Optimizing Energy Efficiency and Increasing Scalability in 6G-IoT Networks Through SDN, Duty Cycling, and AI-Driven Slicing

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***Abstract*—As sixth-generation (6G) and Internet of Things (IoT) networks expand rapidly, concerns are growing about their energy consumption and scalability. This is primarily because more devices are being connected, resulting in increased energy consumption.energy consumption.This study examines three primary strategies for optimizing energy efficiency and improving scalability in 6G-IoT networks.This research looks at three experimental setups: 1) using software-defined networking (SDN) with dynamic slicing to organize devices based on when they are most and least used, 2) duty cycling, which turns devices on and off to save energy, and 3) AI-optimized network slicing that uses both convolutional neural networks (CNN) and bidirectional long short-term memory (BiLSTM) models. In the first setup, SDN with dynamic slicing helped reduce unnecessary power consumption by matching device activity to peak times. As more devices were added, this method kept energy use low and improved the network's ability to handle growth without requiring significantly more power. This resulted in a 66.28 percent decrease in power usage. In the second setup, duty cycling allowed only some devices to be active at a time, which reduced power use by over 60 percent during slow periods. In the third setup, the CNN-BiLSTM model effectively classified service types and reduced power use by 60.14 percent. While these methods were not combined into a single solution, each utilized slicing techniques to more effectively allocate resources and manage power.**

Keywords*—6G-IoT; energy efficiency; scalability; SDN; duty cycling; network slicing; CNN; BiLSTM; AI-driven optimization

I. INTRODUCTION

This study addresses the urgent need for smart, energy-efficient slice management solutions in 6G networks, targeting the challenge of supporting advanced AI services with new QoS requirements. By developing innovative management strategies, the research contributes to improving energy efficiency, reliability, and adaptability in next-generation SAGIN-enabled 6G-IoT networks [1] [2]. Many technologies, including mobile phones, transportation systems, food production, housing, healthcare, clothing, and remote monitoring, are being transformed by the Internet of Things (IoT). As these advances occur, creating energy-efficient 6G-IoT networks becomes crucials [3].

Existing studies have shown that 6G-IoT networks will link billions of devices worldwide, resulting in high energy consumption. While prior research highlights the significance of energy efficiency for the long-term profitability of network operators, the current study distinguishes itself by focusing on the integration of space, air, and ground networks into a Space-Air-Ground Integrated Network (SAGIN) [4].

Unlike earlier works centered on terrestrial networks, this research emphasizes global coverage and intelligent management of network slices to ensure specific Quality of Service (QoS) needs [5]. Network slicing, as described in prior studies, enables logically isolated virtual networks for different services; this research extends the discussion by analyzing cost-effective slice management strategies throughout the slicing life cycle, which past research has only partially addressed.

Unlike earlier generations, which typically managed network resources within a single domain, 6G network slicing must coordinate across heterogeneous segments in SAGIN. Previous studies have not fully considered the additional complexity that emerges from integrating space, air, and ground networks. The current research addresses this gap by focusing on unique challenges and management strategies necessary for effective slice orchestration across these domains.

Therefore, the development of smart slice management solutions in 6G networks is required.

The current research addresses this need by proposing an approach for efficient and intelligent network slice management specific to SAGIN-based 6G-IoT environments. This work aims to advance current practice by focusing on enhanced resource allocation and tailored slice management strategies that specifically address the emerging challenges identified above. In addition, with the availability of powerful computing capabilities and advanced.

AI services are being enhanced with new QoS requirements, such as data quality, training latency, and inference accuracy. As a result, dedicated network slices must be established to support emerging AI services in 6G networks. To address these challenges, innovative solutions are urgently needed to enhance energy efficiency without compromising network performance [6]. The objective of this paper is to:

- Analyzing the impact of SDN on energy consumption in 6G-IoT networks, by evaluating the dynamic allocation mechanism for devices based on peak and idle periods.
- Evaluating the effectiveness of Duty Cycling in reducing unnecessary energy consumption by regulating device on- and off-duty times based on daily work schedules.

- Testing the performance of a deep learning model consisting of CNNs and BiLSTM networks in classifying network data into multiple categories and accurately estimating the energy requirements for each category.
- Identifying the energy efficiency differences between each technology separately without combining them, to obtain a clear and independent picture of the impact of each approach under different operating conditions.
- Providing a scientific basis for comparing energy management methodologies to enable 6G-IoT network developers to choose or develop flexible and scalable solutions based on the nature of network load and future applications.

This study presents a set of contributions used to reduce energy consumption and increase efficiency in the 6G-IoT network through the following points.

- SDN-based dynamic slicing was combined into one model to reduce energy consumption and increase energy efficiency.
- Slicing and duty cycling to reduce energy consumption and increase energy efficiency.
- Explain how energy efficiency changes with increasing device density, ensuring the ability to adapt to network expansion processes.
- hybrid CNN-BiLSTM model was implemented, achieving 99% classification accuracy, enabling intelligent slicing and adaptation.

This paper is organized as follows. To begin, Section II covers the key features of 6G and the role of AI-powered network chips, laying the groundwork for the subsequent discussion. Building on this, Section III reviews previous work on energy efficiency and scalability in 6G IoT. Then, Section IV outlines our research approaches, which are expanded upon in Section V with details on the proposed approaches, including SDN-based chips, duty cycle, and AI-enabled chips. Following that, Section VI reviews the results and effectiveness of these techniques. In Section VII, we further discuss our experimental results on energy usage. Finally, Section VIII concludes the paper and suggests future research directions.

II. BACKGROUND

Network slicing is a technology that divides a network into multiple dedicated "slices". Each slice operates independently, allowing flexible allocation of resources based on specific needs. This technology significantly enhances network performance and quality, particularly in expanding IoT environments [7]. With network slicing, resources can be given to each slice based on its unique needs.

For example, one slice can serve IoT applications that require steady connectivity and low power, while another can support high-speed data, such as HD video. Allocating resources based on actual service or application needs reduces waste and improves network efficiency [9]. Each slice works independently, reducing interference between applications. 6G networks can support a wide range of diverse applications, from self-driving cars to virtual and augmented reality services. Each of these applications requires specific network characteristics, such as instant response or high bandwidth. With network slicing, these specific needs of each application can be met individually. In addition, robust security strategies can be applied to each slice to ensure data protection and provide faster response.

Machine learning can monitor network activity and predict the needs of devices and services [10]. It can analyze large datasets to provide the optimal allocation of resources. In addition, it helps reduce network congestion by optimizing data distribution. Machine learning can be used to improve services such as security, spam detection, and power management automatically. 6G networks will provide a range of different services that will benefit users. These services include enhanced mobile broadband, ultra-reliable low-latency communication, and massive machine-type communications [11]:

- Super-eMBB: means broadband connectivity via mobile phones, with a focus on energy efficiency.
- Massive MTC: means connecting a very large number of devices, such as IoT devices, that need constant connectivity.
- Super URLLC: provides highly reliable communications with minimal delay, such as remote control of devices.
- Ultra-high resolution: means using technologies to provide high resolution in data transmission.
- Super-immersive reality: includes virtual reality and augmented reality experiences that provide enhanced interaction.

III. RELATED WORK

Sixth-generation - 6G networks rely on network slicing, a technology that is still in its infancy but is rapidly evolving and offering a variety of services.

