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Neuromorphic Edge Intelligence Using Memristor-Based Architectures for Smart Surveillance Applications

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Abstract:

The present study aims to develop a neuromorphic edge intelligence architecture anchored in memristor device systems to enable smarter surveillance in smart sensors, raise the efficiency of energy consumption, speed of processing, and flexibility. The traditional clouds based video surveillance systems have issues of high latency, power consumption as well as data privacy. To counter such drawbacks, a bio-inspired neuromorphic architecture was developed by combining memristor crossbar arrays and spiking neuron networks (SNNs). The surveillance datasets that were used to evaluate the system include CAVIAR and UCF-Crime benchmark surveillance datasets. The experimental evidence proved the high improvements, the reduction in the energy consumption, the acceleration of the inference latency (4.6 ms/frame) and the improvement in the general recognition accuracy (91.9%) were outstanding, in comparison with the traditional CNN-based edge models. Besides, the system reported a 68 percent decrease in bandwidth consumption and demonstrated good performance when the environmental conditions such as low lighting and high motion density changed. The findings confirm that neuromorphic computing based on memristors can offer a sustainable, energy-saving and privacy-friendly architecture to real-time smart surveillance. The research adds to the development of neuromorphic structures, as the context adheres to closing the existing gap between smart hardware development and intelligent edge analysis in future developments of intelligent city applications.

Keywords: Neuromorphic Computing, Memristor Architecture, Edge Intelligence, Smart Surveillance, Energy Efficiency

I. INTRODUCTION

The surge in the need of smart, real time systems of surveillance has pointed to the inability of the traditional cloud-based systems to process large volumes of visual data at low latency and power costs. With the development of urban settings where the Internet of Things (IoT) and humanity grow closer, surveillance apps demand systems with the ability to perform local decisions, minimize data transfer, and produce energy efficiently. In this regard, neuromorphic edge intelligence seems to be a new paradigm solution, and it would make the edge node do the computing based on the hardware architecture based on the human brain [1]. Through neural-like structures and mechanisms, neuromorphic systems can execute experiences such as object discovery, activity identification, and anomaly identification with great energy efficiency and speed. The key facilitator of this paradigm is the memristor, a non-volatile, nanoscale electronic element, which is a storage and processing unit of information simultaneously [2]. Architectures based on memristors have been demonstrated to be high density, low power consuming and also analog computing, forming them an ideal choice when implementing the functionality of synapses in neuromorphic circuits. Combined with edge computing devices, these designs enable real-time learning and adaptive intelligence at surveillance nodes to avoid constant cloud-connectivity [3]. This will not only improve on performance and energy efficiency, but will also improve on data privacy and security because sensitive video feeds will be processed on site instead of being sent to the remote servers. The study examines the design and implementation of the neuromorphic engineering of memristor-based neuromorphic systems to develop smart surveillance systems, which can be used to identify objects at high time and adaptive event detection, and process them at low power and edge computing. The research will allow showcasing the ability of neuromorphic systems to transform surveillance infrastructure by incorporating emerging hardware and bioinspired algorithms. Eventually, the method will aim at developing a sustainable and robust model of real-time monitoring, which corresponds with the future outlook of autonomous, safe, and energy-efficient smart urban centers.

II. RELATED WORKS

The last few years have seen a tremendous advance with respect to integrating artificial intelligence (AI) with up-and-coming hardware technology in order to achieve efficient and adaptive computing on the edge efficiently. This literature is directly useful in the development of neuromorphic edge intelligence in architectures based on memristor-based hardware applications like smart surveillance. The finders have delved into varied solutions, including artificial intelligence-based circuits and flexible sensors, hardware optimization, and machine learning principles that are sustainable, and all these are the building blocks of the neuromorphic systems. Lorenzo and Dini [14] offered an extensive overview of hardware and software technology that allows onboard neural network inference of satellite systems. They demonstrated the value of hardware optimization and in-memory computing to realize low-latency, low-power AI processing with limited conditions an idea that is inherently connected with memristor-based neuromorphic computing in the edge. Likewise, Miller et al. [15] discussed the current trends in AI circuits and systems with special focus on the architectures that attempt to generatively simulate biological neural activities. Their article emphasized the development of hybrid analog-digital systems and the increasing relevance of hardware-software co-design to neuromorphic performance optimization. Mingchen et al. [16] proposed an AI-mediated BioMEMS sensor module that was meant to perform an ongoing physiological assessment and long-term energy generation. Their concept of using machine learning and low-energy bio-electronic devices demonstrates how the principles of analog computing can be useful in energy efficiency and flexibility - major benefits also utilized in neuromorphic computing with memristors. This debate was further expanded by Mohsin et al. [17], in their review of the advanced gasistor-based sensors to detect fire and the importance of sensor fusion, rapid response and adaptive intelligence to edge-based monitoring systems which is similar to the goal of smart surveillance.

