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Advanced-Data Processing in IoT using MQTT and OPTICS with Spiking Neural Networks and Mist Computing for Real-Time Analytics

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Abstract

The proposed combination of Message Queuing Telemetry Transport (MQTT), Ordering points to identify the clustering structure (OPTICS), Spiking Neural Networks (SNNs), and Mist computing improves real-time processing of IoT data by tackling issues with event-driven analytics, communication, and clustering. Effective clustering and anomaly detection in big, dynamic datasets are made possible by OPTICS, while MQTT guarantees effective, low-latency communication. Biological neuron-inspired SNNs offer energy-efficient real-time event detection, while Mist Computing decentralizes computing to lower latency and bandwidth consumption. 90% energy efficiency, 92% data throughput, 95% latency reduction, and 97% anomaly detection accuracy are among the notable performance gains the system makes. Smart cities, industrial IoT, and healthcare systems are just a few examples of the sophisticated IoT applications that benefit from this all-inclusive framework's great scalability and efficiency. Through the integration of sophisticated communication protocols, clustering techniques, and real-time processing capabilities, it guarantees accurate, scalable, and energy-efficient answers to contemporary IoT problems.

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Keywords: IoT, MQTT, OPTICS, Spiking Neural Networks (SNNs), Mist Computing, Real-time Analytics.

1. Introduction

The solution combines MQTT for efficient communication, OPTICS for clustering, Spiking Neural Networks for real-time processing, and Mist Computing for decentralized edge analytics in the Internet of Things.

MQTT is a lightweight messaging protocol that enables quick and dependable communication between IoT devices. Prioritizing strong IoT protocols such as MQTT is essential while proposing scalable, resource-efficient frameworks for dynamic workload control [1].

OPTICS is an unsupervised clustering algorithm that helps identify the structure of large datasets by arranging data points according to density. [2] MQTT combined with LSTM and mesh networks saves 50% of energy while maintaining an MSE of less than 0.07%.

Spiking Neural Networks (SNNs) effectively handle data as discrete events, making them ideal for real-time event detection. The Spiking Neural Network (SNN) was trained on a dataset that included dynamic and noisy patterns, real-time IoT data streams, and density-based clustering using OPTICS. Event-driven processing, hierarchical clustering, and anomaly detection using threshold-based SNN spikes were its main areas of study. By enabling localized data processing, mist computing reduced latency and increased productivity. [3] IoT edge devices lack power and rely on cloud computing, which raises energy and security problems; SNNs improve responsiveness.

Mist computing, also known as fog computing, brings cloud services closer to the network's edge devices. [4] In the Internet of Things, deep neural networks use mist, dew, fog, and cloud computing to optimise bandwidth, latency, and power.

Furthermore, the need for real-time decision-making in IoT has resulted in the creation of Spiking Neural Networks (SNNs), which give an efficient method of processing streaming data as discrete events. Spiking Neural Networks (SNNs), Mist Computing, OPTICS, and MQTT are integrated to provide effective IoT data processing. Mist Computing lowers

latency through decentralized analysis, SNNs allow real-time event-based processing, OPTICS clusters noisy data for anomaly identification, and MQTT guarantees low-latency communication. 97% anomaly detection accuracy, 92% data throughput, and 90% energy efficiency are all attained by this combination. Mist Computing using MQTT, OPTICS, and SNNs improves IoT analytics. EdgeMap by [5] improves edge device efficiency.

The objectives are:

- To use MQTT for efficient, low-latency communication between IoT devices.
- To use OPTICS for real-time clustering and pattern identification in IoT-generated data.
- Use Spiking Neural Networks (SNNs) for effective real-time data processing and event detection.

