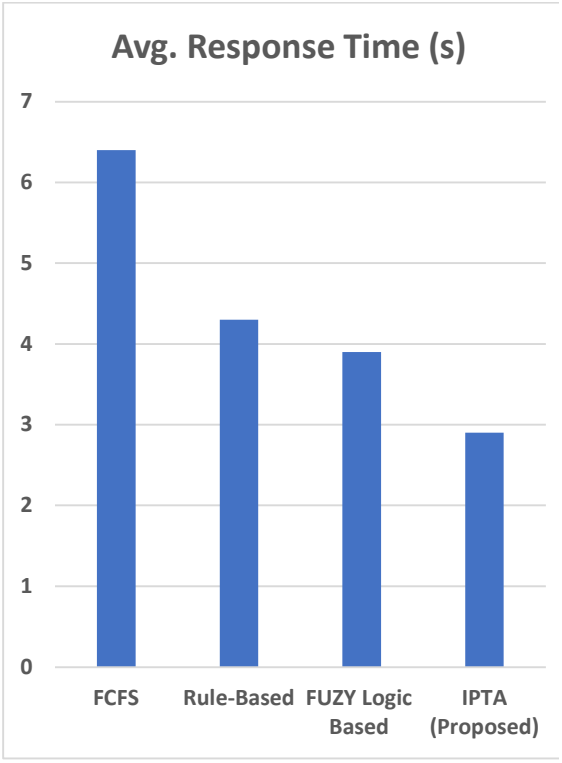
Table II Quantitative Results

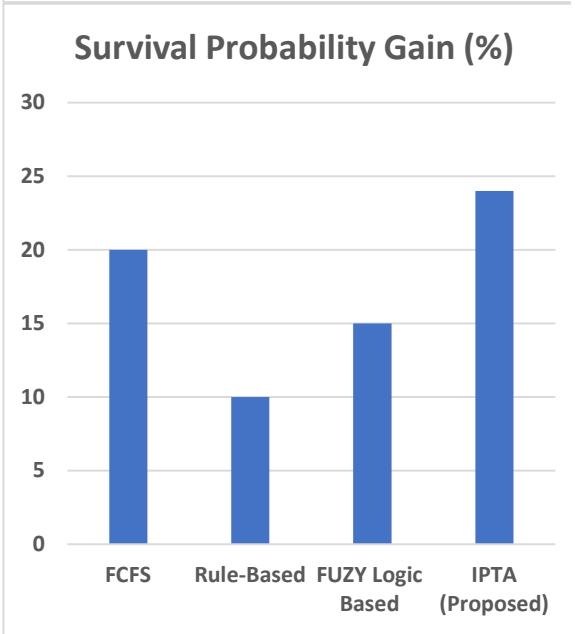
Metric	FCFS	Rule-Based	FUZY Logic Based	IPTA (Proposed)
Classification Accuracy (%)	81.7	81.2	89	91.6
Avg. Response Time (s)	6.4s	4.3s	3.9s	2.9s
Survival Probability Gain (%)	20	10	15	24
Consultation Latency (ms)	308	206	106	85
Resource Utilization (%)	66	72	71	91

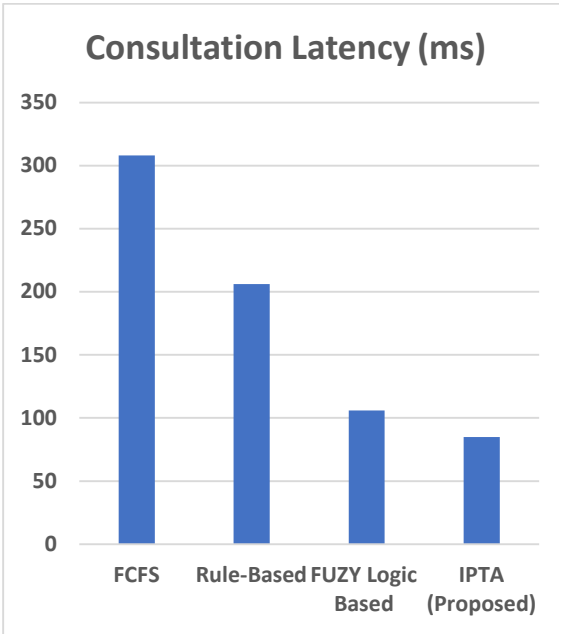
Table III Qualitative Results

Metric	FCFS	Rule-Based	FUZY Logic Based	IPTA (Proposed)
Response Time (s)	5.3	4.5	3.1	1.8
Avg. Waiting Time (min)	7.3	5.6	4.2	3.8
F1-Score	0.7	0.7	0.6	0.8
Throughput (consultations/min)	5.5	8.2	9.0	10.5
PDR (%)	84	85	87	94