A. Using Software-Defined Networking

The study [16] used the energy-aware routing, multi-level, and mapping problem (EARMLP) algorithm, which achieves better performance by reducing the number of active nodes and integrating the use of network resources. The number of controllers and their optimal placement have a significant impact on energy savings. In [17], the authors present a comprehensive survey on SDN for various smart applications. This survey covers the infrastructural details of SDN hardware, OpenFlow switches, controllers, simulation tools, programming languages, open issues, and challenges in SDN implementation using advanced technologies.

B. Using Machine Learning

Several studies have used different methods to reduce power consumption. In a study [18], collaborative communication was used. This means that mobile phones or smart devices work together as a team, rather than working separately. When these devices work together, energy can be more efficiently saved, which helps extend battery life. Machine learning, specifically artificial neural networks (ANNs), is utilized to enhance network slicing in 6G networks, focusing on energy consumption. This approach involves a multifaceted strategy that integrates various techniques to improve energy efficiency while maintaining high performance. In [19], the data rate allocation (DTRA) method was used to improve data transmission efficiency in 6G networks. The residual energy cluster head (RECH) method was used. Furthermore, this work used the dynamic multipath routing protocol (DMRP)method to improve the reliability and speed of 6G networks. After evaluating performance metrics, the DTRA method improved the lifetime and energy efficiency of the network by 95.3% based on 6G networks.

C. Using Network Slicing

Flexible network slicing is one of the essential components of 6G networks, allowing the creation of customized network environments to meet the needs of specific applications and services. The study of Sheena [27] aims to improve the efficiency of the network by designing a Deep Learning-based Network Slicing with Data Aggregation (EENS-DA) technique, which allocates the necessary physical resources to specific applications clearly and efficiently. The study of Phyu [28]aims to address the problem of activating/ deactivating slicing to reduce energy consumption while maintaining Quality of Service (QoS) for users. The researchers relied on two Multi-Armed Bandit (MAB) agents to make activating/deactivating decisions at the level of individual base stations. Researchers in the study [31] propose a hybrid model that combines CNN and BiLSTM. The CNN was used to extract automatic features from the input data. The BiLSTM was used to classify and determine the appropriate network segment for each request. The results showed that the hybrid model achieved an overall accuracy rate of 97.21%, demonstrating the effectiveness of this approach in allocating the appropriate network segments to end users.

D. Research Gap

After reviewing existing research, several gaps in the literature become apparent. Some studies focus on specific techniques, such as network slicing, machine learning, and energy-aware routing. However, a comprehensive framework that integrates these methods to improve energy efficiency in 6G-IoT networks remains absent. Although energy efficiency has generally improved, challenges persist in maintaining quality of service (QoS), which includes factors such as latency and throughput. Only a limited number of studies have successfully addressed the simultaneous enhancement of both energy efficiency and QoS, as demonstrated in the work by [28]. Flexible network slicing is widely recognized as a crucial component for the success of 6G; nevertheless, established guidelines for the design, implementation, and management of such slices are lacking, as noted in studies [27] and [28]. Addressing these gaps is expected to contribute to significant advancements in energy efficiency and scalability in 6G-IoT networks through the use of advanced technologies such as machine learning, network slicing, and SDN. Table I provides a comparison of the relevant studies.

IV. Study Contributions

The current study significantly expanded the scope of previous research by simultaneously combining three independent and integrated technologies: software-defined networking (SDN)-based dynamic slicing, workflow, and AI-assisted slicing using CNN-BiLSTM, to improve energy utilization and scalability in 6G-IoT environments. Although each previous study focused on a single aspect, such as software-defined networking (SDN) control plane (Study[16]),or an artificial neural network (ANN)-based collaboration (Study [18]), These efforts often faced critical limitations, including high complexity, poor scalability, and limited accuracy in traffic management.

The current study addresses the gaps in previous research through a diverse experimental design. In the first scenario, the study used Software-Defined Networks (SDN) to dynamically operate devices during peak usage periods. This technology addressed the limitations of static routing in previous studies based on SDN. By applying the second scenario, the study was able to improve selective activation strategies, such as those found in studies [18] and [19]. A duty cycle was implemented in the third scenario to reduce energy consumption during periods of low activity, which is considered the most innovative.

It utilized CNN-BiLSTM technology to intelligently classify traffic types and allocate resources accordingly, surpassing previous models like random forests or DRL in terms of accuracy and energy saving. Table II presents a comparative analysis of related studies and the contribution of the current research.

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TABLE I. COMPARATIVE ANALYSIS OF RESEARCH ON ENERGY EFFICIENCY IN 6G NETWORKS

Author	Idea	Methodology	Features	Challenges
[16]	Energy-aware routing to reduce active nodes and improve resource utilization	EARMLP (Energy-Aware Routing Multi-Level and Mapping Problem)	Reduces number of active nodes; integrates network resource usage	Impact of number and optimal placement of controllers on energy savings
[17]	Survey on SDN for smart applications	Comprehensive survey	Covers SDN hardware, OpenFlow switches, controllers, simulation tools, programming languages; open issues and challenges	Implementation challenges of SDN with advanced technologies
[18]	Reducing power consumption through collaborative communication	Collaborative communication + ANN	Smart devices work together as a team; saves energy; extends battery life	Coordinating collaboration while maintaining high performance
[19]	Improving energy efficiency and lifetime of 6G networks	DTRA; RECH; DMRP	Improved transmission efficiency, reliability and speed; network lifetime/energy efficiency improved by 95.3%	Managing multiple methods together in real 6G environments
[27]	Efficient network slicing with deep learning and data aggregation	EENS-DA (Deep Learning + Data Aggregation)	Allocates physical resources clearly and efficiently to specific applications	Balancing energy saving with application needs
[28]	Energy saving by activating/deactivating slicing while keeping QoS	Multi-Armed Bandit (MAB) agents	Activate/deactivate decisions at base-station level	Maintaining QoS while reducing energy consumption
[31]	Hybrid model for network-slicing classification	Hybrid CNN + BiLSTM	CNN for feature extraction; BiLSTM for classification; overall accuracy 97.21%	Complex training and computational resources

V. METHODOLOGY

In this section, deep learning methods are introduced for tackling the problem of network slicing.

A. Convolutional Neural Network

1) Reasons to use CNN: CNNs [8] can find hidden patterns in data without needing any manual adjustments. High Efficiency: The convolutional layer focuses on specific parts of the data, making it highly effective for analyzing data related to networks. CNNs [12] can create systems that communicate using. Human speech [32]. Making Overprocessing Simpler: Pooling simplifies the data while retaining most of the essential information. CNNs consist of several layers connected in sequence: the first layer is the input layer, followed by hidden layers, and the last one is the output layer. The hidden layers process the input data and extract important features using filters. Overall, the combination of convolutional layers, pooling layers, and fully connected layers in CNNs enables the network to learn and recognize patterns effectively in complex data [33].

B. Long Short Term Memory

1) Reasons to use LSTM : [13]: Long Short-Term Memory Reasons to use LSTM are that it is a unique type of recurrent neural network (RNN) [20] [21] specifically designed to address issues such as vanishing and exploding gradients. These problems can make it challenging for neural networks to learn effectively. For network slicing classification, a deep learning [15]approach was applied. LSTMs [22]are better suited for this task because they can handle both the fading and growing gradient issues, as well as the long-term dependency challenges [14] that regular RNNs face. This makes LSTMs typically more effective than traditional RNNs[33].

