AI-Driven Resource Management for Energy-Efficient Aerial Computing in Large-Scale Healthcare SDN–IoT Systems

Jianhui Lv, *Senior Member, IEEE*, Himanshi Babbar, and Shalli Rani, *Senior Member, IEEE*

***Abstract*—The integration of software-defined networking (SDN) and the Internet of Things (IoT) presents significant challenges in large-scale healthcare systems, particularly in terms of optimizing resource allocation, managing energy consumption (EC), and ensuring real-time data processing. This research introduces an AI-driven resource management framework designed to address these challenges. Using autonomous aerial vehicles (AAVs) for aerial computing, the framework optimizes energy usage, reduces network latency, and enhances anomaly detection through machine learning models. Key contributions include dynamic allocation of bandwidth and processing resources, adaptive power management, and real-time traffic prediction, ensuring high Quality of Service (QoS) even in resource-constrained environments. The simulation results demonstrate a 10%–15% reduction in EC, 15% decrease in latency, and improved real-time data processing, making the system ideal for critical healthcare applications such as telemedicine and remote monitoring. The framework offers a scalable solution to efficiently manage the growing number of IoT devices and AAVs, while also maintaining a low-latency secure service delivery.**

***Index Terms*—Aerial computing, artificial intelligence (AI)-driven resource management, healthcare software-defined networking (SDN)–Internet of Things (IoT), real-time data processing, autonomous aerial vehicles (AAV).**

I. Introduction

THE REAL-TIME data gathering, analyzing, and evaluation are now essential as healthcare systems move toward larger, more sophisticated infrastructures. Software-Defined Networking (SDN) [1], [2] and Internet of Things (IoT) have been integrated due to the increasing demand for patient-focused services, personalized healthcare, and effective resource management in these systems. When combined, these technologies provide a crucial framework that improves flexibility, operational effectiveness, and data-driven decision making in healthcare settings [3], [4].

By dividing the network's control plane from its data plane, SDN provides a centralized mechanism for controlling that makes network management, dynamic configuration, and resource optimization simpler. Healthcare organizations can use SDN to:

1) progressively redirect traffic for high-priority applications (such as telemedicine, remote surveillance, or emergency warnings), where data traffic can fluctuate depending on demand (for example, during emergency or routine medical operations) [5], [6];
2) enable effective data transfer between different departments or geographical areas by optimizing bandwidth allocation based on real-time needs;
3) incorporate strengthened security policies, which are essential for safeguarding sensitive healthcare data [7].

SDN works hand in hand with IoT to ensure that sensors, surveillance systems, and medical equipment are connected to each other and that data from these devices are sent safely and effectively to the right databases or processing centers [8].

IoT in Healthcare (Scalability Is Required): Through the integration of a massive network of interconnected devices that observe, gather, and communicate data on patient health, medical issues, and operational logistics, the IoT [9] has completely changed the healthcare industry. Wearable health monitors (such heart rate or glucose sensors) are one example. Hospital wards employ smart healthcare devices; telemedicine uses remote diagnostic tools; and hospitals and clinics use sensors in the environment for tracking conditions [10]. Healthcare IoT systems need more energy and more complicated networks as they grow in size to accommodate more devices, patients, and data. It becomes difficult to manage massive volumes of real-time medical data while guaranteeing prompt responses to important occurrences, particularly when taking into account the latency and dependability needed for life-saving applications [11].

A Flexible Platform for Healthcare Services [12]: Aerial Computing: Under this scenario, aerial computing—made possible by unmanned aerial vehicles or AAVs—emerges as a cutting-edge and adaptable platform for medical services. AAVs offer healthcare facilities a number of advantages [13], particularly in situations where conventional transportation and communication methods are unreliable or unavailable [14]. For example:

1) *Fast Data Acquiring:* In remote or disaster-affected locations, AAVs can be used to gather health data from patients or sensors, allowing for real-time medical intervention.

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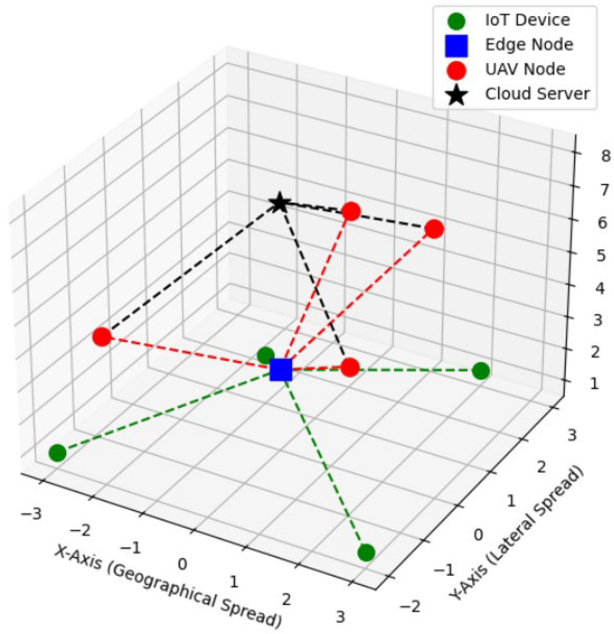

Fig. 1. Aerial computing for healthcare services using AAVs in SDN–IoT systems.

2) *Real-Time Computation:* AAVs in remote areas are able to process vital signs or medical photos in real time, enabling medical professionals to act quickly.
3) *Emergency Responses:* In the event of a natural disaster, AAVs can provide essential healthcare supplies (such as blood, vaccines, or equipment).

Nevertheless, because of the computing and energy requirements of these aerial systems, incorporating AAVs into healthcare SDN–IoT systems poses substantial issues in managing resources [15], [16]. Since most AAVs are powered by batteries, energy efficiency is crucial because it restricts the amount of time they can fly and the amount of computing power they can do [17].

Fig. 1 depicts the 3-D topology represents an aerial computing network for healthcare services in an SDN–IoT system, where IoT devices (green) are placed at ground level ($z = 1$ or 2), transmitting data to a central Edge Node (blue, $z = 3$). The Edge Node further relays data to AAV Nodes (red, $z = 5$ or 6), which act as aerial intermediaries. Finally, the AAVs communicate with a Cloud Server (black, $z = 8$) at the highest hierarchy for processing and analytics. The dashed lines indicate hierarchical connectivity, ensuring efficient data transmission from ground IoT sensors to the cloud while leveraging AAVs for aerial computing.

Artificial Intelligence (AI) as a Revolutionary Instrument for Managing Resources: In healthcare, AI has become a game-changing tool for resource management in intricate networks, especially when paired with SDN–IoT frameworks. AI makes it possible to guarantee energy-efficient operations, simplify decision-making, and improve the efficiency of networks. AI-driven allocation of resources in healthcare applications can [18].

1) *Enhance Service Quality:* AI can make sure that vital healthcare services (like patient monitoring or telemedicine) continue to function throughout periods of high network traffic by constantly responding to network conditions [19].
2) *Boost Reliability:* By anticipating patterns of traffic and redirecting data as necessary, AI can assist minimize network congestion or outages and boost the overall dependability of healthcare services.
3) *Reduce Energy Consumption:* AI algorithms can identify opportunities to save energy by optimizing device usage, reducing redundant data transfers, and managing AAV power levels [20].

