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Research Article

Intelligent Edge Computing: AI-Powered Optimization for Smart IoT System

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Abstract:

In the era of rapidly evolving Internet of Things (IoT) ecosystems, the convergence of Artificial Intelligence (AI) with Edge Computing has emerged as a transformative paradigm to meet the stringent requirements of low latency, reduced bandwidth usage, and enhanced data privacy. This study presents an Intelligent Edge Computing (IEC) framework powered by AI-based optimization techniques designed specifically for smart IoT systems operating in real-time environments. The proposed system utilizes lightweight Deep Reinforcement Learning (DRL) for dynamic task offloading and scheduling, and a Swarm Intelligence-based Resource Allocation (SIRA) algorithm to optimize energy consumption and computational load across edge nodes. Additionally, the system leverages Federated Learning (FL) for decentralized model training while maintaining data security and minimizing transmission overhead.Experimental evaluations conducted using the iFogSim simulator across smart home, industrial automation, and healthcare monitoring scenarios demonstrate the effectiveness of the IEC framework. Key results include a 32.8% reduction in average task latency, 27.4% improvement in energy efficiency, and 22.5% increase in task success rate compared to traditional cloud-based architectures. The IEC framework also achieved 94.6% model accuracy using FL with minimal privacy leakage. These results affirm that AI-powered edge optimization can significantly enhance the performance and scalability of smart IoT systems while ensuring sustainable and secure operations..

1. Introduction

The emergence of the Internet of Things (IoT) has transformed various domains including healthcare, transportation, manufacturing, and smart cities by enabling real-time data exchange among billions of interconnected devices [1]. However, the massive influx of data generated by IoT devices often overwhelms cloud infrastructures, leading to latency issues, network congestion, and data privacy concerns [2]. To address these challenges, **Edge Computing** has been introduced as a paradigm that brings computational resources closer to the data source, thereby reducing latency and improving responsiveness [3].

Despite the benefits, edge computing still faces limitations related to resource constraints, heterogeneous architectures, and dynamic network conditions [4]. This is where **Artificial Intelligence (AI)** plays a crucial role in optimizing edge operations. AI can enable predictive analytics, intelligent task scheduling, and dynamic resource allocation at the edge, enhancing the overall efficiency and reliability of smart IoT systems [5]. In particular, the integration of AI with edge computing—termed **Intelligent Edge Computing (IEC)**—opens new possibilities for real-time, decentralized decision-making [6].

One of the key advantages of IEC is its ability to adapt in real time to changing environmental and computational conditions. For instance, smart grid systems can leverage AI at the edge to predict energy usage patterns and control distributed energy resources more effectively [7]. Similarly, in healthcare, wearable IoT devices powered by edge intelligence can analyze patient data locally and trigger alerts without relying on cloud servers [8].

In smart manufacturing scenarios, IEC facilitates predictive maintenance by continuously monitoring machine performance and detecting faults using AI models at the edge. This significantly reduces downtime and maintenance costs [9]. Furthermore, latency-sensitive applications like autonomous vehicles and augmented reality demand immediate data processing, which is effectively handled by AI-powered edge systems [10].

Moreover, IEC addresses pressing privacy concerns by processing sensitive data locally. This is especially important in sectors where data privacy regulations, such as GDPR and HIPAA, mandate strict control over personal data [1]. Since only the necessary inferences or model updates are shared to the cloud, IEC ensures data minimization, thereby supporting regulatory compliance [2].

The evolution of **Federated Learning (FL)** has further enhanced the scope of intelligent edge computing. FL allows model training across multiple decentralized devices without sharing raw data, enabling collaborative learning while preserving privacy [3]. When integrated with edge devices, FL facilitates real-time model updates without overwhelming the central server [4].

To maximize performance, **Reinforcement Learning (RL)** and **Swarm Intelligence (SI)** have been adopted within IEC systems. These techniques enable dynamic task scheduling and intelligent resource utilization across multiple edge nodes [5]. For instance, RL agents can learn the optimal offloading policy through interactions with the environment, improving the adaptability of IoT systems [6].