C. Bidirectional LSTM (BiLSTM)

1) Reasons to use bidirectional LSTM: Bidirectional LSTM (BiLSTM):Reasons to use Bidirectional LSTM (BiLSTM) [15] include adding an LSTM layer that processes information in both forward and reverse orders. The outputs from the two LSTM [14]layers are then combined using techniques such as calculating the mean, sum, multiplication, or concatenation. The main advantage of using BiLSTM is that it allows each part of the input data to include information from both past and present contexts. This results in more accurate output because BiLSTM [22] uses LSTM layers to analyze data from both directions. Although BiLSTM might seem complicated, it produces strong results due to a solid understanding of the data environment. In [34], a multilayer BiLSTM is utilized, where each layer consists of two cells that process information in forward and backward directions separately.

D. Dataset Description

In Case 3, the dataset is sourced from the University of California, Irvine (UCI) Machine Learning Repository [35]. It includes 87 features, each representing details of an IP flow from a network device, such as source and destination IP addresses, port numbers, and connection timestamps. One source collects this information, while another classifies the layer 7 protocol, which corresponds to the application level in network communication [36]. Most features are numerical, with some being categorical (nominal), and one feature captures dates derived from timestamps [37].

E. Data Preprocessing

The diverse data (textual and numerical) were processed to address value errors, gaps, and duplicates in accordance with the model's requirements. Python was used to remove duplicate rows, handle missing values with the column mean, detect and delete errors, then Min-Max normalization was applied to constrain the values between 0 and 1, and the cleaned data was saved in a new CSV file in preparation for machine learning models. The set includes 78 labels, and the labeling process is a pivotal step directed by device requests and scientific literature [37]. The data was divided into five slices: Super-eMBB, Massive MTC, super-URLLC, super-Precision, and super-immersive; these are common categories in 5G/6G research that represent different service requirements, including high speed, low latency, support for a large number of devices, precision, and reliability.

F. Dataset Segmentation

The data is categorized into the following types:

TABLE II. COMPARATIVE ANALYSIS OF RELATED STUDIES AND THE CONTRIBUTION OF THE CURRENT RESEARCH

Field	Studies (Ref.)	Methodology Used	Objective	Strengths	Gaps	How the Current Study Fills the Gaps
ML for Energy Saving	[18], [19]	Collaborative communication; ANN; DTRA, RECH, DMRP	Reduce power consumption and enhance network efficiency/lifetime	Team-based device operation to save energy and extend battery life; improved transmission efficiency and reliability; network lifetime/energy efficiency improved by 95.3%	No explicit SDN integration or traffic-type slicing; limited unified evaluation across scenarios	Integrates ML within an SDN environment with 6G traffic classification and end-to-end energy impact assessment
Slicing	[27], [28], [31]	EENS-DA (Deep Learning + Data Aggregation); two MAB agents for slice on/off; Hybrid CNN+BiLSTM for slice classification	Efficient resource allocation and maintaining QoS while enabling accurate slice selection	Clear and effective allocation to applications; energy reduction via controlled activation/deactivation; 97.21% overall accuracy for classification	Limited/implicit SDN-based orchestration and unified energy evaluation	Uses SDN with CNN–BiLSTM–based traffic classification to allocate resources by data type and quantify energy gains
SDN	[16], [17]	EARMLP algorithm (energy-aware routing, multi-level mapping); comprehensive SDN survey	Enhance network efficiency and reduce energy consumption via resource-aware routing	Reduced number of active nodes; integration of network resources; broad coverage (hardware, controllers, tools, languages, challenges)	Lack of integration with ML-based classification and 6G slicing context	Combines SDN resource control with ML-driven traffic classification and slicing for holistic energy-efficient 6G management

1) Super-eMBB: This chip is designed to deliver high data speeds and large transfer capacities. It is ideal for applications that need fast data transfers, such as streaming 4K/8K videos and online gaming [38].

2) Massive-MTC: This chip is intended for Internet of Things (IoT) applications, which involve communication among many devices. Examples include smart meters, wearable gadgets, and embedded systems. It excels at managing numerous low-power devices [39] [40].

3) Super-URLLC: This chip is used for applications requiring both high reliability and minimal delay, like self-driving cars and telemedicine. It ensures dependable data transfer while keeping delays to a minimum [41] [42].

4) Super-precision: This chip caters to applications needing high spatial resolution or detailed data, such as environmental monitoring, precise measurements, and augmented reality (AR) and virtual reality (VR) [43].

5) Super-immersive: This chip is designed for applications requiring extensive coverage and high efficiency, such as augmented reality (AR) and virtual reality (VR). It facilitates immersive user experiences within advanced network environments [44].

The categorization process is as follows: when a device, such as a smartphone or sensor, sends a request, the type of application or service is evaluated. Based on this evaluation, the appropriate category, or “slice”, is assigned to meet those needs. For example, if high speed is necessary, the request will be routed to the Super-eMBB slice.

In contrast, if minimal delay is essential, as in the case of self-driving cars, the Super-URLLC slice will be employed. Each slice provides distinct performance and resources customized to the current network demands, optimizing resource utilization and minimizing energy consumption.

VI. PROPOSED METHODOLOGY

The approach involves three key experiments designed to address existing research gaps in energy efficiency and scalability of 6G-IoT networks. Each of these experiments employs various methods to reduce energy use in 6G-IoT networks.

A. Case 1 Software Defined Networking with Dynamic Slicing (Scenario 1)

Step 1: The experiment presents a simulation model of a 6G-IoT network in Python using NetworkX [25], starting with 30 devices and gradually expanding to 500-2500 devices to measure scalability and its impact on performance and energy consumption. The network is managed via SDN with dynamic slicing, which adjusts the states of devices (active/inactive) according to peak (6 AM–6 PM) and idle periods. Sensors remain active during peak times, cameras are disabled outside of these periods, and lights operate randomly. The setup relies on networkx, numpy [22], matplotlib [24], and random, and energy is calculated using a function that aggregates the consumption of active devices only, then compares the values before and after slicing. Hourly readings were collected over 24 hours and analyzed using the mean and standard deviation to estimate efficiency gains and assess the contribution of SDN in optimizing consumption and enabling adaptive device management.

Step 2: The code was improved by introducing a new idea to track power consumption in the "No Slicing" state. A baseline was established for the No Slicing case, recording power consumption for each device category with fixed reference values: sensors (10 units), cameras (8 units), and lighting (6 units). Representative device values (10 sensors, 8 cameras, 6 lighting units) were selected based on real-world datasheets such as the NXP SLN-VIZN-IoT platform ($\approx$ 0.9W) when the camera is on) and the LSM6DSV16X sensor from STMicroelectronics, as well as low-power optical sensors (193–277 µW). This distribution is further supported by the results of the paper [26], which provided practical measurements of power consumption in real industrial environments. These values were developed to standardize comparison conditions and highlight the impact of energy optimization techniques, particularly duty cycle and grid slicing [45].

The results of this case are stored in the no-slicing energy history list and are used with different network sizes to test robustness and allow subsequent replacement with real data without changing the methodology. When applying dynamic slicing within an SDN environment, power is allocated according to peak periods; specific categories (such as sensors) remain active while others are disabled during idle times, and power is measured using the calculate energy function. In this case, the readings are stored in the slicing energy history list, and a direct comparison is made between the no-slicing energy history and slicing energy history lists to measure efficiency gains and estimate the actual reduction in consumption.

Step 3: The simulation of the 6G-IoT network was expanded with SDN management to cover multiple slicing use cases across three device categories (50, 500, and 2,500 devices). Slicing divides the network into smaller, service-oriented segments, reducing energy consumption by distributing loads more efficiently. For each category, energy consumption is measured in both the non-partitioned and partitioned states, and then the percentage reduction attributed to the application of partitioning is calculated.