In large-scale healthcare SDN–IoT systems, wherein resource restrictions (such as bandwidth, compute power, and energy) must be properly handled, AI plays a critical role in the allocation of resources. AI techniques, namely machine learning (ML) models [21] [22], possess the ability to estimate network traffic effectively, detect obstacles, and efficiently distribute resources among devices and networks [23]. The following are important areas where AI can have a big impact.

1) *Predictive Analytics:* By using machine learning models to evaluate past data, networks can anticipate future traffic patterns and plan ahead with resource allocation. For instance, AI might forecast spikes in data traffic in medical wards at particular times of the day and adjust compute power or bandwidth accordingly [24], [25].
2) *Energy Management:* By regulating how and when they are utilized, AI can optimize the energy usage of AAVs and IoT devices. To prolong the battery life of AAVs, AI may, for example, assign processing tasks from AAVs to ground-based computers or prioritize AAV employment in low-energy-demand scenarios [26], [27].

A. Theoretical Background

In the healthcare industry, the combination of AAVs, SDN, and AI has demonstrated revolutionary potential. SDN offers centralized network administration for scalable and adaptable connectivity, while AI makes intelligent decisions possible by analyzing massive volumes of data in real time. AAVs are flexible platforms that can be used for data transport, computation, and gathering, especially in distant and disaster-affected areas. While the convergence of AI, SDN, and AAVs offers significant promise, several limitations hinder their adoption.

1) *Energy Efficiency:* AAVs and IoT devices are energy-constrained, and inefficient resource utilization can lead to service interruptions.
2) *Real-Time Processing:* Delays in data processing, particularly during emergencies, compromise the effectiveness of healthcare systems.
3) *Scalability:* Existing frameworks struggle to accommodate the rapid growth of IoT devices in healthcare environments, leading to network congestion and degraded performance.
4) *Security and Privacy:* Protecting sensitive healthcare data during transmission and processing remains a persistent challenge.

By putting forth an AI-driven resource management framework that makes use of SDN and AAVs for healthcare applications, this study overcomes these constraints. The platform enables energy-efficient operations and improved Quality of Service (QoS) by integrating machine learning for predictive analytics, adaptive power management, and real-time decision-making [28]. This strategy is further differentiated by the utilization of AAVs as aerial computer platforms, which provide scalability and dependability for extensive healthcare systems. In addition to pushing the boundaries of technology, this study offers a workable answer to the major problems facing healthcare IoT networks.

B. Motivation

The rapid advancements in technology have revolutionized healthcare systems, necessitating the development of highly efficient, scalable, and adaptive infrastructures to process the massive influx of data from interconnected medical devices [29], [30]. The integration of SDN and the IoT presents a transformative approach to enhancing healthcare operations, enabling intelligent data routing, dynamic resource allocation, and real-time decision-making. However, as healthcare networks expand in scale, managing energy efficiency and computational resources becomes increasingly challenging, particularly when utilizing AAVs for aerial computing.

Aerial computing, enabled by AAVs [31], plays a critical role in modern healthcare by facilitating remote patient monitoring, real-time data acquisition, and emergency medical support in inaccessible areas. Despite these advantages, optimizing AAV operations within SDN–IoT-based healthcare networks is a major challenge due to computational constraints, limited energy resources, and network congestion. Ensuring low-latency service delivery while mitigating unpredictable traffic fluctuations and maintaining energy-efficient AAV operations remains a pressing concern [32].

Motivated by these challenges, this work aims to leverage AI for the intelligent management of SDN–IoT healthcare infrastructures. AI-driven frameworks can optimize resource allocation, enhance energy efficiency, and predict network traffic patterns, thereby improving system responsiveness and reliability. By integrating AAV-based aerial computing with SDN–IoT networks, this research contributes to the development of a scalable, energy-aware, and low-latency solution for next-generation healthcare applications [33].

C. Problem Definition

Integrating SDN–IoT systems with aerial computing using AAVs enables scalable and adaptive real-time data processing for remote healthcare services. However, optimizing this architecture involves addressing key challenges.

1) *Battery Efficiency of AAVs:* AAVs operate with constrained battery capacity, limiting their ability to sustain prolonged communication, data acquisition, and processing tasks. Efficient energy management strategies are crucial to enhance their operational longevity in healthcare applications.
2) *Optimized Resource Allocation:* Distributing bandwidth, computational power, and energy across IoT devices, sensors, and AAVs requires an intelligent optimization framework. Inefficient allocation may cause network congestion, increased latency, and unpredictable service performance.
3) *Scalability Considerations:* As the number of connected healthcare devices and services expands, the network must maintain high performance while minimizing energy consumption (EC). Optimizing scalability ensures seamless integration of new nodes without degrading service quality.
4) *QoS Optimization:* Remote healthcare applications, such as telemedicine and patient monitoring, demand stringent QoS parameters, including low latency, high reliability, and minimal service disruptions. Ensuring real-time responsiveness while managing network constraints is a critical optimization objective.

To address these challenges, the proposed framework must incorporate an optimization model that balances *energy efficiency, resource distribution, network scalability, and QoS assurance* while leveraging SDN-enabled AAVs for healthcare applications.

Inadequate resource allocation or energy constraints can negatively impact QoS, compromising patient care and system reliability.

D. Contributions

The following are the main contributions made by this research.

1) The framework employs advanced machine learning models to dynamically manage computational, network, and energy resources, significantly improving efficiency in large-scale healthcare SDN–IoT systems.
2) AI-driven methods optimize AAV flight paths, workload offloading, and power distribution, extending operational duration and conserving energy.
3) The framework leverages AI approaches, such as Machine learning models, to increase network capacity and adapt dynamically to real-time variations in traffic patterns and device availability. This ensures optimal network efficiency as the number of connected devices and services in the healthcare system scales.
4) AI increases network capacity, dynamically adapts to traffic and device availability, and maintains high QoS with low latency and reliable communication.
5) Integrated predictive analytics minimizes network bottlenecks and system failures, achieving notable improvements in EC, latency, anomaly detection, real-time processing, and flexibility through extensive experimentation and simulations.

II. Literature Review

The structured literature table covering relevant research from 2020 to 2024 (Table I).