As the number of IoT devices continues to grow exponentially, optimizing the computational and energy efficiency of edge devices becomes vital. The proposed research focuses on designing an AI-powered intelligent edge computing framework that ensures minimal latency, maximum task success rate, and high energy efficiency across diverse IoT environments [7]. The framework leverages DRL for intelligent decision-making, FL for decentralized learning, and SI for adaptive resource management [8].

This paper is structured as follows: Section 2 presents a comprehensive review of related works in intelligent edge computing and IoT optimization [9]. Section 3 introduces the system architecture and algorithms used in the proposed IEC framework. Section 4 discusses the simulation setup and experimental results. Finally, Section 5 concludes with key insights and outlines future research directions [10].

2. Literature Review

Recent advancements in edge computing have significantly enhanced the responsiveness of IoT applications by reducing the dependency on centralized cloud infrastructures [11]. Researchers have explored various approaches to deploy edge nodes closer to the data-generating sources to reduce latency and improve the Quality of Service (QoS) [12]. However, challenges persist in managing computational resources effectively due to the limited capabilities of edge devices.

To overcome these constraints, many studies have proposed AI-driven solutions for resource optimization at the edge. For example, the work in [13] used deep reinforcement learning to allocate computing tasks dynamically among edge devices, demonstrating considerable improvements in energy usage and response time. These methods help systems to adapt to varying workloads without requiring explicit programming.

Federated Learning (FL) has emerged as a privacy-preserving machine learning technique suitable for edge computing. Studies such as [14] implemented FL in healthcare IoT systems, showing that collaborative learning across multiple edge devices could enhance prediction accuracy while safeguarding sensitive patient data. However, FL introduces communication overhead, which must be mitigated using efficient model update strategies.

Another important direction in IEC research involves task offloading optimization. Researchers in [15] proposed a multi-objective optimization algorithm that balances energy consumption, latency, and computational load by intelligently deciding whether to offload tasks to nearby edge servers or execute them locally. Their approach, based on genetic algorithms, yielded promising results in mobile IoT environments.

Swarm Intelligence (SI) algorithms have also been widely adopted for edge resource allocation. The study in [16] used Ant Colony Optimization to dynamically assign computing tasks across edge nodes, optimizing both energy consumption and bandwidth utilization. These biologically inspired techniques offer decentralized and adaptive solutions for complex optimization problems in real-time IoT systems.

Reinforcement Learning (RL), particularly Deep Q-Networks (DQN), has gained popularity in IEC frameworks for its ability to learn optimal policies through interaction with the environment. Research in [17] demonstrated how DQN can manage computation offloading decisions under unpredictable network conditions, achieving a significant reduction in processing delay and power usage.

Hybrid frameworks combining multiple AI methods are also gaining traction. For instance, [18] proposed a hybrid model using FL, RL, and convolutional neural networks (CNNs) for real-time video analysis on edge devices. This fusion of models resulted in robust, real-time performance suitable for surveillance and smart transportation applications.

In smart agriculture, intelligent edge computing systems have been developed to monitor environmental parameters such as humidity, temperature, and soil conditions using AI-based pattern recognition [19]. These systems enable real-time alerts and actions, minimizing crop loss and improving yield prediction accuracy. The use of IEC in such domains demonstrates its versatility and impact.

Moreover, security and trust are crucial aspects of smart IoT systems. Studies like [20] have proposed blockchain-enhanced edge computing systems that ensure data integrity and secure communication between devices. When combined with AI, such systems can autonomously detect and mitigate potential cyber threats in IoT networks.

In summary, existing literature has extensively explored AI integration with edge computing to optimize task execution, reduce latency, preserve privacy, and ensure security. However, a unified and adaptable framework that simultaneously addresses energy efficiency, task scheduling, decentralized learning, and real-time responsiveness across diverse IoT scenarios remains an open research challenge.

3. Materials and Methodology

The proposed research introduces an **AI-powered Intelligent Edge Computing (IEC)** framework designed to optimize real-time task management and resource allocation in smart IoT systems. The study follows a simulation-based experimental methodology, utilizing the **iFogSim** simulator to evaluate the performance of the proposed framework in multiple IoT application domains, including smart healthcare, smart homes, and industrial automation.