B. Case 2 Duty Cycling (Scenario 2)

Duty Cycling is applied as a time-based control mechanism to turn devices on and off with the aim of reducing overall energy consumption. In the experimental design, the devices are activated during even hours and deactivated during odd hours, and the consumption of each device is calculated according to its operational state and type. A fixed reference power is used to represent the nominal consumption during continuous operation: sensors 10 watts, cameras 8 watts, and lighting 6 watts. The SDN controller holds the control layer. It activates/deactivates devices according to the duty cycle schedule, ensuring consistent transitions between the two states (active/inactive) at the network level. A baseline without duty cycling is defined where devices are considered always active, Energy is calculated hour by hour as the sum of the consumption of active devices only, allowing the isolation of the impact of scheduling from other factors.

For evaluation purposes, measurements are collected hourly and stored in two separate lists: one for the baseline (no duty cycling energy history) and another for the scheduled case (duty cycling energy history). A direct comparison is made between the two lists to derive the reduction ratio in consumption, with a stratified analysis comparing performance during peak hours versus quiet periods to measure the system's response to load changes. This procedure provides a clear, systematic description: defining reference capabilities for each device category, enforcing scheduling via SDN, consistent hourly measurement, and then an organized before/after comparison, which allows for a more accurate estimation of the efficiency gains resulting from managing on/off states according to a duty cycling schedule.

C. Case3 CNN + BiLSTM (Scenario 3) Model Training

A new AI-driven network slicing model (Scenario 3) has been developed to dynamically improve resource allocation. It relies on a hybrid architecture that combines (CNN for feature extraction) and (BiLSTM for capturing temporal dependencies), classifying network flows into five categories: (super-eMBB, massive-MTC, super-URLLC, ultra-precise applications, and ultra-immersive experiences). The Unicauca IP Flow dataset was used with an 80testing split, and performance was measured using Precision, Recall, and F1 metrics. The classification outputs guide the decision on slice assignment and resource allocation, and then the energy consumed before and after allocation is compared; this demonstrates a better alignment between network traffic requirements, reduced energy consumption, and support for efficient slice management in 6G environments. The study examined the scalability by increasing the number of devices between 500 and 2500 devices, measuring the power consumption of each device as the size changed, and analyzing the relationship between the number of devices and energy efficiency. The features of CNN and BiLSTM were combined through a concatenation layer, and the model was trained on 80% of the data and evaluated on the remaining portion; the results indicate an improvement in efficiency after model-based optimization, as shown in Fig. 1

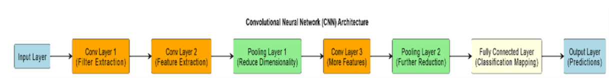

Fig. 1. The architecture of a basic convolutional neural network (CNN).

Components of the CNN Model Used:

- Input Layer: This layer takes in the data that has already been prepared for processing
- Shape Used: The data is organized in a one-dimensional format for each feature, represented as (features. Shape [1], 1).
- Convolutional Layer: This is the first layer of the model, where it applies a mathematical operation. The model examines three interconnected values simultaneously, which enables it to recognize patterns
- Kernel Size: The model looks at three connected values at once, which helps it recognize patterns.

- Activation Function: The ReLU (Rectified Linear Unit) function is used here. It helps the model handle complex, non-linear relationships in the data.
- Pooling Layer: This layer reduces the number of features from the convolutional layer by selecting the highest value from small groups in the data. The pooling size is set to 2, meaning it looks at every two values.
- Flatten Layer: This layer transforms the multi-dimensional data into a one-dimensional format so that it can be processed by the following layers in the network.
- Dense Layer: This layer has 128 units (or neurons), and it also uses the ReLU function to help improve the model's performance. This layer is key in identifying and finalizing the important patterns from the features extracted earlier.
- Dropout Layer: To prevent the model from becoming too reliant on specific neurons (a problem known as overfitting), this layer randomly ignores 30% of the neurons during training.

Integration with BiLSTM: The features extracted from the CNN are combined with the results from the BiLSTM's analysis of time dependencies in a concatenation layer, which enhances the overall accuracy of the model. To strengthen the proposed methodology, we integrated our hybrid CNN–BiLSTM segmentation model into a broader comparison framework that considers recent energy-efficient approaches such as Reinforcement Learning (RL) and Federated Learning (FL). While our primary focus remains on deep sequence modeling of traffic flows, RL-based network slicing has demonstrated strong adaptability for energy-aware policy design, and FL has shown the ability to train collaborative intrusion/traffic models with high accuracy in distributed IoT settings. Therefore, we included these techniques in our benchmarking to contextualize the CNN–BiLSTM results within state-of-the-art 6G-IoT optimization strategies. This integration not only allows a fair benchmarking against RL and FL approaches but also directly relates to our core objectives of reducing energy consumption and improving scalability in 6G-IoT environments.

D. Conceptual Unified Framework Integrating

Conceptual Unified Framework Integrating AI-Slicing, Duty Cycling, and SDN for Energy-Efficient and Scalable 6G-IoT Networks.

Fig. 2 illustrates the proposed conceptual unified framework. First, node-level application requirements are clustered using the AI-slicing module, which uses artificial intelligence to create logical network segments based on similar needs. Next, the duty cycling module, which controls when devices are active or inactive to save energy, filters the grouped nodes based on set energy thresholds. Finally, the SDN (Software-Defined Networking) controller, which centralizes the management of data flow across the network, routes and allocates resources to the active nodes in an energy-aware manner. The combined workflow ensures optimized energy usage and scalable operation in large-scale 6G-IoT deployments.

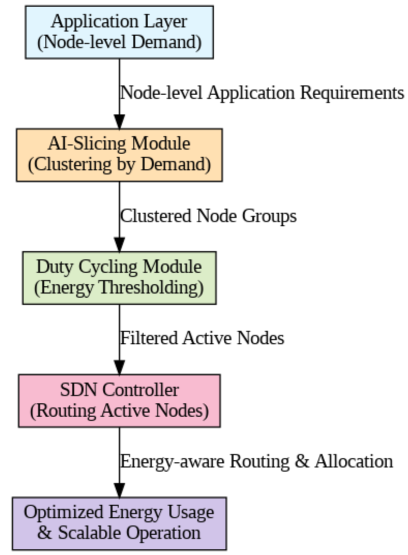

Fig. 2. Conceptual unified framework integrating AI-slicing, duty cycling, and SDN for energy-efficient and scalable 6G-IoT networks.

VII. Result

This section presents the experimental results obtained from the three proposed scenarios: SDN-based dynamic slicing, duty cycling, and the hybrid CNN–BiLSTM model. The evaluation focuses on energy consumption, scalability with increasing numbers of devices, and classification accuracy for traffic flows. To provide a broader perspective, the CNN–BiLSTM results are further compared with recent energy-efficient approaches, including Reinforcement Learning (RL) and Federated Learning (FL). Figures and tables are included to illustrate the performance metrics and highlight the improvements achieved.

A. Scenario 1: Result of Implementing SDN Technology in 6G-IoT Networks Scenario 1)

1) First implementing SDN technology in 6G-IoT networks: A simulation model for a 6G-IoT network was developed using SDN technology to reduce energy consumption and improve network performance by applying dynamic slicing. The model was built using the networkx library to create and analyze network diagrams, the numpy [23] library for mathematical calculations, the matplotlib library for visualizing data, and the random library for generating random number [31]s.