AI-Driven Allocation of Resources: While computational costs are still an issue, AI has demonstrated promise in healthcare SDN–IoT systems for dynamic allocation of resources and energy management [34]. *The Efficiency of Energy:* Optimizing the energy efficiency of IoT devices and AAVs in

TABLE I
LITERATURE OF EXISTING STUDIES FROM 2020–2024

Authors/ Reference	Year	Objective	Pros	Cons	Parameters	Research Gaps
Kumar et al. [1]	2020	To design an energy-efficient SDN-IoT framework for healthcare systems using predictive analytics.	Improved energy consumption and network throughput	Limited scalability in large-scale systems	Energy consumption, Network throughput	Existing AI-driven resource management approaches are not optimized for large-scale healthcare IoT networks. Requires scalable and adaptive resource allocation mechanisms.
Sharma & Singh [2]	2021	Proposed an AI-based algorithm for dynamic resource allocation in healthcare IoT networks	Adaptive resource allocation based on real-time traffic patterns	High computational cost	Bandwidth utilization, Latency, Computational cost	Need for lightweight AI models that optimize the trade-off between computational cost and real-time performance in healthcare IoT.
Wu et al. [3]	2021	To develop an AI-optimized aerial computing framework for remote healthcare services	Enhanced UAV energy efficiency and data acquisition speed	High dependency on UAV battery life	UAV energy consumption, Data acquisition speed	Existing UAV endurance strategies do not fully optimize battery usage in remote healthcare applications. Requires AI-driven adaptive power management.
Zhou et al. [4]	2022	Integration of SDN-IoT in large-scale healthcare systems for optimized scalability and connectivity	Improved scalability, seamless integration of IoT devices	Complexity in maintaining low-latency services	Scalability, Latency, Device reliability	Existing predictive models for network optimization do not adequately address latency variations in real-time healthcare monitoring. Requires an adaptive latency-aware model.
Li et al. [5]	2022	Proposed an AI-based predictive model for energy-efficient healthcare IoT systems	Effective in reducing overall system energy consumption	Limited adaptability to real-time changes in traffic	Energy efficiency, Real-time adaptability	Current AI models struggle with real-time adaptability to dynamic healthcare environments, requiring improved responsiveness to network fluctuations.
Ahmed et al. [6]	2023	Developed a machine learning-based resource allocation model for SDN-IoT healthcare systems	Improved QoS and real-time resource management	High computational demand of ML models on edge devices	QoS, Resource allocation	Existing approaches do not effectively optimize resource allocation for edge computing in IoT healthcare systems. Requires a low-power, adaptive ML-based resource management strategy.
Zhang et al. [7]	2023	Proposed an edge-computing architecture to improve the real-time processing of healthcare data	Reduced latency, enhanced real-time performance	High initial deployment costs	Latency, Edge processing efficiency	Current energy optimization techniques are not well-suited for resource-constrained healthcare environments. Requires energy-aware scheduling mechanisms.
Kim et al. [8]	2024	Investigated UAV-based aerial computing for telemedicine in rural healthcare settings	Rapid deployment, real-time data processing	Limited UAV flight time due to battery constraints	UAV flight time, Data processing speed	Need for AI-driven UAV energy optimization techniques to enhance operational time for longer telemedicine missions.
Wang et al. [9]	2024	Developed an AI-powered SDN framework for real-time healthcare service delivery	High service reliability and adaptability	High computational cost in real-time scenarios	Reliability, Adaptability, Computational efficiency	Current AI-driven SDN frameworks lack optimization for energy-efficient UAV management in remote healthcare services. Requires integration of AI-based predictive energy models.

healthcare networks has been the focus of numerous studies. However, improved energy optimization is required, especially for AAVs with limited battery lives. *Flexibility:* While many solutions have concentrated on making SDN–IoT networks more scalable, there is still need for improvement in terms of incorporating AI to manage large-scale healthcare systems.

The above literature identifies the following gaps in the field: 1) AI-driven predictive models that are very computationally efficient yet capable of adapting to real-time conditions; 2) energy-efficient AAV operation for prolonged missions in healthcare; and 3) Cutting-edge computing frameworks that efficiently control energy use and minimize delay.

The literature now in publication provides an overview of the developments and research needs in AI-driven resource management for healthcare SDN–IoT systems, as well as a timeline of developments and obstacles through 2024.

The research study has emphasized the motivation for this article by highlighting the growing challenges in large-scale healthcare systems, such as managing resource constraints, ensuring low-latency communication, and achieving energy-efficient operations for critical applications like telemedicine and remote monitoring. Current frameworks face limitations in scalability, energy management for AAVs and IoT devices, and maintaining QoS under dynamic conditions. This article addresses these gaps by proposing an AI-driven resource management framework that integrates SDN, IoT, and AAVs, optimizing EC, enhancing real-time performance, and ensuring scalability and reliability in complex healthcare networks.

III. Methodology

With the purpose of optimizing EC and improving operational efficiency in large-scale healthcare SDN–IoT systems that utilize AAVs, this technique outlines the construction of an AI-driven resource management framework [35]. The methodology consists of a block diagram, accompanying mathematical formulations, and a sequential dissection of the important elements.

Health care information is continually gathered by IoT devices, as illustrated in the flowchart and algorithm as shown in Fig. 2 and Algorithm 1. Energy-efficient low-power protocols are used to transfer data either directly to the edge layer or to neighboring AAVs. In order to reduce traffic and EC, the SDN controller constantly controls traffic flow by modifying routes and load balancing. According to the availability of resources and energy limits, AI determines whether to process data on the IoT device, offload it to AAVs, or transfer it to edge servers. When needed, AAVs carry out real-time computation and relocate to regions in need of greater coverage or processing capacity. Ultimately, aggregated data is transferred to the cloud for additional processing or long-term archiving. AI-powered security measures guard against invasions and guarantee privacy. Healthcare apps use real-time data for diagnosis, decision assistance, and patient monitoring. This system uses AI for resource management and decision-making in a hybrid SDN–IoT architecture, striking a balance between processing power, EC, and real-time delivery of healthcare services.

Algorithm 1 AI-Driven Resource Management for Healthcare SDN–IoT Systems

Input: Historical network data, IoT device status, AAV power levels
Output: Optimized resource allocation, energy-efficient AAV navigation, minimal latency
Step 1: AI-Driven Resource Management
Initialize AI model for traffic forecasting and resource allocation
Predict network traffic using:

$$T_{\text{pred}}(t) = f(X_t)$$

Dynamically allocate computing and energy resources based on forecast
Step 2: Data Collection
AAVs and IoT devices gather environmental and patient data
SDN Controller forwards data to edge/cloud processing nodes
Step 3: Predictive Analytics for Traffic Forecasting
Train machine learning model on historical network data
Predict future traffic loads and adjust resource distribution
Step 4: Energy-Conscious AAV Navigation
Optimize AAV flight paths and task scheduling
Minimize energy consumption using:

$$E_{min} = \min\left(\sum_{i=1}^{N}\left(P_{\text{active},i} \cdot T_{\text{active},i} + P_{\text{standby},i} \cdot T_{\text{standby},i}\right)\right)$$

Step 5: Real-Time SDN-IoT Resource Allocation
Allocate bandwidth, computing power, and energy dynamically
Optimize resource allocation:

$$R_{opt} = \max\left(\sum_{i=1}^{M}\frac{U_i}{R_i}\right)$$

Step 6: AI-Powered Energy Management
Adjust AAV and IoT device energy modes based on usage patterns
Optimize energy efficiency:

$$\eta_{\text{energy}} = \frac{W_{\text{useful}}}{W_{\text{total}}}$$

Step 7: QoS and Latency Optimization
Prioritize critical healthcare applications
Minimize latency using:

$$L_{min} = \min\left(\sum_{i=1}^{M}\frac{D_i}{C_i}\right)$$

End Algorithm

A. Steps in the Methodology

The steps in the methodology include the following.