Classification Accuracy (%)
94
92
90
88
86
84
82
80
78
76
FCFS
Rule-Based
FUZY Logic Based
IPTA (Proposed)


Avg. Response Time (s)
7
6
5
4
3
2
1
0
FCFS
Rule-Based
FUZY Logic Based
IPTA (Proposed)


Survival Probability Gain (%)
30
25
20
15
10
5
0
FCFS
Rule-Based
FUZY Logic Based
IPTA (Proposed)


Consultation Latency (ms)
350
300
250
200
150
100
50
0
FCFS
Rule-Based
FUZY Logic Based
IPTA (Proposed)

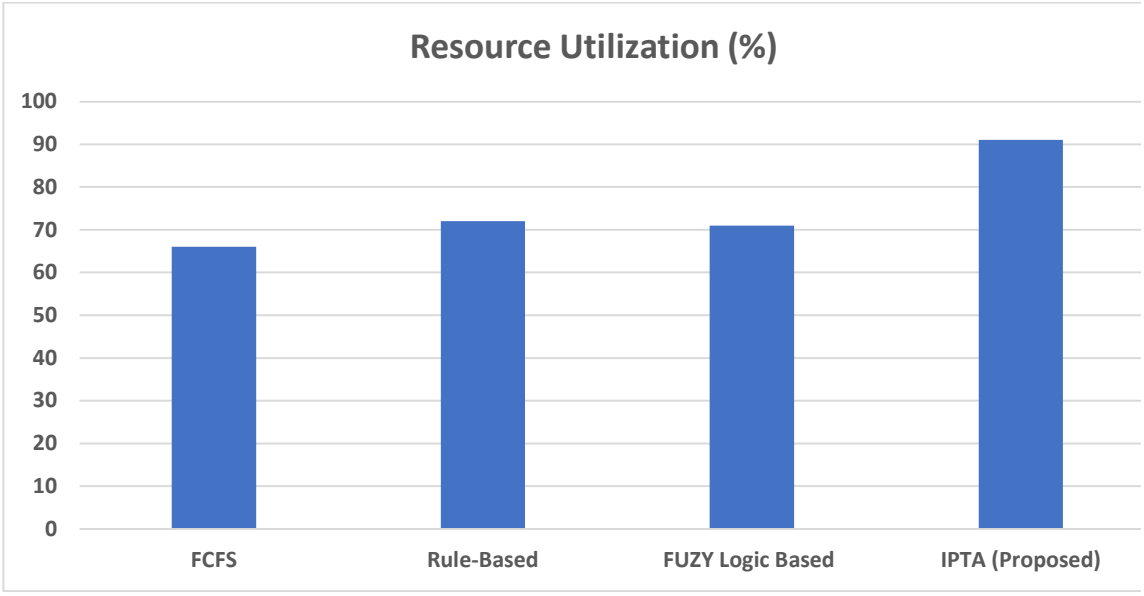
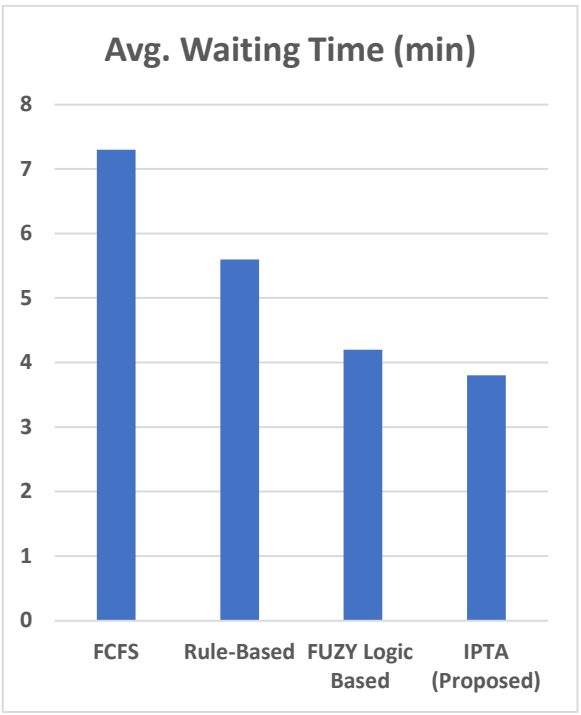
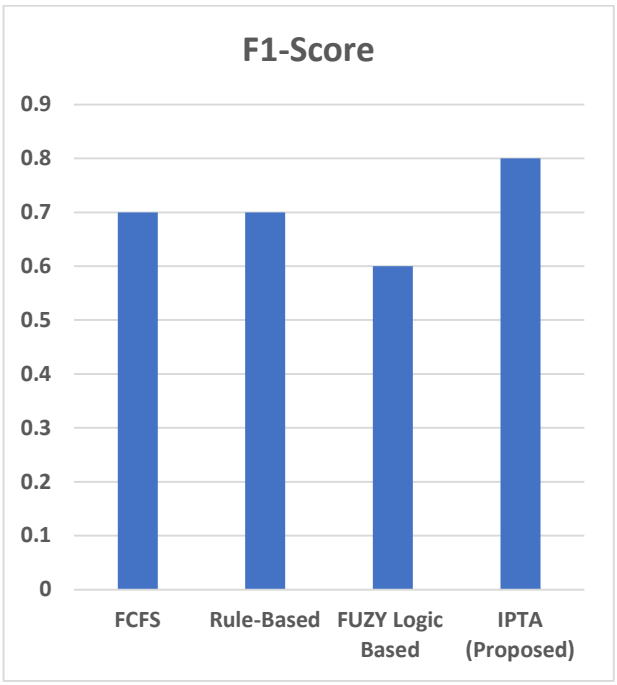