Thirty devices were integrated into the network, including sensors, cameras, and lighting, with each device's status assigned as active or passive based on specific rules such as peak hours and energy requirements.

Fig. 3 shows a comparison of energy consumption in a 6G-IoT network before and after implementing dynamic slicing. The results show that the dotted blue line, representing the power consumption without slicing, remains almost constant at approximately 115 units across all hours of the day. In contrast, the green line, representing the system with dynamic slicing, shows a clear variation in consumption, ranging from 60-106 units depending on peak times.

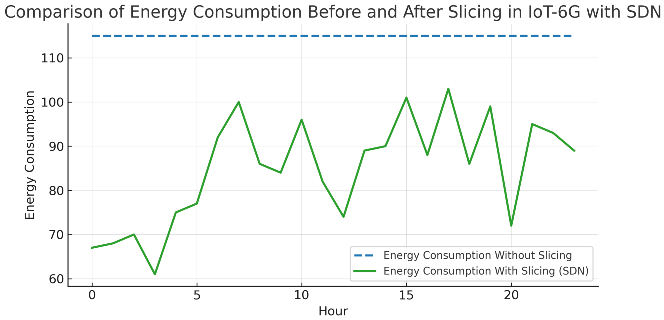

Fig. 3. Comparison of energy consumption before and after network slicing in 6G-IoT using SDN (Step 1).

2) Second, improving the measurement model: In the second phase, the model was developed by assigning specific power consumption values to each type of device(Sensors: 10 units (continuously active) - Cameras: 8 units (continuously active)- Lighting: 6 units (continuously active)

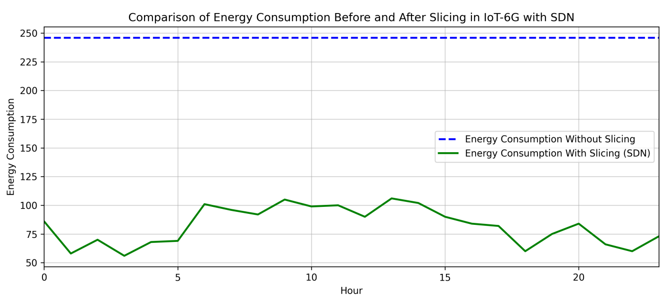

Fig. 4. Comparison of energy consumption before and after network slicing in 6G-IoT using SDN (Step 2).

Fig. 4 compares energy usage in a 6G IoT network with (SDN) before and after implementing dynamic slicing.

Energy Consumption Without Slicing (No slicing):
Mean: 246.00, Standard Deviation: 0.00, Min: 246, Max: 246
Energy Consumption With Slicing (SDN):
Mean: 82.96, Standard Deviation: 15.53, Min: 53, Max: 106
Energy Savings Percentage: 66.28%
Energy Consumption (No Slicing) - Peak Hours:
Mean: 246.00, Standard Deviation: 0.00
Energy Consumption (No Slicing) - Non-Peak Hours:
Mean: 246.00, Standard Deviation: 0.00
Energy Consumption (With Slicing) - Peak Hours:
Mean: 94.62, Standard Deviation: 8.16
Energy Consumption (With Slicing) - Non-Peak Hours:
Mean: 69.18, Standard Deviation: 9.86

Fig. 5. Evaluating energy consumption using (SDN) before and after implementing dynamic slicing.

Fig. 5 shows that energy consumption in the no-slicing scenario remained constant at an average value of 246 units, with no variation between peak and off-peak hours. In contrast, the SDN-based slicing Implementation showed a significant decrease in consumption, averaging 82.96 units with variations ranging from 53 to 106 units, achieving an energy savings rate of up to 66.28%. The results also showed that energy consumption during peak hours reached 94.62 units, while it decreased further during off-peak hours to 69.18 units, reflecting the ability of dynamic slicing to adapt to demand fluctuations.

In this phase, estimated power consumption values were assigned to each type of device based on values reported in scientific papers and manufacturer datasheets. As explained previously in the proposed Methodology section.

Energy consumption without slicing for 50 devices (6G): 508.3 units
Energy consumption with slicing for 50 devices (6G): 295.8 units
Energy reduction percentage for 50 devices (6G): 41.81%

Energy consumption without slicing for 500 devices (6G): 5450.2 units
Energy consumption with slicing for 500 devices (6G): 3218.1 units
Energy reduction percentage for 500 devices (6G): 40.95%

Energy consumption without slicing for 2500 devices (6G): 26661.95 units
Energy consumption with slicing for 2500 devices (6G): 16124.5 units
Energy reduction percentage for 2500 devices (6G): 39.52%

Fig. 6. Energy consumption with and without network slicing in 6G networks across three device categories (50, 500, and 2,500) devices.)

Fig. 6 presents the results of Scenario 1, where the energy consumption of 6G-IoT networks was measured with and without the application of SDN-based dynamic slicing. The experiments were conducted across three different device scales (50, 500, and 2500). The results show a clear reduction in energy usage when slicing is enabled, highlighting the ability of SDN to optimize resource allocation under varying traffic loads.

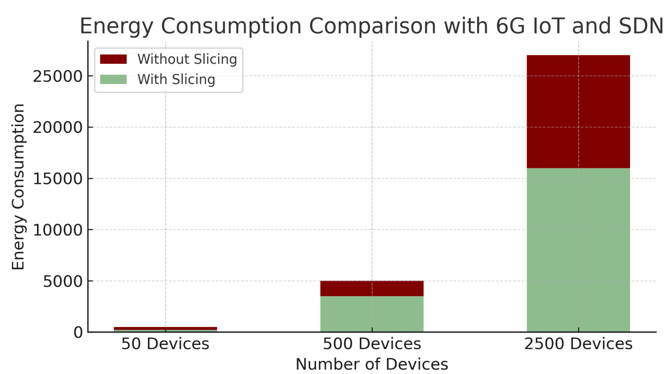

Fig. 7. Comparison of power consumption with and without slicing.

3) Thrid, the simulation of the 6G-IoT network was expanded: SDN management to cover multiple slicing use cases across three device categories (50, 500, and 2,500 devices). Slicing divides the network into smaller, service-oriented segments to reduce energy consumption by distributing loads more efficiently. For each category, energy consumption is measured in both the non-partitioned and partitioned states, and then the percentage reduction attributed to the application of partitioning is calculated.

Fig. 7 illustrates a comparison of power consumption under the following scenarios:

- Without Slicing: This reflects the power drawn when slicing techniques are not implemented.
- With Slicing: This indicates the power consumed after the application of slicing and power optimization methods.

Dark red signifies power consumption in the absence of slicing. Light green indicates power consumption when slicing is utilized. In the graph, it is evident that the power consumption with slicing is substantially lower in each scenario compared to the cases without slicing. As observed an increasing the number of devices correlates with a greater percentage reduction in power usage.

B. Scenario 2: Results of Energy Consumption With and Without Applying Duty Cycling

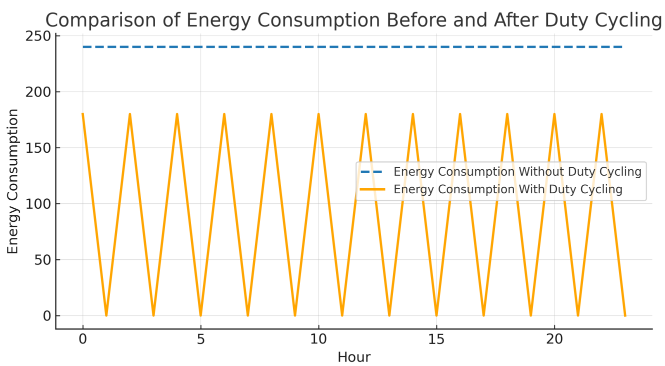

Fig. 8. Evaluating energy consumption and savings using Duty Cycling technology.