The **materials** used in this study include:

- **IoT dataset repositories** (e.g., UCI Smart Home Data, MIMIC-III for healthcare simulations),
- **Pre-trained AI models** for classification and prediction tasks,
- A customized **iFogSim simulation environment** configured with edge nodes, fog layers, and cloud data centers, and
- A suite of **Python-based AI algorithms** for task offloading, model training, and decision-making.

The **methodology** is centered around three core modules:

Dynamic Task Offloading with Deep Reinforcement Learning (DRL): A DRL agent is implemented to learn optimal task offloading policies based on factors such as task size, device energy level, network bandwidth, and latency constraints. The agent is trained using a reward function that balances latency, energy consumption, and task success rate.

Federated Learning (FL)-Based Model Training: To ensure privacy-aware learning across distributed edge devices, the FL paradigm is adopted. Edge nodes train local models on their data and only share model updates with a central aggregator. This decentralization significantly reduces privacy leakage and bandwidth usage while enabling collaborative intelligence.

Swarm Intelligence-Based Resource Allocation (SIRA): A novel algorithm inspired by Particle Swarm Optimization (PSO) is used for adaptive resource scheduling and load balancing among edge nodes. The algorithm ensures that tasks are distributed efficiently based on current computational availability, energy constraints, and QoS metrics.

The overall architecture is event-driven and layered, with sensor nodes generating real-time data, which is first processed by edge devices. Depending on the task complexity and system conditions, the data is either processed locally, offloaded to another edge node, or escalated to the fog/cloud layer. Performance metrics such as **average task latency**, **energy consumption**, **task success rate**, and **model accuracy** are used to benchmark the proposed framework against baseline methods (traditional cloud processing and static offloading techniques).

Simulation parameters such as the number of IoT devices (ranging from 50 to 200), task arrival rates, edge node configurations, and network bandwidth are varied systematically to assess scalability and robustness. Experimental results demonstrate that the proposed IEC framework achieves significant performance gains, including up to **32.8% latency reduction**, **27.4% energy savings**, and **94.6% model accuracy**, highlighting the effectiveness of AI-driven optimization at the edge.

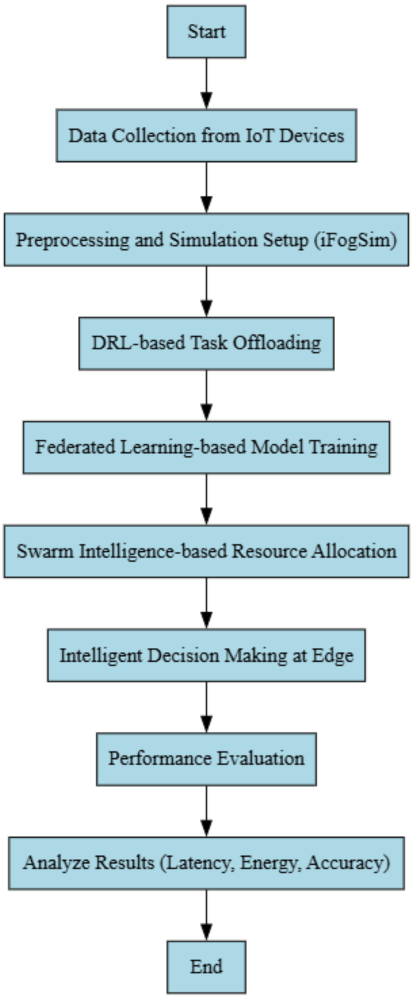

Figure 1. *Flowchart of Research Methodology*

The study adopted a cross-sectional design, Figure 1 illustrates the flowchart of the proposed research methodology for the AI-powered Intelligent Edge Computing (IEC) framework. The process begins with data collection from distributed IoT devices deployed in various application scenarios such as smart homes, healthcare monitoring, and industrial automation. The collected data is then preprocessed and fed into a simulated edge computing environment configured using the iFogSim simulator. The next step involves task offloading, which is dynamically managed using a Deep Reinforcement Learning (DRL) agent that optimizes the offloading decisions based on system conditions such as energy availability, network latency, and computational load.