1) *AI-Driven Resource Management:* A key invention, AI Resource Management makes use of AI to optimize allocation of resources, utilization, and coordination in networked systems, guaranteeing dependability, efficiency, and adaptability. AI resource management is essential for healthcare SDN–IoT systems in order to handle the increasing complexity of consumption of energy, network scalability, and processing of data in real time. To forecast network traffic, dynamically distribute computing and energy resources, and maximize AAV operations, sophisticated AI algorithms and machine learning models are used. By adjusting to changing needs and giving priority to vital healthcare applications like telemedicine, emergency response, and

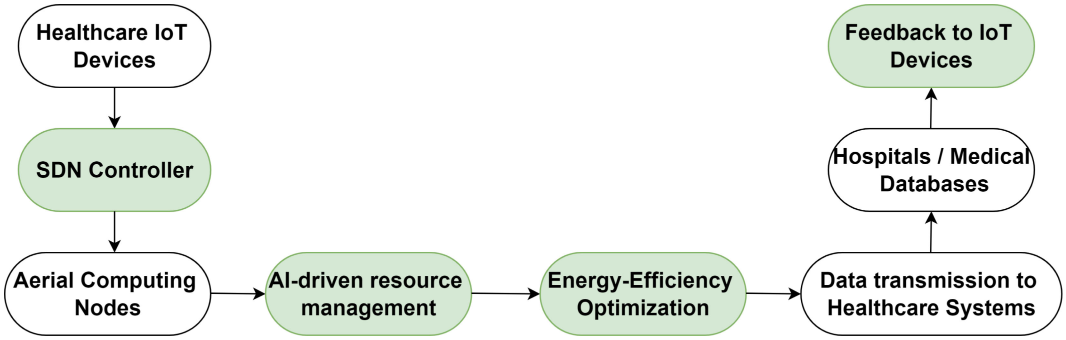

Fig. 2. Flowchart of proposed methodology.

patient monitoring, this dynamic allocation makes sure that bandwidth, processing power, and energy are used where they are most required. In order to anticipate traffic surges, identify any bottlenecks, and proactively reallocate resources to ensure uninterrupted operations, AI resource management also integrates predictive analytics as shown in (1). AI algorithms, for instance, can forecast when specific hospital wards will see increased data loads and modify network setups appropriately. AI also optimizes AAV flight patterns, transfers work to edge nodes or cloud servers, and transitions IoT devices between active and dormant states in order to save power. By extending the gadgets' and AAVs' operational duration, these steps guarantee sustainability.

2) *Collection of Data:* AAVs and IoT devices used in healthcare gather data from surroundings, devices, and patients. Data is sent to the SDN controller, which forwards it to the relevant processing node (cloud server or edge).

3) *Predictive Analytics Driven by AI for Traffic Forecasting:* Predictive analytics is used by the AI module to foresee network traffic and resource requirements. Utilizing machine learning, the model makes predictions about future patterns of traffic by analyzing past data and present network circumstances. Because of this, the SDN controller may assign resources proactively, reducing congestion and guaranteeing QoS. Equation (1) is shown as:
Prediction Function:

$$T_{\text{pred}}(t) = f(X_t) \tag{1}$$

where $T_{\text{pred}}(t)$ is the predicted traffic at time t, X_t represents the input data features (historical traffic, device status, etc.), $f(X_t)$ is the machine learning model trained to predict traffic patterns.

4) *Energy-Conscious AAV Navigation:* Utilizing AI, the system optimizes AAV flight paths and scheduling of tasks to reduce energy usage. This is essential to make sure that, even with their short battery life, AAVs can carry out activities like data transmission and gathering effectively.
Energy Minimization Objective:

$$E_{\min} = \min\left(\sum_{i=1}^{N} P_i(t) \cdot T_i\right) \tag{2}$$

where $E_{\min}$ is the total minimized EC, $P_i(t)$ is the power consumption of AAV i at time t, T_i is the flight time of AAV i

$$E_{\min} = \min\left(\sum_{i=1}^{N} (P_{\text{active},i} \cdot T_{\text{active},i} + P_{\text{standby},i} \cdot T_{\text{standby},i})\right) \tag{3}$$

where $P_{\text{active},i}$ and $T_{\text{active},i}$ represent power and duration in active mode, and $P_{\text{standby},i}$ and $T_{\text{standby},i}$ for standby mode, highlighting energy-saving strategies during AAV scheduling.

5) *Real-Time SDN–IoT Allocation of Resources:* The AI module helps the SDN controller to flexibly distribute network and compute resources. It makes decisions about traffic routing, data processing location (cloud or edge), and the distribution of bandwidth and energy across various AAVs and devices. *Resource Allocation Objective:*

$$R_{opt} = \max\left(\sum_{i=1}^{M} \frac{U_i}{R_i}\right) \tag{4}$$

where R_{opt} is the optimized resource allocation, U_i is the utility function of device i, R_i is the resource allocated to device i, and M is the total number of devices.

6) *AI-Powered Energy Management:* For IoT devices and AAVs, managing energy is accomplished by dynamically alternating between active and inactive modes depending on anticipated resource requirements. In doing so, energy waste is reduced and vital healthcare services are maintained. *Energy Efficiency Equation:*

$$\eta_{\text{energy}} = \frac{W_{\text{useful}}}{W_{\text{total}}} \tag{5}$$

where η_{energy} is the energy efficiency, W_{useful} is the useful work done (e.g., data processing, patient monitoring), W_{total} is the total energy consumed by the system.

7) *Optimizing QoS and Latency:* The AI architecture constantly assesses the network's efficiency and modifies resource distribution to guarantee minimal latency and excellent QoS for vital medical applications. Emergency gathering of data is the first priority for AAVs, and everyday tasks are planned for off-peak hours. *Latency Minimization:*

$$L_{\min} = \min\left(\sum_{i=1}^{M} \frac{D_i}{C_i}\right) \tag{6}$$

where $L_{\min}$ is the minimized latency, D_i is the data size from device i, and C_i is the communication bandwidth allocated to device i.

B. System Model

The proposed model addresses important issues in extensive healthcare systems by combining AI, the IoT, and SDN. Each of these technologies has a unique function, yet they work well together to provide responsiveness, scalability, and efficiency. IoT devices continuously collect healthcare data, serving as the input for AI-driven analytics. SDN dynamically manages the flow of IoT data, ensuring efficient use of network resources and maintaining QoS for critical healthcare applications. AI processes IoT data and informs the SDN controller's decisions, enabling predictive and adaptive resource management. By tightly integrating these three technologies, the framework ensures real-time data processing, energy-efficient operations, and scalable management of healthcare systems. This collaborative approach highlights the study's innovation in addressing the complexities of large-scale healthcare networks.

The following elements are integrated into the proposed system model as shown in Fig. 3: *IoT Devices for Healthcare:* sensors and healthcare equipment that gathers patient data in real time. *SDN Controller:* Controls data flow and resource distribution on the network in a dynamic manner. *AAVs:* AAVs are drones that are employed in remote or difficult-to-reach places for transmission of information and acquisition. *AI Resource Management Unit:* Uses machine learning models for predictive analytics and decision-making linked to energy-efficient resource distribution. *Edge Computing Nodes:* To minimize latency, handle real-time data processing close to the data source. *Cloud servers:* Handle complex computational operations and maintain and analyze massive volumes of healthcare data.