Fig. 8 shows a comparison between energy consumption before and after use of duty cycling.

- The X-axis shows time measured in hours.
- The Y-axis shows power consumption, but the units are not specified.

Shows a comparison between energy consumption with and without duty cycling. The dashed blue line remains constant at a high level, close to the upper limit (240), reflecting the continuous operation of the devices without responding to load changes. In contrast, the orange curve exhibits a periodic oscillating behavior, peaking during activation hours and dropping sharply to nearly zero during deactivation hours, which is consistent with an alternating on/off schedule. The peaks are below the fixed baseline, and the low periods reduce the area under the curve throughout the day, resulting in a lower daily average and a lower total consumption. This pattern demonstrates the effectiveness of duty cycling in aligning consumption with actual demand, with an expected increase in temporal variation against a clear improvement in energy efficiency. It is recommended to conduct a complementary statistical analysis (mean, standard deviation, and area under the curve) and assess the impact on service quality during downtime hours to adjust the optimal cycle parameters.

Fig. 9 shows that power consumption during no-duty cycling remained constant at 240 units, with no variations

Energy Consumption Without Duty Cycling (No Duty Cycling):

Mean: 240.00, Standard Deviation: 0.00, Min: 240, Max: 240

Energy Consumption with Duty Cycling:

Mean: 87.50, Standard Deviation: 87.50, Min: 0, Max: 175

Energy Savings Percentage: 63.54%

Energy Consumption (No Duty Cycling) - Peak Hours:

Mean: 240.00, Standard Deviation: 0.00

Energy Consumption (No Duty Cycling) - Non-Peak Hours:

Mean: 240.00, Standard Deviation: 0.00

Energy Consumption (With Duty Cycling) - Peak Hours:

Mean: 94.23, Standard Deviation: 87.24

Energy Consumption (With Duty Cycling) - Non-Peak Hours:

Mean: 79.55, Standard Deviation: 87.14

Fig. 9. Figure X: Energy consumption results under two settings: (i) no duty cycling, and (ii) with duty cycling. Includes detailed statistics (mean, standard deviation, minima, maxima), comparison during peak and non-peak hours, and overall savings percentage.

during peak and off-peak hours. In contrast, applying duty cycling reduced average consumption to 87.50 units, with a fluctuation range of 0–175 units. This mechanism achieved an energy savings rate of 63.54%. The results also showed that average consumption during peak hours was 94.23 units, while during off-peak hours it decreased to 79.55 units, reflecting the effectiveness of duty cycling in adjusting device consumption according to periods of activity and inactivity.

C. Scenario 3: CNN + BiLSTM Model Powered by Machine Language

The key performance metrics—accuracy, precision, recall, and F1-score are calculated using specific formulas [31].

Recall is a measure of how many true positives were identified, which means it reveals how many correct results were found among the total cases that should have been recognized.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{1}$$

Precision: The proportion of hits that are truly positive or accurate is known as precision.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

F1 Score: The F1 score is a metric that combines both recall and precision (accuracy). It ranges from 0 to 1 and is calculated as an asymmetrical mean of recall and accuracy.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

Accuracy: The percentage of accurately anticipated values for the test data is used to evaluate accuracy. By dividing the total number of forecasts by the total number of accurate guesses, one can easily determine the result.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Python is used to develop a simulation model using the “TensorFlow” and “Keras libraries”. These packages are important tools for creating neural network-based designs. In this work, the performance of the proposed hybrid CNN-BiLSTM model is evaluated using several performance metrics, including accuracy, recall, precision, and F1 score. The parameters of the performance matrices are described in the following: In Fig. 10, the model achieved consistently high performance with precision and recall values exceeding 0.98 across most classes, leading to strong F1-scores ¿ 0.98. The large support for classes such as super-eMBB further reinforces the reliability of these metrics.

Experimental results demonstrate that the proposed CNN–BiLSTM model achieved high accuracy in traffic flow classification, reaching approximately 99%, with a remarkable balance between precision and recall. When compared to other algorithms such as reinforcement learning (RL) [29] and federated learning (FL) [30], several distinct strengths emerged. Reinforcement learning-based segmentation demonstrated strong adaptability to dynamic network loads, resulting in stable energy efficiency during periods of heavy traffic. In contrast, federated learning demonstrated high scalability by supporting distributed training across a large number of IoT devices, while reducing communication costs. Although RL and FL techniques demonstrated competitive performance, CNN–BiLSTM maintained the lowest false positive rate and achieved the highest sustained energy reduction (approximately 60%), enhancing network sustainability and delivering greater efficiency as the number of connected devices increases.

Classification Report:

	precision	recall	f1-score	support
0	0.99	1.00	1.00	347683
1	0.99	0.98	0.99	57808
2	0.99	0.97	0.98	9891
3	0.99	1.00	0.99	111056
4	0.93	0.86	0.89	14530
accuracy			0.99	540968
macro avg	0.98	0.96	0.97	540968
weighted avg	0.99	0.99	0.99	540968

Fig. 10. Results of the hybrid CNN–BiLSTM model.

Fig. 10 of the classification report shows that the CNN–BiLSTM model achieved high performance in almost all categories, with precision ranging from 0.93 to 0.99, while recall ranged from 0.86 to 1.00. The F1-score metric demonstrated a good balance between precision and recall, with a minimum of 0.89 and a maximum of 1.00. The overall accuracy of the model reached 99% with a weighted mean of nearly 0.99, confirming the model’s strength in classifying traffic flows across different categories.

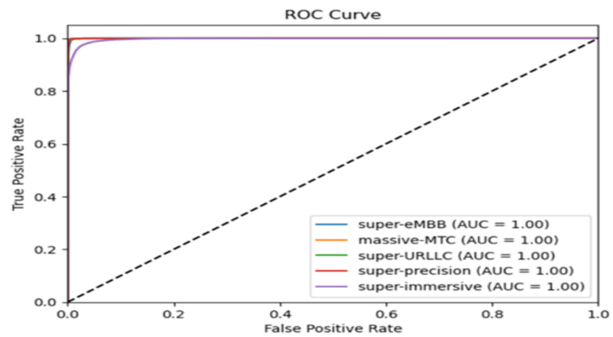

Fig. 11. ROC curve results of the proposed model.

Fig. 11 shows that all IoT network models achieved an Area Under the Curve (AUC) of 1.00, confirming excellent classification performance. This indicates that the models consistently deliver the intended results with high accuracy.

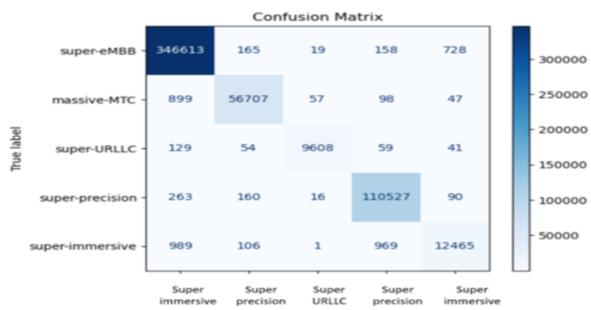

Fig. 12. Confusion matrix.