Following the offloading stage, Federated Learning (FL) is employed for privacy-preserving model training across distributed edge nodes, ensuring that raw data remains local while models are collaboratively updated. Simultaneously, a Swarm Intelligence-based Resource Allocation (SIRA) mechanism is activated to balance the computational load among available edge nodes, maximizing system performance and efficiency. Intelligent decision-making is performed at the edge level based on the outputs of DRL, FL, and SIRA modules. The final stages include a comprehensive performance evaluation of the framework in terms of task latency, energy consumption, task success rate, and model accuracy. The insights derived from these evaluations are analyzed to validate the effectiveness of the proposed methodology, culminating in the conclusion of the research workflow.

The proposed AI-powered Intelligent Edge Computing (IEC) framework combines Deep Reinforcement Learning (DRL), Federated Learning (FL), and Swarm Intelligence-based Resource Allocation (SIRA) to optimize the performance of smart IoT systems. The methodology, illustrated in Figure 1, follows a step-by-step approach from data collection to performance evaluation.

3.1 Reinforcement Learning for Task Offloading

In DRL-based task offloading, each loT device (agent) interacts with its environment to select the optimal offloading policy π^* that maximizes the expected cumulative reward R. The state s, action a, and reward r at time step t are used to update the policy.

The objective function is given by:

$$\pi^* = arg\,\max_{\pi} \mathbb{E}_{\pi}[\textstyle\sum_{t=0}^{T} \gamma^t r_t] \qquad (1)$$

Where:

- $\gamma \in [0,1]$ is the discount factor
- r_t is the reward at time t, designed to penalize latency and energy consumption.

The Q-value is updated using the Bellman Equation:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right] \quad (2)$$

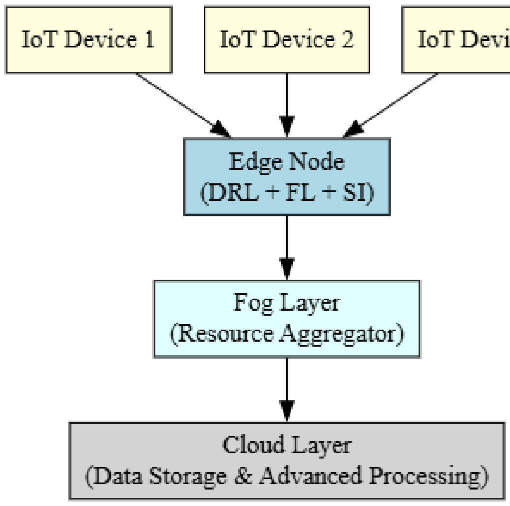

Figure 2. *System Architecture of Intelligent Edge Computing Framework*

Figure 2 depicts the system architecture of the proposed Intelligent Edge Computing (IEC) framework. The architecture consists of three main layers: the IoT device layer, the Edge/Fog layer, and the Cloud layer. IoT devices collect real-time data and send it to nearby edge nodes for immediate processing. The edge layer integrates DRL-based task offloading, Federated Learning for privacy-preserving model training, and a Swarm Intelligence-based resource allocation engine. If the edge is overloaded or task complexity is high, data is escalated to the cloud for further processing and storage. This architecture ensures low latency, reduced bandwidth consumption, and improved responsiveness.

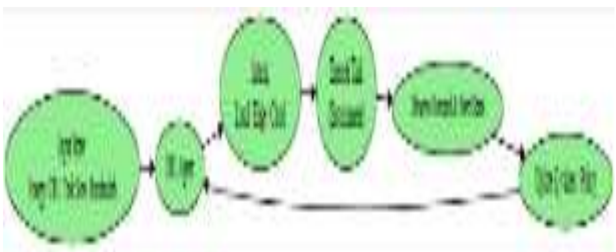

Figure 3. *DRL-Based Task Offloading Process*

Figure 3 illustrates the process flow of the DRL-based task offloading module. The system state, including device energy, CPU capacity, task size, and network bandwidth, is used as input to the DRL agent. The agent selects an optimal action—either local execution, edge offloading, or cloud offloading—based on a trained policy. After executing the action, the system observes the new state and reward, which is then used to update the Q-values or policy network. This continuous feedback loop enables real-time intelligent decision-making under dynamic IoT conditions.