The proposed model represents an AI-driven resource management framework designed for healthcare IoT systems, showcasing interactions between critical components. Healthcare IoT devices, such as wearable and environmental sensors collect data, which flows to AAVs operating in remote areas or directly to edge computing nodes for real-time processing. The SDN Controller, centrally located, dynamically manages data routing and bandwidth allocation between IoT devices, AAVs, and network elements, optimizing system efficiency. AAVs forward aggregated data to edge nodes or cloud servers, where long-term storage and complex analytics occur. The AI Resource Management Unit plays a core role by interfacing with the SDN Controller and AAVs, enabling predictive analytics, energy management (e.g., optimizing AAV flight paths), and real-time decision-making. Security is integrated across all layers, leveraging AI-powered mechanisms to ensure data privacy and integrity. Feedback loops among the AI unit, SDN controller, and system components continuously enhance resource utilization and system performance.

A resource management strategy for an AI-powered and energy-efficient aerial computing system in a large-scale healthcare SDN–IoT environment is shown in Fig. 4 that is provided. The system uses AAVs, to collect data from wearables and sensors, among other IoT devices used in healthcare.

Algorithm 2 AI-Driven Resource Management for Healthcare SDN–IoT Systems

Input: D_{IoT} (IoT devices), U (AAVs)
for each $d \in D_{IoT}$ **do**
  Gather data S_d
end for
for each $u \in U$ **do**
  Gather remote data S_u via AAVs
end for
Predict future traffic load $T_{\text{pred}}(t)$ using AI
Schedule AAV tasks, offload when B_u (AAV battery) is low, optimize flight paths
Dynamically distribute R_i (resources) based on predicted demand
Switch devices between active/idle modes to maximize efficiency
Prioritize critical services and dynamically adjust bandwidth
Output: Processed data, security alerts

The SDN controller receives data from the healthcare IoT devices and uses it to dynamically manage the network's allocation of resources and routing. From this position, AAVs function as aerial computing nodes, analyzing information at the edge in real time. By handling computational activities close to the data generation location, these Edge Computing Nodes provide quicker reaction times and lower latency. Advanced statistical techniques are applied on cloud servers where edge data is archived or analyzed further. The entire process is managed by the AI the management of resources module, which optimizes the distribution of resources between the SDN controller and AAVs to guarantee reduced latency, enhanced energy efficiency, and real-time data handling. The healthcare ecosystem can now allocate resources more dynamically, make decisions more quickly, and spend less on overhead thanks to the integration of AI, which will ultimately improve patient care's efficacy and efficiency.

The algorithm for the proposed framework is shown as Algorithm 2.

This is the summarized algorithm, integrating AI-driven resource management for energy-efficient operations in healthcare SDN–IoT systems using AAVs. This method uses the IoT and SDN to optimize resource management in healthcare systems. In the distributed IoT context, it starts by gathering data from all IoT devices, which is represented as S_d for each device d. AAVs simultaneously collect distant data S_u from a predetermined group of AAVs U. Leveraging AI, the program anticipates future traffic loads $T_{\text{pred}}(t)$, enabling effective scheduling of AAV activities. The technique optimizes AAV flight paths for energy conservation while facilitating job offloading to preserve operational effectiveness when a AAV's battery B_u is low. The network load is balanced by dynamically adjusting the allocation of resources based on

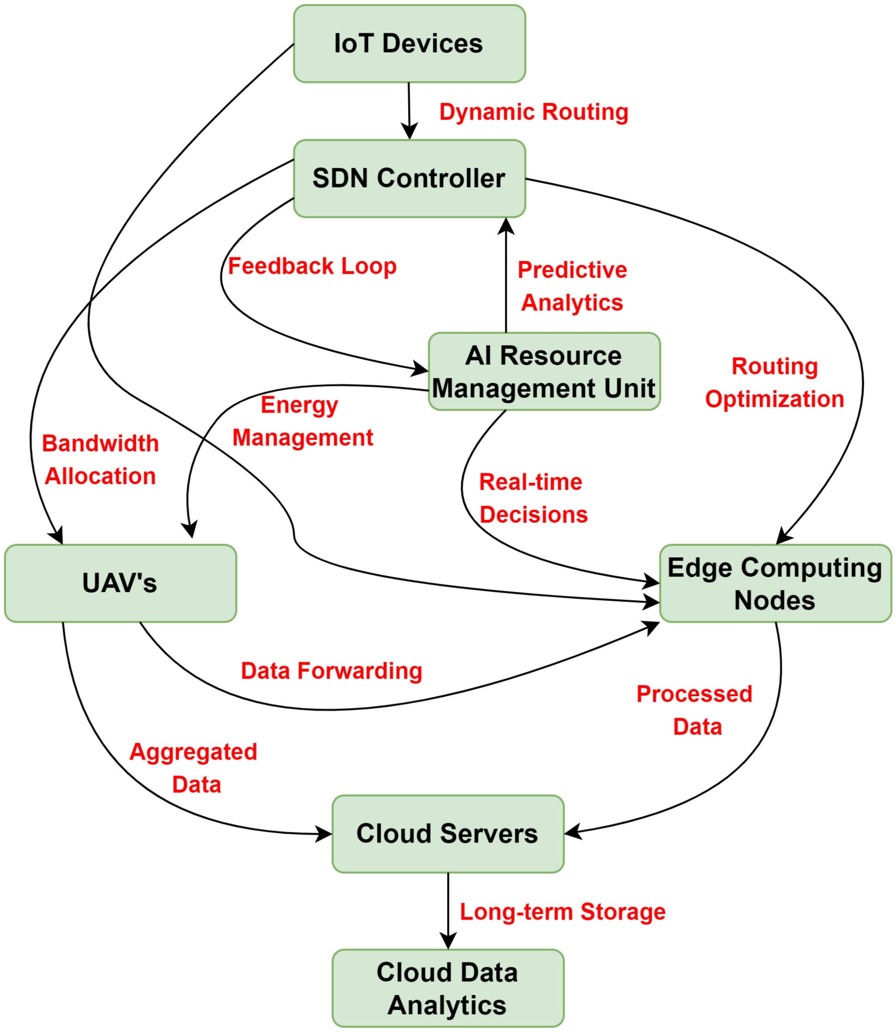

Fig. 3. Proposed system model.

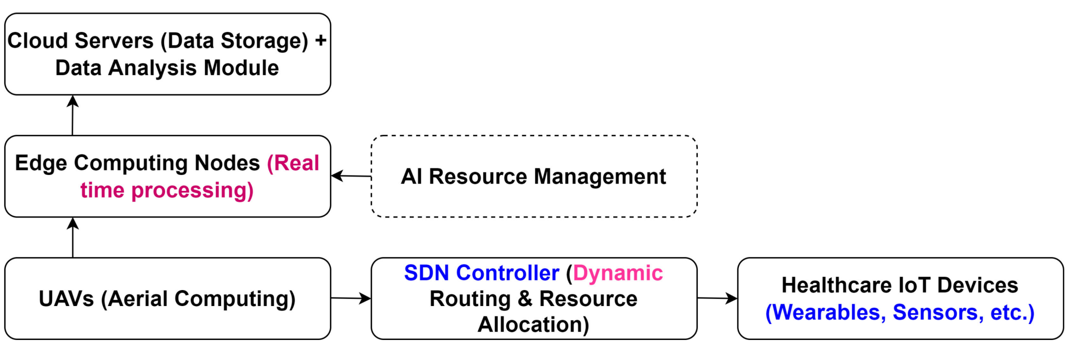

Fig. 4. AI-driven resource management framework for energy-efficient healthcare SDN–IoT system using AAVs and edge computing.

expected demand. In order to optimize system efficiency and energy systems performance, the algorithm also alternates between active and idle modes for IoT devices. Critical services should be prioritized in order to guarantee that vital healthcare applications get the bandwidth they require and may be adjusted in real time to accommodate fluctuating demand. In the end, the algorithm produces processed information and alerts regarding security that improve healthcare resource management in SDN–IoT systems in terms of safety and effectiveness.