Fig. 12 presents the confusion matrix used to evaluate the model’s classification accuracy. The matrix highlights the performance across different data classes using standard evaluation parameters.

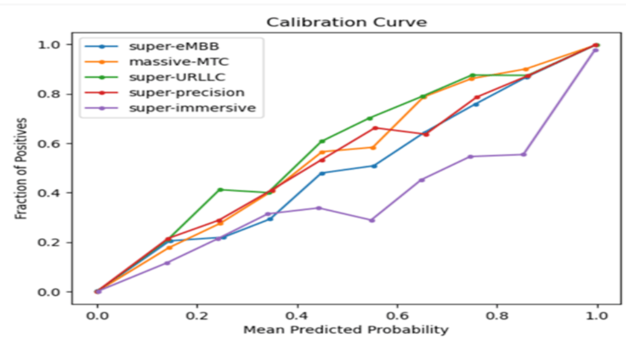

Fig. 13. Calibration curve of the proposed model.

Fig. 13 illustrates the calibration curve analysis for network slice classification in 6G-IoT, specifically examining the model’s ability to predict probabilities accurately. The calibration curve is a valuable tool for evaluating the accuracy of a system’s operation based on specific parameters.

Fig. 14 compares power consumption before and after slicing:

```
Energy Consumption Comparison:
Energy Consumption Before Slicing: 10000.00 watts
Energy Consumption After Slicing: 3986.42 watts
Percentage Reduction in Energy Consumption: 60.14%

Details of Energy Consumption per Slice:
super-eMBB: 833.33 watts
massive-MTC: 769.23 watts
super-URLLC: 800.00 watts
super-precision: 714.29 watts
super-immersive: 869.57 watts
```

Fig. 14. Comparison of power consumption before and after slicing.

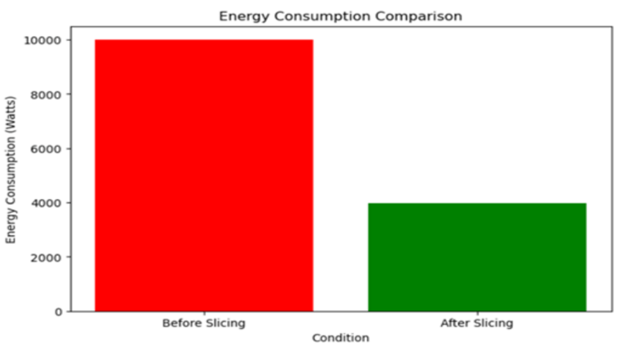

Fig. 15. Comparison of energy consumption with and without the proposed techniques.

Fig. 15 compares the energy usage of 6G-IoT networks before and after the introduction of network slicing technology.

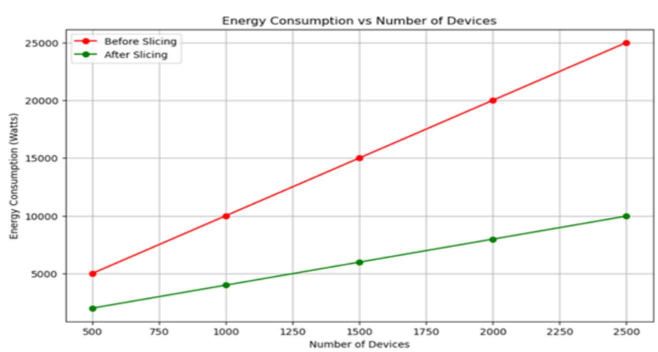

Fig. 16. Energy consumption vs. number of devices in 6G-IoT.

Fig. 16 shows the relationship between the number of connected devices (500–2500).

D. Summary of the Results

1) Scenario 1 – Segmentation via SDN: Reduced overall consumption by 66.28%. In the scalability test, the savings reached 41.81% (50 devices), 40.95% (500), and 39.52% (2500), confirming the effectiveness of slicing independent of network size.

2) Scenario 2 – Duty Cycling: Achieved a reduction of 63.54%; consumption was 94.23 units during peak hours and 79.55 units during off-peak hours.

3) Scenario 3 – Machine Learning-Driven Segmentation: Previous studies indicate that reinforcement learning (RL) [29]in the 6G–IoT context achieved energy reductions of 45–55% with high adaptability to changing network loads. Federated learning (FL)[30] demonstrated an efficiency of 40–50% energy reduction, with clear superiority in scalability across thousands of connected devices without the need to transfer raw data. Compared with these methods, our CNN–BiLSTM model achieved the highest consistent energy reduction of 60% with a classification accuracy of 99%, demonstrating its superior combination of energy efficiency and high accuracy.

VIII. Discussion

Scenario 1 Fig. 5 highlights the importance of slicing as a dynamic mechanism for adapting to varying network loads. While the traditional system (without slicing) exhibited constant, inflexible consumption, slicing allowed for intelligent control of energy consumption based on traffic intensity. This variation between peak and off-peak hours indicates that SDN-based slicing not only achieves an overall reduction in consumption but also enhances network sustainability by balancing energy efficiency with maintaining quality of service. This lays the foundation for adopting slicing techniques as an essential part of energy management strategies in 6G-IoT environments.

Fig. 6, the results indicate that slicing technology significantly reduced energy consumption across different network sizes, with consumption decreasing by 41.81% at 50 devices, by 40.95% at 500 devices, and by 39.52% at 2,500 devices. Although the energy savings gradually decrease with the increasing number of devices, this reflects slicing's ability to achieve stable energy efficiency even in environments with high device density. This highlights the importance of adopting SDN-based slicing as a strategic option for improving scalability in 6G-IoT networks, as it provides a balance between reducing energy consumption and ensuring quality of service amid the massive expansion of the number of connected devices.

Scenario 2 Fig. 9 indicates that adopting a duty cycle mechanism is an effective strategy for reducing energy consumption in IoT environments within 6G networks. This mechanism periodically shuts down devices during idle periods, contributing to a significant reduction in energy consumption. The variation in consumption between peak and off-peak hours highlights the flexibility of this technology in adapting to different usage patterns, enhancing its scalability as the number of connected devices increases. Therefore, duty cycle not only provides a significant reduction in energy consumption but is also a practical option that can be combined with other strategies such as SDN slicing to achieve greater energy management efficiency.

Scenario 3 This result reflects that the proposed model has a very high level of reliability and generalizability. The model's superior performance is attributed to the combination of the capabilities of CNNs to extract spatial features with the strength of BiLSTMs to capture temporal dependencies. The proposed model exhibits similar or superior performance to recent models such as [47]which achieved 99% accuracy using Attention-Based CNN-BiLSTM on N-BaIoT data, and also Sinha et al. (2025) with 99.87% accuracy and a very low false positive rate [48], supporting that fusion provides a real improvement in deep learning for similar problems.

Fig. 10 show this result:

Precision: The ratio of the number of samples correctly classified for a given class to the total number of samples classified as belonging to that class.

High precision (> 0.99) for classes such as super-eMBB and massive-MTC shows the model's ability to reduce false positives.

Recall: the ratio of the number of samples correctly classified for a given class to the total number of actual samples for that class.

Strong recall (0.98–1.00) for most classes shows the model's ability to capture almost all correct samples.

F1-Score: A metric that balances precision and recall.

High values (> 0.98) for a model show its strong and balanced performance.