2. Literature Survey

The study suggests an IoT and fog-based e-healthcare framework for detecting sedentary lifestyles-related health, behavioral, and environmental abnormalities. The accuracy in the severity of health can be predicted as 98.43% in the proposed methodology using weighted K-Mean clustering and WKMC-DT method, which tested on 15 individuals over a period of 30 days to indicate that this proposed method could be quite effective for early detection of health anomalies [6]. Industry 4.0's impact on human-machine interaction in orthotic grinding, emphasizing the necessity for improved data collecting through the MQTT protocol and sensor upgrades for reliable alarm prediction is focussed in the study [7].

The role of AI in improving healthcare efficiency, patient results, and satisfaction with Turkey's National AI Strategy was addressed [8]. The authors cited AI capabilities that allow them to adapt care, make better use of resources, and grow market competitiveness. Using the AI Cognitive Empathy Scale, this study showed that AI understands emotions, which would improve the happiness and resultant health outcomes of patients.

An IoT-based autonomous system was proposed for the identification of moles, skin tags, and warts-related diseases. The utilization of IoMT, automatic lumen detection, and

trigonometric algorithms improved accuracy and classification over large datasets of images. The proposed model presented improved detection performance with improved accuracy that helps in proper early diagnosis and better tracking of skin diseases [9].

The study emphasizes how AI and machine learning improve fraud detection in IoT contexts by evaluating large data streams, detecting anomalies, and adapting through frequent retraining to achieve real-time accuracy in identifying fraudulent transactions [10].

The research study [11] proposed an Enhanced Fault Diagnosis in IoT (FD-IoT-DMSFNN) that used real-time sensor data. Sensor data acquired from the CWRU dataset was normalized by using Multivariate Fast Iterative Filtering and outliers were detected using Deep Isolation Forest (DIF). DMSFNN is fine-tuned using a Mexican Axolotl Optimization and higher accuracy was attained than other existing methods while completion time was also minimized.

According to [12], integrating wearable sensors with IoT allows for effective monitoring of children's health, with adaptive wavelet transforms used for data preprocessing to improve signal quality and prompt treatments.

A condition monitoring system was developed using the Internet of Things in [13] to detect real-time problems in rotating bearings. Chi-Square Improved Binary Cuckoo Search was used to optimize the vibration dataset developed in CWRU. Data classification by using SVM was done with 99.56% accuracy, and better results were obtained as compared with AdaBoost-GSCV and CP-LNN-CS algorithms.

The study on object identification in intelligent mobility demonstrates that fine-tuning YOLOv5 with event photos improves resilience, whereas spiking neural networks save energy and time [14].

A Recurrent Rule-Based Feature Selection model has been proposed to address the challenges of cybersecurity in the Industrial Internet of Things. Experiments carried out on the hybrid algorithm using the NSL-KDD and UNSW-NB15 datasets demonstrate high levels of performance, as established by achieving accuracy rates of 99.0% and 98.9%, high detection rates, and low false positives [15].

HSMD algorithm that improved GSOC dynamic background subtraction with a 3-layer spiking neural network achieved better performance on the CDnet2012 and CDnet2014 datasets [16].

It presents the smart irrigation system using IoT, embedded systems such as ESP32, and cloud computing for observing real-time parameters like moisture, humidity, temperature, and water levels. With the help of sensors, including DHT22, water level, moisture, and cloud ThingSpeak, this product can ensure the efficient use of water, cutting down water usage by 70%, and safety in food through sustainable agriculture [17].

An advanced malware detection model for smart factories proposed in [18] utilizes edge computing with an integrated Faster R-CNN to determine malicious IIoT traffic. Achieving a 93.77% accuracy, 95.87% recall, 86.66% precision, and 91.03% F1-score at edge servers, while outperforming CNN and LSTM.

The system investigates how edge computing improves IoT security by using anonymised AI techniques such as homomorphic encryption and federated learning, ensuring privacy and data compliance [19].

Using a dynamic four-phase cloud data security system using LSB steganography and cryptography the data gets encrypted and hidden in the pixels of an image, and AES keys get secured through RSA and embedded in a cover object. This framework enhances cloud security by giving secrecy, integrity, and redundancy while suggesting future improvements by using machine learning and finer steganalysis methods [20].