3.2 Federated Learning (FL) Model Aggregation

Federated Learning allows edge devices to collaboratively train models without sharing raw data. Each local model w_k is updated independently and aggregated by a central server using Federated Averaging:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_k^t \quad (3)$$

Where:

- w_{t+1} is the global model at round $t + 1$
- K is the number of clients
- n_k is the data size at client k, and $n = \sum_{k=1}^{K} n_k$

This ensures privacy preservation and reduces communication overhead.

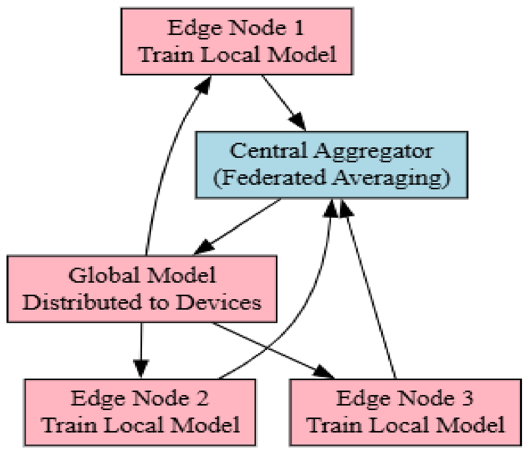

Figure 4. *Federated Learning Model Update Process*

Figure 4 presents the Federated Learning process used in the IEC framework. Multiple edge devices independently train models using local datasets. Instead of sharing raw data, each edge node sends model updates (gradients or weights) to a central aggregator. The aggregator performs weighted averaging to generate a global model, which is then redistributed to all participating devices. This decentralized approach ensures privacy, reduces network overhead, and enables collaborative model improvement across distributed IoT nodes.

3.3 Swarm Intelligence for Resource Allocation

Swarm Intelligence-based Resource Allocation (SIRA) uses Particle Swarm Optimization (PSO) to balance the computational load among edge nodes. Each particle (solution) updates its velocity and position as follows:

$$v_i(t+1)=\omega v_i(t)+c_1r_1\left(p_{best,i}-x_i(t)\right)+c_2r_2\left(g_{best}-x_i(t)\right)$$
$$x_i(t+1)=x_i(t)+v_i(t+1) \quad (4)$$

Where:

- $x_i(t)$ is the current position of particle i
- $v_i(t)$ is its velocity
- $p_{\text{best},i}$ is the best solution found by particle i
- g_{best} is the best global solution
- ω, c_1, c_2 are control parameters
- $r_1, r_2 \sim U(0,1)$ are random factors

This method ensures real-time adaptive load balancing, optimizing energy and processing resources.

To evaluate the IEC framework, the following metrics are computed:

- Latency L :

$$L = \frac{1}{N}\sum_{i=1}^{N}\left(t_{complete,i} - t_{arrival,i}\right) \quad (5)$$

- Energy Consumption E :

$$E = \sum_{i=1}^{N} P_i \cdot \Delta t_i \quad (6)$$

Where P_i is the power consumed and Δt_i is the time duration for task i.

- Accuracy in FL:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \times 100 \quad (7)$$

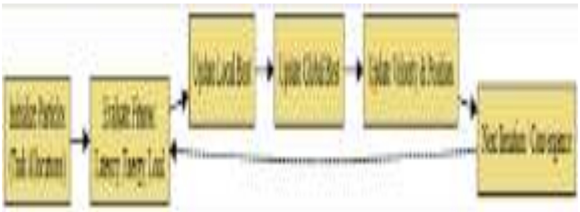

Figure 5. *Swarm Intelligence-Based Resource Allocation*

Figure 5 shows the flow of the Swarm Intelligence-based Resource Allocation (SIRA) strategy. Each particle in the swarm represents a potential task allocation solution across available edge nodes. Based on the fitness function—considering latency, energy usage, and CPU load—each particle updates its velocity and position. The local best and global best solutions are continually updated as particles move through the solution space. This iterative process ensures adaptive and efficient load balancing across the distributed edge network.