Figure 2 Quantitative Results





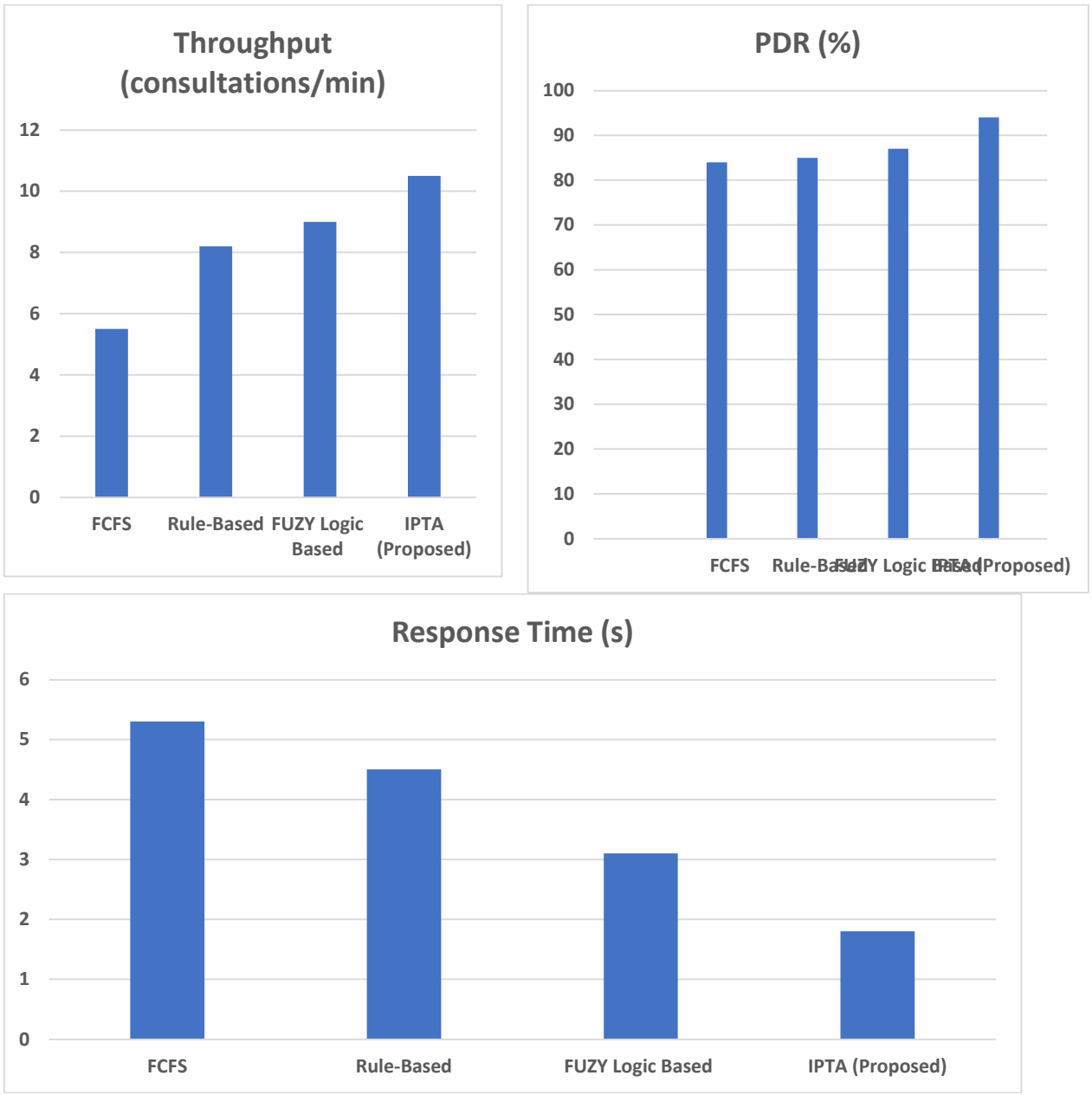


Figure 3 Qualitative Results