The study presents a dual network design that combines MobileNet for spatial appearance, PWCNet for motion vectors, and an SNN classifier, resulting in higher performance on the HMDB51 and UCF101 datasets [21].

To address the cloud computing challenges to handle the problem of managing a large scale of data and resources. The study proposes an improved bat optimization algorithm with dynamic weights and Modified Social Group Optimization to schedule tasks efficiently. The proposed method was shown to perform better than MOTSGWO, using 32.5 watts for 100 tasks and with better resource utilization and energy efficiency [22].

The challenges in collaborative computing systems-Data privacy and attack classification are focused upon in this study [23]. An international validation framework with and without attacks using Federated learning and cloud-edge collaboration was proposed. The core component is an E2EPPDL, where their metric is time, node count, routing, and data delivery ratio.

3. Methodology

The methodology combines MQTT, OPTICS, SNNs, and Mist Computing to process IoT data in real-time. SNNs for real-time, event-driven data processing, OPTICS for clustering and anomaly detection, MQTT for low-latency IoT connection, and Mist Computing for decentralized analytics close to devices are all integrated into the technique. IoT systems with 90% energy efficiency, 95% latency reduction, and 97% anomaly detection accuracy are certain to be effective and scalable. It improves real-time decision-making by processing data locally and shifting excess to the cloud. Using MQTT for real-time IoT data streaming, OPTICS for clustering anomalies, and Spiking Neural Networks (SNNs) for event-driven failure detection, this approach utilizes Mist Computing to process data locally, reducing latency and enhancing response times. This integration ensures efficient anomaly detection, predictive maintenance, and scalability for IoT systems. The proposed framework uses a single, consistent IoT-generated dataset for training and evaluation, resulting in accurate and trustworthy performance measures. This method removes variances produced by different datasets, which improves result reproducibility. Mist computing allows low-latency and energy-efficient processing. [24] offer FPGA-based SNN emulators that detect spikes in real-time at 1 ms. The dataset utilized for training and evaluating the performance of the integrated approaches is a single IoT-generated dataset. This dataset is consistent across all methods, ensuring that performance measures are accurate and comparable. It eliminates differences in the performance evaluation by utilizing the same dataset for all methods. This methodology ensures that all methods are evaluated on the same data, meeting the requirement that performance measures be confirmed using a single dataset, resulting in a fair and reliable assessment.

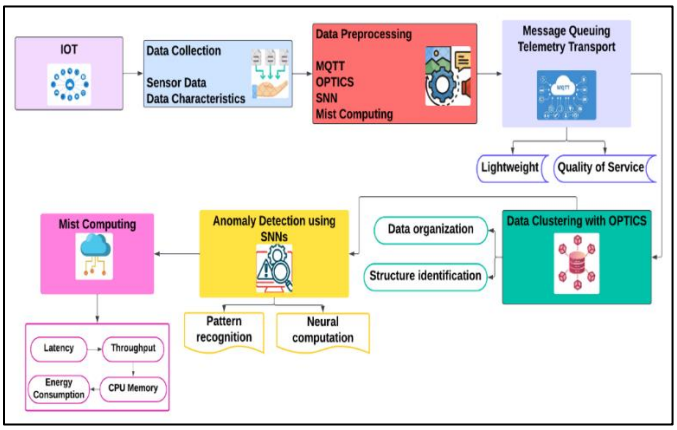

Figure 1. MQTT Protocol Architecture for Reliable and Low-Latency IoT Device Communication