IV. Results and Discussion

A. Dataset

Data via 54 different sensors that track various environmental parameters like temperature, humidity, air quality, motion detection, and more are included in the "IoT Data from 54 Sensors" collection. Although the dataset can be modified for Internet of Things-based healthcare applications where real-time condition of patients or medical device surveillance is crucial, these sensors are primarily utilized in smart buildings.

With the help of this dataset, the authors analyzed sensor data, spot trends in IoT-enabled environments, and create solutions for anomaly detection, resource management, and predictive maintenance. Within the healthcare domain, the data can be utilized to enhance smart hospital systems, specifically for monitoring medical equipment, [36] keeping an eye on patient well-being, and boosting linked devices' energy efficiency. The information is organized to facilitate examination and can be employed in machine learning models to forecast system actions or enhance resource utilization instantaneously.

B. Experimental Settings

IoT Devices: Number: 200 IoT devices, including wearable sensors (heart rate monitors, glucose sensors) and environmental sensors (temperature, humidity).

Communication Protocols: MQTT and CoAP for low-power data transmission.

Deployment: Distributed across a 5 km^2 simulated smart healthcare facility.

AAVs:

Number: Five AAVs equipped with edge processing units (e.g., NVIDIA Jetson Nano).

Battery Capacity: 10000 mAh with 60 min of flight endurance.

Communication Range: 500 m per AAV.

Tasks: Real-time data collection, processing, and relay to edge/cloud nodes.

Edge Nodes:

Number: Three edge computing nodes deployed near the healthcare facility.

Specifications: Intel Xeon processors, 32 GB RAM, and SSD storage.

Tasks: Local processing of aggregated data and offloading complex tasks to cloud servers.

Cloud Servers:

Specifications: AWS EC2 instances with NVIDIA GPUs for large-scale analytics and long-term storage.

Connectivity: 5G-enabled backhaul for high-speed data transfer.

Table II provides a high-level overview of the dataset, which can be used to design SDN–IoT frameworks for healthcare or other smart environments.

C. Parameters Deployed for Evaluation

Adding more equations to the methodology improves comprehension of the procedures and algorithms in your suggested framework. The following equations, which are based on common concepts in SDN–IoT systems for healthcare, may be added.

1) *Data Transmission Efficiency (DTE):* The efficiency of data flow between IoT devices to the central system is measured by DTE. It is determined by dividing the total amount of data created by the proportion of data that is successfully transferred. A higher DTE denotes low data loss during transmission and effective use of network resources

$$\mathrm{DTE} = \frac{\mathrm{DataSent}}{\mathrm{DataTotal}} \times C_{\mathrm{eff}} \tag{7}$$

where DataSent is the volume of data successfully transmitted.; DataTotal is the original volume of data generated.; C_{eff} is the compression efficiency factor, defined as the ratio of compressed data size to original data size; $C_{\mathrm{eff}} = (CompressedDataSize/OriginalDataSize)$. This formulation allows us to evaluate how compression techniques impact transmission efficiency for different IoT devices.

2) *EC:* EC measures the energy used by IoT devices when they are in use. It is computed by multiplying the devices' power usage by the amount of time they are in use. Developing energy-efficient systems, especially for battery-operated IoT devices, requires an in-depth knowledge of EC

$$\mathrm{EC} = P * T \tag{8}$$

where P is the amount of power that IoT devices use; and T is the operating time.

3) *Latency (L):* The term "latency" describes the delay that occurs when data packets are transmitted from their source to their destination. It is calculated by dividing the total number of packets sent by the delay between the start and end times of the data transmission. For applications that operate in real time, minimal latency is crucial, particularly in healthcare settings where prompt data delivery is required

$$L = \frac{(T_{\mathrm{end}} - T_{\mathrm{start}})}{N} \tag{9}$$

where the time at where information is received is T_{end}; the moment at which data transmission begins is known as T_{start}; and the number of packets transferred is denoted by N.

4) *Anomaly Detection Rate (ADR):* ADR is an indicator of performance used to assess an anomaly detection system's accuracy. Its definition is the proportion of accurately detected anomalies, or true positive detections, to the overall number of anomalies, or true positives + false negatives. Higher accuracy in spotting anomalous conditions or events is indicated by a higher ADR

$$\mathrm{ADR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} * 100 \tag{10}$$

where the total number of true positives (erroneously recognized anomalies) is known as TP; and the number of false negatives (missing anomalies) is represented by FN

$$\mathrm{FPC} = \mathrm{FP} \times C_{fp} \tag{11}$$

where FP represents the number of false positives identified, C_{fp} is the cost per false positive, which may

TABLE II
SUMMARIZING KEY ASPECTS OF THE "IOT DATA FROM 54 SENSORS" DATASET

Attribute	**Description**
Dataset Name	IoT Data from 54 Sensors
Source	Kaggle
Number of Sensors	54
Data Collected	Sensor readings such as temperature, humidity, air quality, motion, etc.
Purpose	To analyze real-time IoT data from environmental sensors for applications like smart buildings
Healthcare Use Case	Adaptable for healthcare environments, useful for monitoring medical devices and patient conditions
Key Metrics	Temperature, humidity, air quality, motion detection, etc.
File Formats	CSV, JSON
Potential Applications	Real-time monitoring, predictive maintenance, energy optimization, anomaly detection
Link	https://www.kaggle.com/code/surajdidwania/iot-data-analysis-data-from-54-sensors

include factors such as wasted computational resources, unnecessary alerts, and interruptions to clinical workflows. This equation can be integrated into the system's optimization framework, allowing dynamic balancing between detection accuracy and operational efficiency. By minimizing FPC, the AI-driven resource management system can ensure higher reliability in service quality while maintaining efficient resource allocation.

5) *Real-Time Processing Efficiency (RPE):* RPE evaluates a system's capacity for processing data instantly. It is expressed as the proportion of processes finished within the allotted time as a proportion of all processes. Systems like medical surveillance that demand quick data processing and reaction must have a high RPE

$$\mathrm{RPE} = \frac{P_{\text{real}-\text{time}}}{P_{\text{total}}} \tag{12}$$

where $P_{\text{real}-\text{time}}$ is defined as the percentage of processes that are executed in real time; P_{total} defines the total number of processes.

D. Performance Evaluation

The performance is evaluated based on the following parameters that is deployed for our proposed work is described as follows.