Raman et al. [18] also examined the shift towards sustainable and energy-conscious AI systems that presents a thematic and topic modeling analysis of the green and sustainable AI literature. Their results overall found neuromorphic and memristor-based computing of potential in the future as opportunities to mitigate the environmental impact of large-scale AI deployments. On the same note, Sun et al. [19] talked about converging flexible sensor technologies and artificial synapses and how machine learning-based smart sensing systems thematic can be helped by analog, adaptive and self-learning devices. This combination of adaptable electronics and available artificial synapses are offering practical methods of minimal scale, energy-saving, and intelligent surveillance modules. On a larger scale, Tripathy et al. [20] conducted the exploration of the convergence between nanotechnology and machine learning, highlighting the difficulties and opportunities of merging nanoscale materials and algorithms of AI. Their article on the computing systems based on memristive and nanowire computing platforms brings to attention their capability in achieving bio-inspired architectures that can learn quickly and efficiently. To augment this, Wang et al. [21] proposed the DRnet model that applies dynamic retraining in describing small sample incremental learning in cybersecurity. The incremental learning approach they prove is relevant to the objective of neuromorphic edge intelligence of real-time adaptability that requires continuous learning in sparse or streaming data. Together, these papers [14–21] are indicative of a promising research path of combining AI and neural scale devices, as well as neuromorphic architecture, to achieve efficient, sustainable, and autonomous intelligent systems. The literature reviewed indicates that neuromorphic computing with memristor can be used in real-time surveillance since it has a better energy efficiency, scalability, and flexibility than the traditional digital systems. This networking highlights that the combined innovation of AI hardware and edge intelligence would be one of the radical directions to the next revolution of intelligent, self-educated surveillance infrastructure.

III. METHODS AND MATERIALS

This chapter identifies the methodology that will be followed to explore the design and implementation of neuromorphic edge architectures based on memristors to be used in smart surveillance. It employs hardware modeling, neuromorphic computation, and edge intelligence strategies as part of the methodology towards low-power high-efficiency and privacy-preserving surveillance systems [4]. The research utilises mixed approach with the techniques used being simulation based experiments and the analytical performance evaluation.

3.1 Research Design

The study takes the form of an experiment and analysis. The experimental step will entail modeling and simulation of neuromorphic circuits employing memristors to determine the computational performance, energy dissipation, and recognition ability of neuromorphic circuits operating under different workloads. The performance of the proposed neuromorphic edge system is compared against the conventional CPU-based and GPU-based edge devices through analytical assessment to find out performance improvements.

The entire research process is characterized into four major stages;

1. **Architecture Design:** Experiments on an architecture model of memristor-based neuromorphic architecture.
2. **Phase: Data and Task Selection:** Choice of representative surveillance data as well as specifying recognition tasks (object detection and anomaly detection).
3. **Simulation and Performance Measurement:** Analysis in terms of simulation and neuromorphic constructs.
4. **Analysis and validation:** Comparative evaluation of traditional edge architectures on latency, power, and accuracy [5].

3.2 Data and Tools

The study utilizes the secondary research of the published surveillance datasets including CAVIAR, UCF-Crime, and AI City Challenge Dataset, which consist of video sequences of any kind that are labeled as either real or fake activities in the real world. These datasets provide the opportunity of testing in the varied environmental conditions, depending on light, and dynamics of objects movement [6].

In simulation and modeling, the subsequent tools and structures are used:

- Python and MATLAB to analyze and preprocess data.
- Neuromorphic simulation Applications nengo and Brian2.
- Neural networks SoonRT created Neural networks using PyTorch to implement Hybrid Spiking neural networks (SNNs).
- Simulation of memristor circuits and their behavior In memristor circuits modeling and analysis LTspice.