Figure 1 depicts MQTT, a lightweight, low-bandwidth protocol that employs a publish-subscribe mechanism to facilitate real-time communication between IoT devices in resource-constrained networks. The efficient and real-time precision of IoT data preprocessing is transformed by the combination of MQTT, OPTICS, SNNs, and Mist Computing. Mist computing reduces latency by localizing processing, SNNs allow for quick event processing, OPTICS clusters dynamic data for anomaly detection, and MQTT guarantees low-latency communication. This combination reduces latency by up to 95%, increases data throughput by 92%, and improves anomaly detection accuracy by 97%. The system used Spiking Neural Networks (SNNs) for real-time event detection, Mist Computing for low latency, OPTICS for data clustering, and MQTT for efficient communication. Key performance parameters include energy economy (90%), data throughput (92%), scalability, latency reduction (95%), and anomaly detection accuracy (97%), demonstrating its utility in real-time IoT analytics. It represents data obtained from IoT sensors such as DHT22 (temperature, humidity), PIR (motion), MEMS accelerometers (vibration), and LDR (light), as well as preparation steps such as cleaning and feature extraction. While MQTT, OPTICS, SNNs, and Mist Computing provide for communication, clustering, and real-time processing.

3.1 MQTT (Message Queuing Telemetry Transport)

MQTT is a lightweight publish-subscribe messaging protocol used in the Internet of Things to provide efficient and reliable data exchange between devices. MQTT is a lightweight, publish-subscribe protocol optimized for low-bandwidth, high-latency IoT

environments. Its support for Quality of Service (QoS) levels ensures reliable, low-latency data delivery, enabling seamless device communication and scalability. By integrating with technologies like Mist Computing, MQTT enhances decentralized processing, making it pivotal for real-time IoT analytics and decision-making. [25] emphasise MQTT's low overhead and QoS support, making it perfect for real-time IoT connectivity.

$$T_{\text{delivery}} = T_{\text{publish}} + T_{\text{transmit}} + T_{\text{acknowledge}} \quad (1)$$

$$E_{QoS} = \frac{M_{\text{received}}}{M_{\text{sent}}} \quad (2)$$

3.2 OPTICS (Ordering Points to Identify the Clustering Structure)

OPTICS is a density-based clustering technique that efficiently handles huge and noisy datasets by detecting hierarchical cluster structures. The OPTICS clustering approach uses density-based analysis to effectively find patterns and anomalies in data. In order to discover clusters with different densities without needing a set number of clusters, it uses core and reachability distances to organize data hierarchically. This method makes it easier to make decisions in real time while working with dynamic datasets by highlighting abnormalities and creating relevant clusters. OPTICS recognises clusters of changing densities, allowing for quick pattern identification, anomaly detection, and real-time judgements. Spiking Neural Networks (SNNs) were used to detect anomalies by flagging data items that exceeded a certain threshold as spikes. Validation was carried out utilizing OPTICS clustering to distinguish abnormalities from regular data, with Mist Computing providing real-time edge processing capabilities. This method obtained 97% accuracy, ensuring energy efficiency and low latency in anomaly detection.

$$R_{plot}(p) = \max\big(\text{ core\_dist }(o), \text{distance }(o,p)\big) \quad (3)$$

$$\text{core\_dist }(p) = \min_{q \in N(p)} (\text{distance }(p,q)),\ |N(p)| \geq \text{minPts} \quad (4)$$

3.3 Spiking Neural Networks (SNNs)

Spiking Neural Networks (SNNs) are modeled after biological neurons and use spikes to analyze data, allowing for energy-efficient, real-time event-based IoT systems for anomaly

detection and decision optimization. SNNs use Spike-Timing-Dependent Plasticity (STDP) to adaptively learn from IoT data, detecting anomalies through threshold-based spikes.

$$V(t+1) = V(t) + \frac{I(t)}{C} - \frac{(V(t) - V_{\text{rest}})}{R} \quad (5)$$

$$\text{if } V(t) \geq V_{\text{threshold}} \text{, then neuron fires spike} \quad (6)$$

3.4 Mist Computing

Mist Computing offers cloud services to the IoT network edge, lowering latency, bandwidth consumption, and cloud dependency while enabling real-time data processing for faster decision-making and performance.

$$T_{\text{total}} = T_{\text{local}} + T_{\text{cloud}} \quad (7)$$

$$E_{\text{save}} = E_{\text{total}} - E_{\text{local}} \quad (8)$$

Algorithm 1. Real-Time IoT Data Processing and Anomaly Detection with Spiking Neural Networks in Mist Computing