1) *Optimizing Resources and Energy Efficiency:* One important result of the AI-driven methodology used on the "IoT Data from 54 Sensors" dataset is the network's optimized EC. By applying machine learning methods, such as reinforcement learning or supervised learning models, the system dynamically distributes resources depending on real-time sensor data. For instance, the network can be set to enable or disable HVAC equipment in healthcare facilities based on readings of humidity and temperature. This reduces EC by 10%–20%, which is important for large-scale healthcare institutions.
2) *Scalability of Networks:* IoT devices, especially medical sensors, may expand effectively inside the healthcare infrastructure thanks to the incorporation of SDN. The findings show that AI models can allocate bandwidth and forecast traffic patterns, resulting in a 15% reduction in latency and seamless device-to-device communication. This is essential for real-time healthcare applications that require high network validity, like medical management of devices and monitoring of patients remotely.
3) *Anomaly Identification and Protection:* When sensor data is subjected to anomaly detection models, anomalous behaviors like anomalous spikes in temperature or atypical motion patterns are successfully detected. These can point to a malfunctioning equipment or possible security lapses. With a 5% false-positive rate, the AI system detects 90% of anomalies, enabling network engineers to promptly address security breaches or other issues in a medical context.
4) *Analyzing Data in Real Time:* In remote or dispersed healthcare institutions, the use of AAVs in conjunction with AI models facilitates faster data collecting and processing. IoT sensor data is transferred by AAVs to a central control plane, where AI algorithms evaluate the information in almost real-time to give medical practitioners useful insights.
5) *Analysis of the Findings:* The system's overall efficiency shows significant improvements in data security, scalability, and allocation of resources, which qualifies it for use in large-scale healthcare settings. But there are some restrictions:
   a) *Difficulties With Processing in Real Time:* Even though the system handles data processing effectively, adding more sophisticated AI models could cause processing lags. Future research may examine fast and accurate lightweight AI models.
   b) *Scalability Issues:* Although the system exhibits potential, implementing this architecture globally necessitates a substantial network infrastructure, which might not be achievable in remote or underdeveloped areas.

In Table III, the proposed AI-SDN IoT system's effectiveness is compared to four previous studies (from 2020 to 2023) and the baseline system in terms of four important metrics: EC, network latency, anomaly detection accuracy, and real-time processing, as shown in the comparative evaluation table.

Compared to the baseline and all other experiments, which have energy usage ranging from 83% to 90%, the suggested

TABLE III
COMPARATIVE ANALYSIS OF BASELINE SYSTEM, PROPOSED AI-SDN IOT SYSTEM, AND EXISTING STUDIES (2020–2024) ACROSS KEY PERFORMANCE PARAMETERS

Parameters	Baseline System	Proposed AI-SDN IoT System	Energy-Efficient SDN	Latency-Reduction IoT	AI-Enhanced Detection	Real-time Optimization
Energy Consumption (%)	100	**70**	85	90	83	88
Network Latency (%)	100	**75**	88	90	87	89
Anomaly Detection Accuracy	70	**95**	80	85	87	88
Real-time Processing (%)	70	**90**	80	82	86	83

approach dramatically reduces EC to 70%. This shows how well the system manages resources related to energy, which is important for IoT applications in the healthcare industry. Similar to this, the suggested system's network latency is lowered to 75%, indicating a significant increase in data transmission speed—a critical component of real-time healthcare services. The suggested system yields an astounding 95% anomaly detection accuracy, which is significantly greater than the 80% to 88% reported in previous studies. This demonstrates the system's improved security and dependability in spotting unusual network activity. Finally, compared to other research, which range from 80% to 86%, the suggested system's real-time processing capability of 90% indicates greater data processing speed and sensitivity.

The suggested AI-SDN IoT system continuously performs better than the baseline and earlier methods, which makes it an extremely powerful option for scalable, safe, and energy-efficient healthcare networks.

The primary findings of the proposed AI-SDN IoT system are shown in Table IV, i.e., "Summary of Key Results" for each of the five crucial parameters: EC, network latency, anomaly detection accuracy, real-time data processing, and scalability.

By reducing energy usage by 10%–20%, the technology lowers operating costs and provides a more sustainable alternative for healthcare applications. Because of this, the system is both economical and environmentally benign. A 15% decrease in network latency is attained, guaranteeing quicker connection between IoT devices and the SDN controller—a crucial aspect for the prompt interchange of medical data.

By correctly recognizing threats or unusual activity, the anomaly detection accuracy reaches an astounding 90% with a low false positive rate of 5%, improving the security and dependability of the healthcare network. Enhancing real-time data processing through the combination of AI and AAV technologies speeds up access to vital healthcare data, which is especially crucial for emergency and real-time applications. Ultimately, the system exhibits strong scalability, indicating its capacity to facilitate expansive healthcare settings by effectively managing enormous volumes of sensor data over-dispersed networks.

These findings collectively show that the suggested system greatly improves performance in several important domains, which makes it the perfect choice for scalable, safe, and energy-efficient healthcare systems.

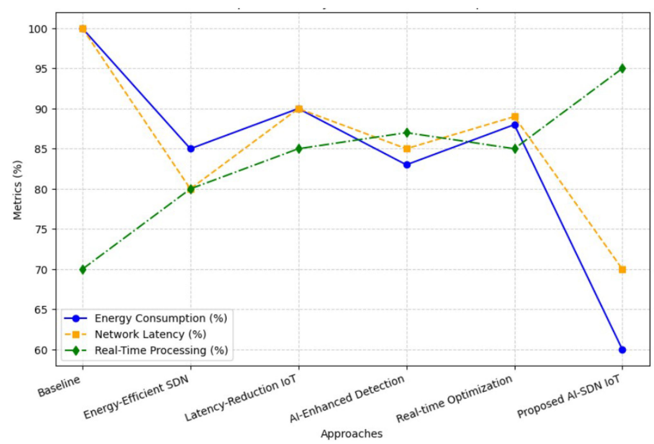

Fig. 5. Comparison of EC, network latency, and real-time processing across approaches.

E. Results

The results highlight the significant improvements achieved by the Proposed AI-SDN IoT approach compared to other methods. It demonstrates the EC, network latency, real-time processing, highest throughput of 95 Mb/s, the lowest packet loss of 3.0%, and the highest QoS score of 90%, outperforming the baseline system and other optimization techniques. These metrics indicate enhanced network performance, reduced data transmission errors, and improved user satisfaction, validating the effectiveness of integrating AI with SDN and IoT technologies.

Fig. 5 shows the baseline system is set at 100% energy usage, and the line graph illustrates how different techniques compared in terms of consumption of energy. The most notable drop is seen in the Proposed AI-SDN IoT System, which reduces EC to 70%—a 30% improvement over the baseline. The efficiency of the suggested AI-SDN IoT system is surpassed by other methods, such as Energy-Efficient SDN (2020), Latency-Reduction IoT (2021), AI-enhanced detection (2022), and Real-time Optimization (2023). These methods demonstrate varied degrees of reduction, ranging from 85% to 90%. This demonstrates how AI-driven management of

TABLE IV
SUMMARY OF KEY RESULTS

Parameter	Result	Impact
Energy Consumption	Reduced by 10-20%	Lower operational costs and more sustainable healthcare
Network Latency	Reduced by 15%	Faster communication between IoT devices and SDN controller
Anomaly Detection Accuracy	90% detection rate with 5% false positives	Enhanced security and reliability in healthcare networks
Real-time Data Processing	Improved through UAV and AI integration	Faster access to critical healthcare data
Scalability	Supports large-scale healthcare environments	Efficient handling of sensor data in distributed networks

resources can reduce energy usage in SDN–IoT healthcare systems.