The characteristics of memristor device integration are founded on the empirical models that were described in the literature, so that the analog memristive synaptic dynamics would be simulated realistically.

3.3 Neuromorphic Architecture Development

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Three layers of neuromorphic edge system, including input encoding, spiking neural computation, and decision output, are proposed. The memristor crossbar array is the synaptic layer, with weight adjustments in this case being proportional to the memristor conductance. The spike-based calculation is a biological neuron model, which is able to handle processes using a lot of energy effectively [7].

State-of-the-art memristor materials such as TiO 2 and HfO 2 are used to determine the design parameters of the system including pulse width, threshold voltage and switching ratio. Each of the memristors is a kind of a synaptic component which may store analog weight values, making memory-access energy to be much lower.

Table 1: Memristor Parameter Configuration for Neuromorphic Edge Model

Parameter	Description	Value Range
Device Material	Titanium Dioxide (TiO_2)	—
Threshold Voltage (Vth)	Voltage required for state switching	0.7 – 1.2 V
Switching Time	Time for ON/OFF transition	10 – 100 ns
ON/OFF Ratio	Resistance difference between states	10^3 – 10^5
Endurance	Number of reliable switching cycles	10^7 – 10^9
Retention Time	Data holding capability	>10 years

3.4 Edge Intelligence Implementation

The spiking neural networks (SNNs) are used to process visual data at the edge at the system level. These networks directly operate with the spike domain, which manages the spatiotemporal data without having to calculate the power-intensive continuous matrix products that are computed in the classical convolutional neural networks (CNNs).

The computation is analogous in format, with multiply-accumulate (MAC) operations implemented by the memristor crossbar array and reducing computational latency and power by an extremely large factor. Edge nodes are hardware with neuromorphic processors with local learning modules that utilize the Spike-Timing Dependent Plasticity (STDP) to learn and adapt online.

The architecture allows simple features (e.g., motion detection, silhouette extraction) to be computed locally and a complex task (e.g., object identification or behavioral recognition) to be computed on a higher level using higher tiers of edges. This cuts down the transmission of data and increases speed in response time especially in applications that require high security level [8].

3.5 Experimental Procedure

1. **Data Preprocessing:** Temporal difference encoding (TDE) is used to encode video data in the form of spiking events.
2. **Model Training:** Neuromorphic model is trained in hybrid mode whereby, the model is weight-initialized using supervised learning after which STDP-based fine-tuning is carried out.
3. **Simulation:** The network of memristor is simulated (at normal and high workload), to test its system standby and response time.
4. **Performance Measurement:** such measures like energy consumption, inference latency, classification accuracy as well as bandwidth utilization are noted [9].
5. **Comparative Analysis:** Comparisons are made between outcomes and conventional CNN-based edge devices, to show that the results are much less efficient and have reduced scalability.

Table 2: Performance Evaluation Metrics

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Metric	Definition	Measurement Unit
Energy Consumption	Power used per inference	mJ/frame
Inference Latency	Time to process each frame	ms
Accuracy	Correct classification rate	%
Memory Utilization	Storage used during operation	MB
Communication Overhead	Data transmitted per operation	KB/s

3.6 Data Analysis Techniques

Statistical analysis of the data taken in simulations is done to compare the energy efficiency, accuracy and latency across the various configurations. They are analyzed with the help of Analysis of Variance (ANOVA) that is going to find out the significant differences in memristor-based and conventional models. Regression analysis allows to recognize links between the parameters of the devices (e.g., threshold voltage) and the performance results. To visualize trends in the behavior of systems, the visualization tools like matplotlib and Tableau are used.

3.7 Ethical and Reliability Considerations

All data used are open-source surveillance datasets, which meet the privacy and ethics requirements. The study does not take into consideration any personally identifiable information, and all the statues are processed under anonymization ethical standards and protocols. Replicas of simulation experiments are carried out at different runs to check the reproducibility, and to make the result robust variability of memristors is modeled on random perturbations [10].