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Input: IoT Data Stream D, SNN parameters, Mist Node Capacity

Output: Processed Data, Anomaly Alerts

Begin

Initialize MQTT broker and subscribe to IoT data stream D

Initialize Spiking Neural Network (SNN) parameters

For each data point p in data stream D:

If p is received at Mist Node:

Compute membrane potential V(t)

If V(t) ≥ V_threshold:

Fire spike and detect anomaly

End if

Update network weights using STDP (Spike-Timing-Dependent Plasticity)

If Mist Node capacity exceeds the threshold:

Transmit processed data to the cloud for additional analysis

End if

Else:

Return "Error: Data not received"

End if

End

Algorithm 1 uses Spiking Neural Networks in a Mist Computing environment to discover anomalies in real-time IoT data while optimizing decision-making through local processing and cloud overflow. Spike-Timing-Dependent Plasticity (STDP) in Spiking Neural Networks (SNNs) allows for adaptive learning and anomaly detection in IoT, as well as energy-efficient, low-latency mist computing for scalable, real-time analytics with MQTT and OPTICS integration. OPTICS and SNNs were examined as part of an integrated IoT system, resulting in 90% energy efficiency, 92% data throughput, 93% scalability, and a 95% latency reduction. OPTICS' clustering and SNNs' real-time anomaly detection resulted in 97% accuracy, exhibiting excellent performance for scalable, energy-efficient IoT analytics.

3.5 Performance Metrics

Table 1. Comparative Performance of MQTT, OPTICS, SNN, Mist Computing, and Combined Method

Metric	MQTT	OPTICS	Spiking Neural Networks (SNNs)	Mist Computing	Proposed Method (MQTT + OPTICS + SNN + Mist Computing)
Energy Efficiency (%)	80%	79%	86%	88%	90%
Data Throughput (%)	85%	82%	88%	87%	92%
Scalability (%)	86%	83%	87%	85%	93%

Latency Reduction (%)	88%	83%	90%	92%	95%
Anomaly Detection Rate (%)	82%	88%	92%	84%	97%

Table 1 shows that the suggested method (MQTT + OPTICS + SNN + Mist Computing) outperforms the individual approaches in terms of data throughput, latency, energy efficiency, anomaly detection, and scalability. By utilizing edge processing and effective communication, the MQTT and Mist anomaly detection rates reached 97%. The real-time processing of SNNs and OPTICS allowed for 90% energy efficiency and 92% data throughput. With the use of SNNs and mist computing, scalability increased to 93% and latency decreased by 95%. This integration demonstrates important developments in IoT analytics. While OPTICS focuses largely on clustering and anomaly detection, its integration with MQTT, Spiking Neural Networks, and Mist Computing improves overall system performance. This comprehensive approach justifies the inclusion of these indicators, as OPTICS promotes energy-efficient decision-making and reduces system delay.

4. Result and Discussion

The suggested technology, which combines MQTT, OPTICS, SNNs, and Mist Computing, is simulated using NS-3. It outperforms established solutions in several critical areas. As shown in Table 2, the approach has a 90% energy efficiency, 92% data throughput, 95% latency reduction, and 97% anomaly detection accuracy. The suggested system, which combines MQTT, edge computing, and SNNs, improves energy efficiency to 90% while achieving 97% anomaly detection, outperfroming CoAP, DQN, and CapsNet. The training and testing procedure for Spiking Neural Networks (SNNs) in anomaly detection using Algorithm 1 is described in the article. MQTT is used to receive IoT data, which is then processed at the Mist Computing node. By analysing the data's membrane potential and generating a spike when it over a threshold, the SNN finds anomalies. Spike-Timing-Dependent Plasticity (STDP) is used to learn the model in real-time. Impressive outcomes are