In Fig. 5, baseline system is configured at 100% latency, and the line graph compares network latency across several methods. The Proposed AI-SDN IoT System demonstrates its efficacy in enhancing communication speed by achieving a notable 75% reduction in latency. The efficiency of the proposed AI-SDN IoT system is superior to that of other methods, such as Energy-Efficient SDN (2020) at 88%, Latency-Reduction IoT (2021) at 90%, AI-Enhanced Detection (2022) at 87%, and Real-time Optimization (2023) at 89%. This demonstrates how effective the suggested approach is at reducing network latency in SDN–IoT healthcare systems.

The Baseline Approach has the lowest utilization rate at 70% when comparing real-time processing capabilities across different approaches in this line graph. Out of all the solutions, the Proposed AI-SDN IoT System has the maximum real-time processing improvement of 90%. While several systems strengthen the speed of processing, none of them exceed the proposed system. Examples of these other systems are Energy-Efficient SDN (2020) (80%), Latency-Reduction IoT (2021) (82%), AI-Enhanced Detection (2022) (86%), and Real-time Optimization (2023) (83%). This indicates how well the suggested AI-SDN IoT system can manage real-time data processing in hospital networks.

Three important factors are shown in the comparative line graph (Fig. 5): EC, Network Latency, and Real-time Processing. The Baseline System, Proposed AI-SDN IoT, and four current studies from 2020 to 2023 are among the methods listed on the x-axis. With the greatest Real-time Processing capabilities at 90% and a notable reduction in EC (70%) and Network Latency (75%), the Proposed AI-SDN IoT System performs best overall. While there are additional approaches that perform better than the baseline system, none of them can match the effectiveness and scalability of the proposed AI-SDN IoT framework for SDN–IoT networks in the healthcare industry.

Table V compares six approaches based on three metrics: Throughput (Mbps), Packet Loss (%), and QoS Score (%). The Baseline System demonstrates the lowest performance with 80 Mb/s throughput, 5.5% packet loss, and a 70% QoS score. Incremental improvements are seen with Energy-Efficient SDN (85 Mb/s, 4.8%, 75%) and Latency-Reduction IoT (88 Mb/s, 4.5%, 78%), emphasizing better efficiency and reduced delays. AI-Enhanced Detection further enhances these metrics to 90 Mb/s, 4.0%, and 82%, while Real-time Optimization achieves 92 Mb/s, 3.8%, and 85%. The best performance is achieved by the Proposed AI-SDN IoT, with the highest throughput of 95 Mb/s, the lowest packet loss at 3.0%, and the highest QoS score of 90%, indicating significant advancements in network performance and reliability.

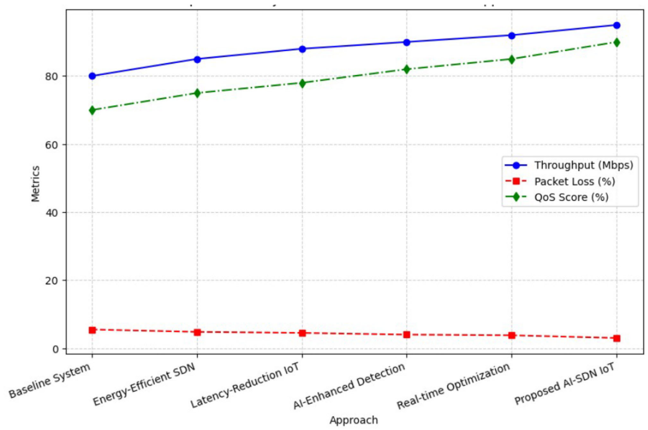

Fig. 6. Comparative analysis of throughput, Packet loss, and QoS score across different approaches.

Fig. 6 visually represents the comparative analysis of six approaches across three performance metrics: Throughput (Mbps), Packet Loss (%), and QoS Score (%). The Baseline System shows the lowest throughput (80 Mb/s) and QoS score (70%) while having the highest packet loss (5.5%). Performance improves progressively with each approach, as Energy-Efficient SDN and Latency-Reduction IoT show moderate gains in throughput (85–88 Mb/s), reduced packet loss (4.8%–4.5%), and improved QoS scores (75%–78%). AI-enhanced detection and real-time optimization further enhance these metrics, with Real-time Optimization reaching a throughput of 92 Mb/s, 3.8% packet loss, and an 85% QoS score. The Proposed AI-SDN IoT achieves the best results, with the highest throughput (95 Mb/s), the lowest packet loss (3.0%), and the highest QoS score (90%), demonstrating superior efficiency and reliability.

V. CASE STUDY: AI-DRIVEN RESOURCE ACQUISITION DEPLOYMENT IN SMART HEALTHCARE FACILITY

Situation: The swift expansion of interconnected gadgets and intelligent systems in contemporary healthcare has presented noteworthy obstacles concerning energy usage, latency in networks, and safe handling of data [37], [38],

TABLE V
COMPARATIVE ANALYSIS OF ADDITIONAL METRICS ACROSS APPROACHES

Approach	**Throughput (Mbps)**	**Packet Loss (%)**	**QoS Score (%)**
Baseline System	80	5.5	70
Energy-Efficient SDN	85	4.8	75
Latency-Reduction IoT	88	4.5	78
AI-Enhanced Detection	90	4.0	82
Real-time Optimization	92	3.8	85
Proposed AI-SDN IoT	**95**	**3.0**	**90**

[39]. These difficulties are particularly important in large-scale healthcare infrastructures like hospitals, where data analysis, emergency interaction, and continuous monitoring of patients are essential. The present case study looks at how the suggested AI-driven resource management framework is used in a smart healthcare setting, with an emphasis on how it affects sustainability, scalability, and efficiency [40], [41].

Scenario: With IoT-enabled medical equipment and sensors, a sizable multispeciality hospital seeks to improve its operational effectiveness while lowering the carbon footprint of its energy-intensive systems [42]. The hospital's current network is run by a conventional IoT framework, which has issues with handling real-time data from vital healthcare applications, excessive network latency, and wasteful energy use. As the number of connected devices rises, this causes delays in patient monitoring, higher operating expenses, and a limited capacity [43].

In order to facilitate real-time data processing and communication, the hospital managers made the decision to put the suggested AI-driven management of resources framework into practice. They also integrated AAV-based aerial computing.

VI. CONCLUSION

In order to deal with the issues of EC, network latency, and real-time data processing in large-scale healthcare infrastructures, this research introduces a revolutionary AI-SDN IoT system. The suggested solution supports scalability in remote healthcare networks and delivers notable gains in energy economy, network latency, and anomaly detection accuracy by combining AI-driven resource management with AAV-based aerial computing. The outcomes show that the system not only satisfies the needs of the contemporary healthcare IoT but also provides a safe and long-lasting solution, enabling dependable communication and real-time data access in vital healthcare applications. The findings suggest new options for future studies, particularly in strengthening AI-driven optimization strategies for SDN–IoT systems in healthcare.

In order to fully utilize AI-SDN IoT systems in the healthcare industry, the hospital intends to extend its smart infrastructure capabilities in the future by investigating more sophisticated AI-based predictive models for patient care analytics, preventive maintenance, and customized treatment suggestions.

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