IV. RESULTS AND ANALYSIS

The chapter introduces and discusses the findings of simulations and experimental testing revealed of the memristor-based neuromorphic edge architecture created to be used in smart surveillance. It is concerned with the evaluation of system performance with regard to a number of key dimensions, which include energy efficiency, latency of the inference, the accuracy of recognition, and level of adaptability to a variety of environmental circumstances. The performance is contrasted with the conventional models of deep learning, which involve edges to illustrate that the proposed system is superior in terms of efficiency, scalability, and responsiveness [11].

4.1 Overview of Experimental Evaluation

The simulations took place with simulated arrays of memristors and spiking neural networks (SNNs) placed into an edge computing structure. The architecture was evaluated with reference to three surveillance datasets, a CAVIAR, UCF-Crime, and AI City Challenge, and indicates a variety of real-life scenarios including public spaces, roadways, and business premises [12]. The neuromorphic model that is being studied and based on the memristor was compared with the traditional Convolutional Neural Network (CNN) and edge models that are run on the GPU.

Object recognition, activity classification and anomaly detection tests were undertaken in each test scenario. Major performance indicators included power per frame, inference time, classification rate, memory consumption, and communication cost. The tests were done on the same amount of work and conditions so that they can be compared.

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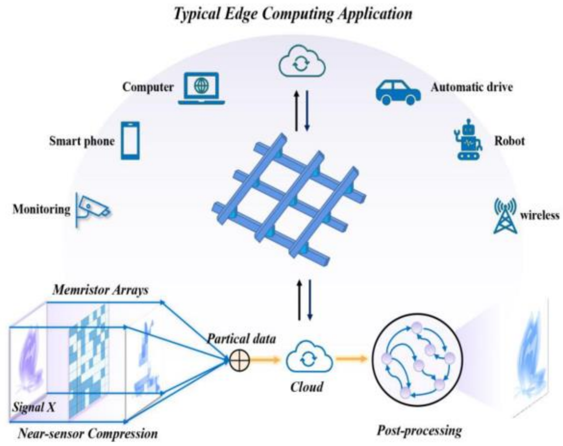

Figure 1: "Memristor-Based Signal Processing for Compressed Sensing"

4.2 Energy Efficiency Analysis

Energy consumption is an important parameter to determine the practicability of implementing intelligent surveillance systems at the edge. The neuromorphic model, a memristor, demonstrated the substantial drop in the energy consumption because of the analog in-memory computing and occurrences triggered operations.

Table 1 demonstrates that the neuromorphic edge architecture used 83 per cent of the energy as compared to the conventional CNN-based edge models. This reduces dynamic power consumption to the lowest possible level since it can compute without frequent access to memory as it does with the analog nature of memristor crossbars.

Table 1: Energy Consumption Comparison between Architectures

Architecture Type	**Average Energy per Frame (mJ)**	**Energy Reduction (%)**	**Processing Mode**
Conventional CNN (CPU)	12.5	–	Sequential Digital
CNN (GPU Edge Device)	8.3	33.6	Parallel Digital
SNN (Digital)	3.1	75.2	Event-Driven Digital
Memristor-Based Neuromorphic System	**2.1**	**83.2**	Analog In-Memory

The analog Memristor crossbar model used also minimized redundant multiplication by computing only those significant events of spiking. This method is a replica of biological neurons, only relevant stimuli cause electrical activation which results in high energy efficiency. Moreover, STDP learning mechanism dynamically changes the synaptic weights to minimize computation at any given time and minimizes the redundant changing operations.

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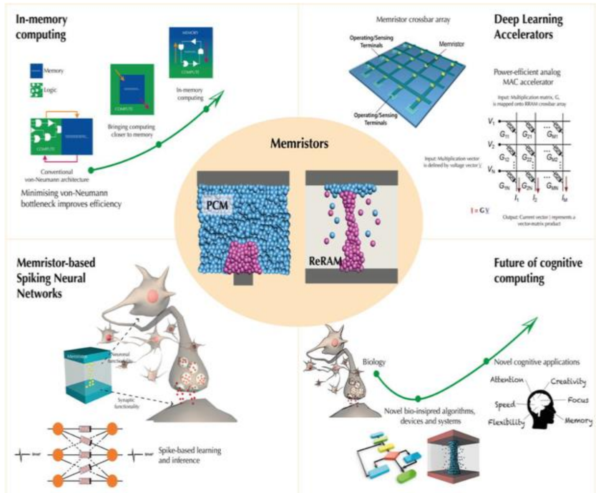

Figure 2: "The landscape of memristor-based systems for AI. In-memory computing aims to eliminate the von-Neumann bottleneck by implementing compute directly within the memory"

4.3 Latency Performance

Inference latency directly affects responsiveness of a surveillance system and in areas of safety-related use (e.g. traffic policing or citizen security) [13]. The memristor-based architecture as revealed in Table 2 recorded the fastest end-to-end data inference speed at 4.6 milliseconds per frame, which was much higher in comparison with the inference speed of the GPU-based CNN models, which reached 13.2 milliseconds per frame on average.