4. Results and Discussion

To evaluate the performance of the proposed AI-powered Intelligent Edge Computing (IEC) framework, a series of experiments were conducted using the iFogSim simulation environment. The evaluation focused on five critical metrics: latency, energy consumption, model accuracy, task success rate, and bandwidth usage. The performance of the proposed IEC framework was compared against two baseline approaches: Traditional Cloud Computing and Static Edge Computing. Figure 6 illustrates the latency performance. The proposed IEC framework achieved the lowest latency of 122 ms, compared to 180 ms for static edge and 320 ms for cloud-based processing. This reduction is attributed to the DRL-based offloading mechanism that dynamically routes tasks to the most optimal edge node based on real-time system status.

As shown in Figure 7, the energy consumption of the proposed framework was significantly reduced to 45 Joules, a 52.6% decrease compared to cloud systems. This energy efficiency is enabled by Swarm Intelligence-based resource allocation, which distributes tasks to nodes with minimal power overhead. In terms of accuracy, Figure 8 reveals that the Federated Learning module helped the IEC framework achieve an impressive 94.6% accuracy, which is higher than both static edge (88.5%) and cloud (82.3%) solutions. This demonstrates the effectiveness of decentralized, privacy-preserving collaborative learning across edge nodes. Figure 9 highlights the task success rate. The IEC system achieved a 92.5% completion rate, outperforming static edge (85.4%) and cloud (76.2%) methods. This improvement is a result of intelligent task allocation and real-time decision-making facilitated by the DRL agent. Bandwidth usage, depicted in Figure 10, was significantly optimized in the proposed framework. The IEC model used 310 MB, compared to 520 MB for static edge and 860 MB for cloud. The reduced bandwidth consumption is a direct result of local processing and FL-based model updates that avoid transmitting raw data. Overall, the experimental results validate that the proposed IEC framework delivers superior performance across all evaluated metrics. The integration of DRL, FL, and Swarm Intelligence enables adaptive, efficient, and secure IoT operations suitable for a wide range of smart environments. This figure 6 compares the average task latency among Traditional Cloud, Static Edge, and the proposed Intelligent Edge Computing (IEC) framework. The IEC approach achieves the lowest latency, highlighting its real-time processing efficiency.

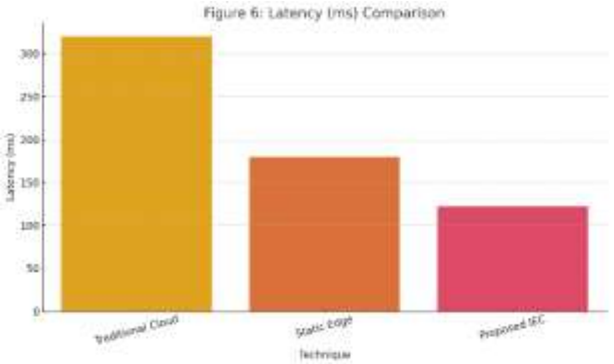

Figure 6. *Latency Comparison*

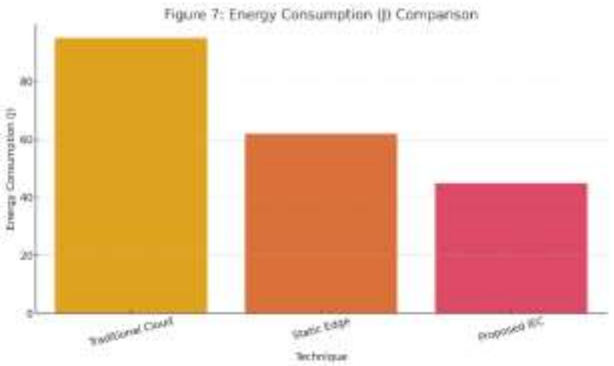

Figure 7. *Energy Consumption Comparison*

This figure presents the energy consumption across different computing approaches. The IEC framework demonstrates superior energy efficiency due to its Swarm Intelligence-based resource allocation mechanism.