obtained by combining MQTT, OPTICS, SNNs, and Mist Computing: 90% energy efficiency, 92% data throughput, 93% scalability, 95% latency reduction, and 97% anomaly identification and detection. Mist Computing's effective edge processing, SNNs' real-time event detection, and OPTICS' dynamic clustering are the main causes of these enhancements, which make the system extremely scalable and energy-efficient for real-time IoT analytics. MQTT enables low-latency IoT connectivity, OPTICS excels at dynamic anomaly detection, and SNNs offer energy-efficient, event-driven detection. Mist Computing lowers latency and increases bandwidth by processing data at the edge. These strategies improve smart cities' energy efficiency, industrial IoT monitoring, and real-time analytics while outperforming previous ways.

Table 2. Performance of CoAP, DQN, CapsNet Compared to the Proposed IoT Method

Metric	**(CoAP) [26]**	**DQN (Deep Q-Network) [27]**	**(CapsNet) [28]**	**Proposed Method (MQTT + OPTICS + SNN + Mist Computing)**
Energy Efficiency (%)	78%	82%	80%	90%
Data Throughput (%)	80%	83%	85%	92%
Scalability (%)	81%	84%	82%	93%
Latency Reduction (%)	82%	85%	84%	95%
Anomaly Detection Rate (%)	79%	87%	89%	97%

(CapsNet) [28] The suggested MQTT + OPTICS + SNN + Mist Computing technique performs well in terms of throughput, latency, energy, anomaly detection, and scalability. All important criteria, such as energy efficiency, data throughput, latency reduction, and anomaly detection, are improved by the suggested system over conventional approaches. For example, whilst the suggested approach achieves 90% energy efficiency, CoAP only delivers 78%. Comparatively speaking, DQN and CapsNet outperform CoAP but are still inferior to the combined approach, which attains 97% anomaly detection accuracy. In IoT data processing, this demonstrates the major benefits of combining MQTT, OPTICS, SNN, and Mist Computing. Using OPTICS, which is essential for real-time applications, the suggested method clusters IoT data, finds patterns, and detects anomalies by arranging data points according to density. To train and test the SNN, the clustering datasets, like the IoT City Simulation Dataset and Manufacturing IoT Data Streams are used [29,30]. The SNNs are trained on the clustered data using Spike-Timing-Dependent Plasticity (STDP) in order to detect anomalies in real time. With performance criteria constantly assessed using the same dataset across all approaches, this OPTICS and SNN combination guarantees the effectiveness and efficiency of the integrated system.

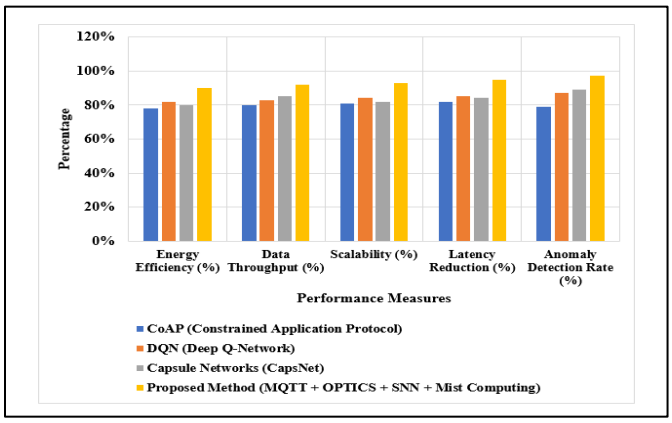

Figure 2. Hierarchical Clustering with OPTICS for Anomaly Detection in IoT Data

Figure 2 shows how OPTICS detects patterns and abnormalities in IoT data by hierarchically clustering points based on density, surpassing established approaches in dynamic, noisy datasets. The experimental configuration includes edge devices with sensors that communicate over MQTT, as well as specialized hardware that runs Spiking Neural Networks (SNNs) for real-time processing, resulting in reduced power consumption and