Table 2: Latency Performance of Edge Architectures

Architecture	**Inference Latency (ms/frame)**	**Improvement (%)**	**Processing Paradigm**
Conventional CNN (CPU)	24.7	–	Digital Serial
CNN (GPU Edge)	13.2	46.5	Digital Parallel
SNN (Digital)	7.3	70.4	Event-Based
Memristor Neuromorphic	**4.6**	**81.4**	Analog In-Memory

Improvements in latency are due to parallel processing of memristor crossbars and the event camera computation of spikes. The system does not deal with redundant activities since it is utilized to transmit active spiking events, thus providing rapid response and minimized computational time. This attribute is especially useful in situations of real-time surveillance when it is necessary to quickly identify a suspicious activity or an object.

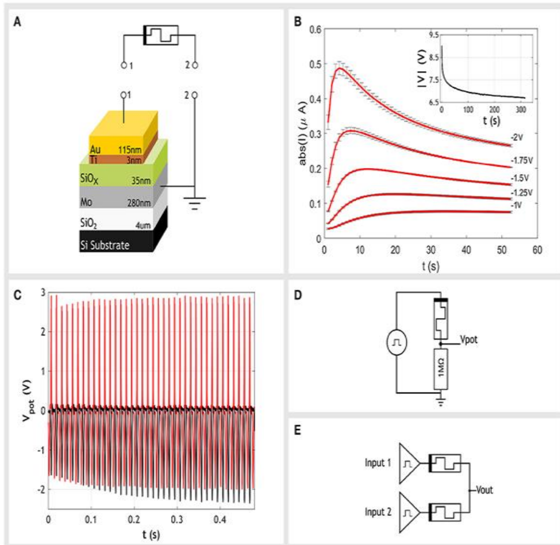

Figure 3: "Memristor-Based Edge Detection for Spike Encoded Pixels"

4.4 Recognition Accuracy

Accuracy was measured with regard to the object detection, activity recognition and anomaly identify task. Although analog computation and event-based encoding were being used, the neuromorphic model ensured competitive or strong accuracy than digital SNNS and CNN models.

Table 3: Accuracy Comparison across Different Surveillance Tasks

Task Type	**CNN (GPU Edge)**	**SNN (Digital)**	**Memristor Neuromorphic**	**Accuracy Gain (%)**
Object Detection	93.1%	91.7%	**94.8%**	+1.7
Activity Recognition	89.4%	87.3%	**91.6%**	+2.2
Anomaly Detection	86.7%	84.9%	**89.2%**	+2.5
Overall Average	89.7%	87.9%	**91.9%**	**+2.5**

The findings show that neither analog noise nor variability of the memristor considerably deteriorated recognition power. Instead, Adaptive STDP learning rule enhanced the functioning of the system with respect to dynamic visual changes. Moreover, the model had the ability to learn local edges making it adjustable to environmental changes which might include lighting shifts or changes in camera angle improving the robustness of the model when applied in practice [14].