Support: Indicates the number of samples in each class. For example, the super-eMBB class has very high support (347,683 samples), which enhances the accuracy of the metrics due to its large representation.

Class Analysis: super-eMBB: Precision: 0.99, Recall: 1.00, F1-Score: 1.00.

- The perfect performance in this class reflects the model's ability to accurately recognize high-bandwidth applications such as video streaming

massive-MTC: Precision: 0.99, Recall: 0.98, F1-Score: 0.99.

- This class has a large number of connected devices, and the high performance shows the success of model in dealing with this challenge.

super-URLLC: Precision: 0.99, Recall: 0.97, F1-Score: 0.98.

- Good performance in latency-sensitive applications such as industrial control.

super-precision: Precision: 0.99, Recall: 1.00, F1-Score: 0.99.

- The strong performance reflects the model's ability to handle high-precision applications.

Super-immersive: Accuracy: 0.93, Recall: 0.86, F1-Score: 0.89.

- Although the performance in this category is lower than the other categories, the model shows a reasonable improvement in applications with complex requirements such as virtual reality.

Finally, the result reflects strong performance of the model across all categories with a particular focus on achieving a balance between precision and recall.

Significant improvement: The results show improved efficiency in classifying different segments, supporting the use of the model to improve resource management in 6G IoT networks.

Areas for improvement: The super-immersive class shows room for improvement, perhaps through more data or improved model architecture.

Fig. 11 presents the Receiver Operating Characteristic (ROC) curve, which illustrates the connection between true positive rates (TPR) and false positive rates (FPR) for IoT networks. Here, the FPR shows how often a test incorrectly identifies a positive result, while the TPR shows how often the test correctly identifies a negative result. All the networks have an Area Under the Curve (AUC) of 1.00, which indicates that they are performing very well and achieving their intended goals efficiently. The fact that every network shows an AUC of 1.00 confirms their effectiveness in delivering the desired results.

Fig. 12 displays the confusion matrix, which is a tool used to determine how accurate a model is when comparing different types of data. This matrix helps in assessing the performance of model. The accuracy of the model is measured using the following parameters:

- **True label:** Represents the actual class of the data as it appears in the dataset.
- **Predicted label:** Represents the class that the model has assigned to the data based on its prediction.
- **Diagonal values:** Indicate correctly classified instances where the predicted label matches the true label. Higher values along the diagonal signify better classification accuracy.
- **Super-eMBB:** The Super-eMBB category has the highest number of correctly classified instances (346,613), indicating strong model performance in this category.
- **Massive-MTC:** The Massive-MTC category demonstrates a high number of correctly classified instances (56,707), though some misclassifications are present.
- **Super-URLLC:** The Super-URLLC category has 9,608 correctly classified instances, with some confusion among other categories, indicating room for improvement in classification accuracy.

Fig. 13 shows the calibration curve. It compares predicted outcomes with actual results [46]. The X-Axis allows us to compare predicted values to the real values, and the Y-Axis shows how many predictions were positive based on those calculations. The diagonal line in the figure represents perfect performance, meaning the predicted probabilities align exactly with the true outcomes. When a point falls on this line, it signifies that the model is making accurate predictions.

For the different classes—super-eMBB, massive-MTC, super-URLLC, and super-precision—most points are very close to the ideal line, showing that the model works well for predicting probabilities in these cases. However, some points deviate from the ideal line, suggesting that there are difficulties in calibrating the model for the class labeled super-immersive.

Use a Model for Power Consumption:

Fig. 14 compares power consumption before and after slicing:

- **Super-eMBB:** This chip used 833.33 W, indicating it is very efficient (efficiency rating of 1.2) for broadband applications, such as video streaming.
- **Massive-MTC**: It consumed 769.23 W, showing an efficiency rating of 1.3, which is suitable for Internet of Things (IoT) applications that need many connections while using less power.
- **Super-URLLC:** This chip used 800.00 W, with an efficiency rating of 1.15, making it fit for low-latency applications like industrial control processes.
- **Super-precision:** It consumed 714.29 W and has the highest efficiency rating of 1.4, making it ideal for tasks such as micro-analysis or working with big data.
- **Super-immersive:** This chip used 869.57 W. Although it is less efficient (efficiency rating of 1.05) compared to the others, it still performs better than the traditional network.

Understanding the results: Energy efficiency measures how much useful energy a system produces compared to the total energy it uses. It shows how well the system can deliver the most output while using the least amount of energy. Enhancing energy efficiency.

$$\eta = \left(\frac{\text{Useful energy output}}{\text{Total energy consumed}}\right) \times 100\% \tag{5}$$

Where:

- η (eta) represents **energy efficiency** as a percentage **[%]**.
- **Useful energy output** refers to the energy that is actually used to perform the necessary work.
- **Total energy consumed** is the complete amount of energy that the system has taken in.

Value for η (eta)

- $\eta = 1$ indicates standard efficiency where there is no improvement or additional energy loss.
- $\eta > 1$ means that the system is operating more efficiently than a conventional grid, either by improving performance or reducing losses.
- $\eta < 1$ indicates less than desired efficiency, meaning that there is significant loss in the grid or system.

Based on the earlier formula and our results shown in Fig. 14:

leftmargin=1.5em

- **Efficiency:** The network slicing allocates resources so that the power usage of each chip is optimized based on its actual needs.
- **Power reduction:** The slicing reduces the power consumption significantly due to the reduction of waste in the network.
- **Balance:** Highly efficient chips (such as super-precision) show greater power savings, while other chips such as super-immersive reflect greater consumption due to their higher requirements.

Fig. 15 compares the energy usage of 6G-IoT networks before and after the introduction of network slicing technology.

- **Before Slicing:** The energy usage is represented by the red column. This shows that before slicing, the network was less efficient ($\eta = 0.5$) because it consumed a lot of power—up to 10,000 watts—even for resources not assigned to any devices.
- **After Slicing:** The energy usage after implementing slicing is illustrated in the green column. As shown, energy consumption decreased to 3,986.42 watts. This reduction indicates that the network's efficiency has improved ($\eta > 1$) because resources are now allocated more effectively based on the individual needs of each network slice.
- **Reduction Ratio:** Network slicing positively affects energy usage, resulting in a significant 60.14% decrease in power consumption.

Fig. 16 shows the relationship between the number of connected devices (500–2500) and power consumption: before slicing (red line), consumption increases linearly with the size, while it decreases after applying network slicing (green line) due to improved resource allocation. The area between the curves represents energy savings, and the increasing gap with the rise in the number of devices indicates improved efficiency and scalability.

IX. Conclusion

This study revealed three separate strategies to optimize energy usage and improve 6G network performance in IoT contexts with escalating device connectivity. Each method was evaluated separately to elucidate its effect: 1) Dynamic slicing utilizing SDN resulted in energy reduction surpassing 66% by synchronizing device operation with actual usage. 2) Duty cycling decreased energy consumption by over 60% through an adaptive on/off mechanism. 3) A CNN–BiLSTM classification model enhanced slice allocation, achieving high Precision and Recall while providing improved estimations of energy requirements by service. These results provide evidence of the efficacy of each technology and establish a foundation for realistic, consumption-conscious, and adaptable resource management frameworks. Due to the complexity and unpredictability of 6G settings, adaptive operational solutions that harmonize energy conservation with service quality are becoming increasingly essential. Future research may expand this study to encompass simultaneous multi-layer resource allocation, including spectrum, power, and processing time, to attain holistic network performance enhancements in 6G–IoT contexts.

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