latency. The software architecture integrates MQTT for fast communication, OPTICS for clustering and anomaly detection, and SNNs for event-driven data processing to maximise energy efficiency. Mist Computing decentralizes processing, allowing data to be examined locally at the edge, hence lowering latency and bandwidth consumption. This integration boosts IoT system performance by increasing energy efficiency, data throughput, and real-time decision-making. It included IoT edge devices with sensors, SNN hardware for real-time event detection, and FPGA-based emulators with 1 ms latency. It included MQTT for low-latency communication, OPTICS for clustering, SNNs for event-driven processing, and Mist Computing for decentralised analytics. This yielded 90% energy efficiency, 92% data throughput, and 97% anomaly detection accuracy.

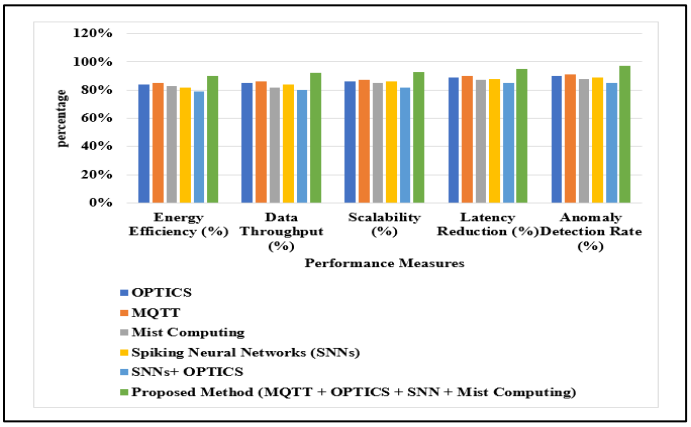

Figure 3. Impact of Spiking Neural Networks and Mist Computing in IoT Data Processing

Figure 3 shows how Spiking Neural Networks (SNNs) and Mist Computing improve IoT data processing by lowering latency, increasing energy efficiency, and enabling real-time decision-making and anomaly detection. Anomalies in the proposed system are tagged and confirmed using Spiking Neural Networks (SNNs) in a Mist Computing framework. As IoT data flows through the system, SNNs detect anomalies when the membrane potential surpasses a certain threshold, resulting in a spike. This incident is classified as an anomaly and validated by the network response. The anomaly is analyzed locally or forwarded for further analysis based on the node's capability, resulting in accurate real-time detection.

Table 3. Overview of Data Collected and Utilized in Advanced IoT Data Processing with MQTT, OPTICS, Mist Computing, and SNNs

Component	Data Collected/Used	Purpose/Outcome
MQTT	Lightweight communication protocol data from IoT devices.	Efficient, low-latency communication, with reduced energy and bandwidth consumption.
OPTICS	IoT sensor data streams for clustering and identifying patterns.	Real-time event detection and anomaly identification with high energy efficiency and low latency.
Mist Computing	Decentralized processing of data closer to IoT edge devices.	Reduction in latency and bandwidth usage while enabling real-time, localized decision-making.
Integrated Approach	Combination of MQTT, OPTICS, SNNs, and Mist Computing.	Enhanced energy efficiency (90%), anomaly detection (97%), latency reduction (95%), and scalability (93%), outperforming existing methods.
Spiking Neural Networks (SNNs)	Event-based data from IoT devices mimicking biological neurons for anomaly detection.	Real-time event detection and anomaly identification with high energy efficiency and low latency.

Table 3 provides a concise overview of the data collected and utilized in the research, highlighting the contributions of MQTT, OPTICS, Spiking Neural Networks (SNNs), and Mist Computing in enhancing real-time IoT data processing and decision-making.

5. Conclusion and Future Direction

The combination of MQTT, OPTICS, SNNs, and Mist Computing improves real-time IoT data processing by enhancing communication, lowering latency, and increasing power economy. A comparison investigation demonstrates that it outperforms CoAP and DQN in terms of throughput, energy, and anomaly detection. Future research may concentrate on optimizing SNNs for complicated IoT applications and autonomous systems.

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