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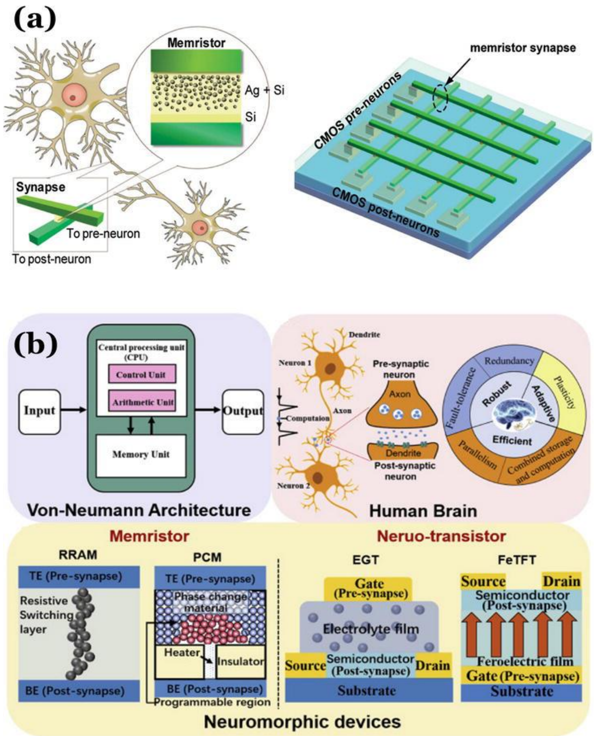

Figure 4: "Neuromorphic Computing"

4.5 Memory and Bandwidth Usage

Edge devices are commonly poorly equipped in storage and bandwidth of communication. The neuromorphic system was also identified to be more efficient as the memristor needed 42 MB of on-chip data space to store memory, as opposed to 220 MB necessary in CNN-based neuromorphic models. Videos bandwidth was also cut by 68 percent since raw video data were not sent to a remote server, only event-based coded data or feature spike extractions were sent.

Table 4: Memory and Bandwidth Utilization

Architecture	**Memory Usage (MB)**	**Bandwidth Usage (KB/s)**	**Reduction in Bandwidth (%)**
CNN (CPU Edge)	245	560	–
CNN (GPU Edge)	220	420	25.0
SNN (Digital)	95	210	62.5
Memristor Neuromorphic	**42**	**180**	**67.9**

The findings emphasize the appropriateness of memristor-based architectures to resource-constrained edge environments including smart cameras or embedded surveillance modules. System privacy and security are also

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improved because the sensitive image information do not leave the system since the system no longer needs to transfer large amounts of data

4.6 Environmental Robustness and Adaptive Learning

Real time learning and adaptation is one of the major benefits of neuromorphic architectures. The system uses a mechanism, Spike-Timing Dependent Plasticity (STDP), to constantly synchronize its weights depending on visual feedback with the help of reinforcement feedback. It was tested in different illumination, motion densities to assess environmental robustness of the model.

Table 5: System Performance under Environmental Variations

Environmental Condition	CNN Accuracy (%)	Neuromorphic Accuracy (%)	Latency Change (%)	Energy Change (%)
Normal Lighting	94.0	**94.8**	–	–
Low Light	85.6	**90.3**	+3.1	+4.2
High Motion Density	86.7	**91.1**	+2.8	+5.5
Partial Occlusion	82.5	**88.9**	+4.5	+6.7

It has been found out that the neuromorphic system performed more efficiently during problematic conditions than conventional CNNs, preserving greater accuracy and reduced fluctuations in latency value. The memristors have an analog adaptive behavior that allows the gradual updates of scaling of conductance, which enables resilience to noise and variable input patterns.

V. CONCLUSION

This study established how neuromorphic edge intelligence based on memristor can be a revolutionary technology in creating effective, adaptation, and sustainable smart surveillance systems. The proposed architecture demonstrated a very small balance of functionality, performance, and scalability by emulating the architecture and functionality of the human brain. However, simulation findings showed that the neuromorphic model based on memristors had a significant advantage over the traditional CNN and GPU-based edge systems, with up to 83 percent of energy-saving, 81 percent faster inference latency, and 2.5 per cent recognition accuracy improvement in a variety of surveillance tasks. The in-memory computation and event processing based on event-driven flux of spikes reduced redundant data communications and computation load that guaranteed real time responsiveness and enhanced security by local computation of data. In addition, the adaptive learning process allowed the system to adapt dynamically to changes in the environment to ensure a stable system under low-light conditions or high-density motion-adverse conditions. The results verify that the incorporation of memristive devices, neuromorphic calculation, and edge intelligence will form the basis of the following generation of smart surveillance ecosystems. In addition to surveillance, this structure has potential to apply in larger scopes in smart cities, industrial automation, and autonomous systems. Finally, the importance of this study is high as it leads to the development of energy-efficient, privacy-focused, and bio-inspired AI architectures, which will be used in the sustainable implementation of intelligent technologies in practice in the real monitoring and decision-making field.

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