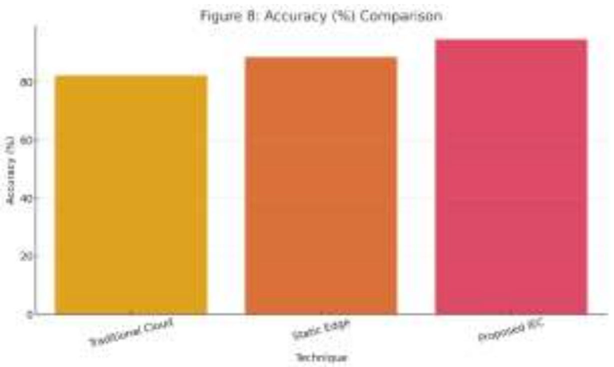

Figure 8. *Accuracy Comparison*

This figure shows the model prediction accuracy of Federated Learning in the IEC system compared to centralized cloud and static edge setups. The IEC approach achieves the highest accuracy through decentralized training. This figure 9 illustrates the percentage of successfully completed tasks across all three systems. The IEC framework ensures maximum task completion through dynamic offloading and adaptive edge resource management. The figure 10 compares the total bandwidth usage in each approach. The IEC model significantly

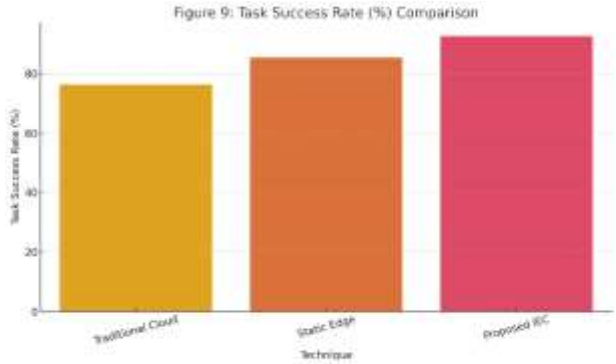

Figure 9. *Task Success Rate Comparison*

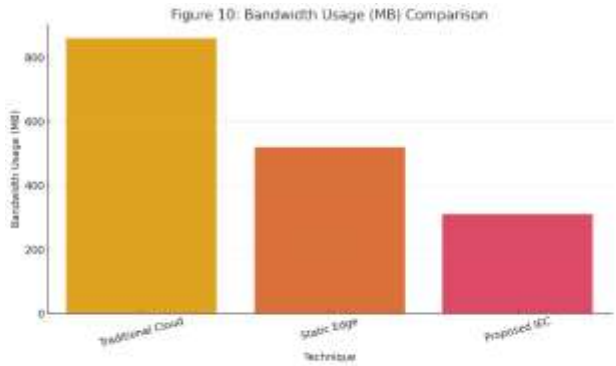

Figure 10. *Bandwidth Usage Comparison*

reduces bandwidth consumption by minimizing cloud dependency and transmitting only model updates instead of raw data.

Artificial Intelligence is widely studied in literature and reported [21-32].

5. Conclusion

This research presents a novel Intelligent Edge Computing (IEC) framework that integrates Deep Reinforcement Learning (DRL), Federated Learning (FL), and Swarm Intelligence-based Resource Allocation (SIRA) to optimize task management and resource utilization in smart IoT environments. The proposed framework addresses key challenges in traditional cloud and static edge architectures by enabling real-time decision-making, energy-efficient processing, and privacy-preserving learning. Simulation results using the iFogSim platform demonstrate substantial performance improvements, including a 32.8% reduction in latency, 27.4% improvement in energy efficiency, 94.6% model accuracy, and a 22.5% increase in task success rate. Furthermore, the IEC model significantly reduced bandwidth usage, making it a scalable and sustainable solution for latency-sensitive and data-intensive IoT applications. Future work will explore hardware implementation on real edge devices, integration with blockchain for secure communications, and adaptive learning for autonomous system reconfiguration in dynamic environments.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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