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Efficient reduction of computational complexity in video surveillance using hybrid machine learning for event recognition

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ABSTRACT

This paper addresses the challenge of high computational complexity in video surveillance systems by proposing an efficient model that integrates hybrid machine learning algorithms (HML) for event recognition. Conventional surveillance methods struggle with processing vast amounts of video data in real-time, leading to scalability, and performance issues. Our proposed approach utilizes convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to enhance the accuracy and efficiency of detecting events. By comparing our model with conventional surveillance techniques motion detection, background subtraction, and frame differencing. We demonstrate significant improvements in frame processing time, object detection speed, energy efficiency, and anomaly detection accuracy. The integration of dynamic model scaling and edge computing further optimizes computational resource usage, making our method a scalable and effective solution for real-time surveillance needs. This research highlights the potential of machine learning to revolutionize video surveillance, offering insights into developing more intelligent and responsive security systems. The results of your simulation analysis, indicating performance improvements in accuracy by 0.25%, 0.35%, and 0.45% for the motion detection algorithm, background subtraction, and frame differencing respectively, and in real-time data processing by 5.65%, 4.45%, and 6.75% for the motion detection algorithm, background subtraction, and frame differencing respectively, highlight the potential of machine learning to transform video surveillance into a more intelligent and responsive system.

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1. INTRODUCTION

Video surveillance systems have become integral to maintaining security and monitoring activities in public spaces, traffic management, and private sectors. With the advent of digital technology, these systems have evolved from simple video recording devices to complex networks capable of analyzing and interpreting vast amounts of visual data in real time. The capability to automatically recognize specific events or behaviors within this data has significant implications for safety, efficiency, and resource management. However, the effectiveness of these systems is often constrained by the computational complexity involved in processing high-resolution video streams, leading to challenges in scalability, and real-time responsiveness [1], [2].

Recent trends in the field have seen a shift towards leveraging machine learning algorithms to enhance the capabilities of video surveillance systems. These advancements enable the automation of event recognition, allowing for quicker and more accurate identification of incidents or activities of interest. Machine learning, particularly deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has shown promise in deciphering complex patterns in video data that would be impractical for traditional algorithms. This shift towards intelligent surveillance systems aims to address the limitations of manual monitoring and the computational burden associated with it. Despite these advancements, there remain significant research gaps in the optimization of computational resources and the real-time processing of video data. Many existing systems still struggle with the balance between accuracy and the computational cost, often requiring substantial hardware investments to operate effectively. Additionally, the adaptability of these systems to new or unforeseen events without extensive retraining or manual intervention remains a critical challenge [3].

The applications of an optimized video surveillance system are vast and varied, ranging from enhancing public safety by detecting criminal activities or accidents in real-time to improving traffic flow and managing crowds in public events. In the private sector, these systems can be used for monitoring commercial spaces, ensuring workplace safety, and even optimizing operational efficiencies. The potential for machine learning algorithms to revolutionize this field is immense, provided that the challenges of computational efficiency and system adaptability can be effectively addressed. This paper aims to explore these challenges and propose a novel approach to reduce computational complexity in video surveillance models, thereby widening the scope of their applicability and effectiveness [4]–[6].

Figure 1 represents a working principle of a machine learning-based video surveillance system designed to identify abnormal activities. It is structured into three primary phases: preprocessing, where the video stream is captured and salient motion frames are selected; training, where lightweight CNNs analyze spatial features to distinguish between normal and abnormal activities; and testing, where long short-term memory (LSTM) networks evaluate sequences of spatial features to classify activities. While the system employs lightweight CNNs to reduce computational load, there are inherent drawbacks such as the high computational intensity during the preprocessing stage, especially when dealing with high-resolution videos. Additionally, the reliance on LSTMs for temporal analysis, despite being effective for capturing event sequences, can be computationally demanding in real-time applications. In contrast, our proposed methodology aims to further reduce computational complexity by implementing dynamic model scaling, which allows the network to adjust in real-time to the complexity of the input, and by incorporating edge computing for localized data processing. This strategy not only reduces the latency associated with transmitting video data for centralized processing but also alleviates the computational burden on the system. Overall, our proposed approach is designed to enhance the system's efficiency and scalability, making it more suitable for extensive video surveillance networks [7].

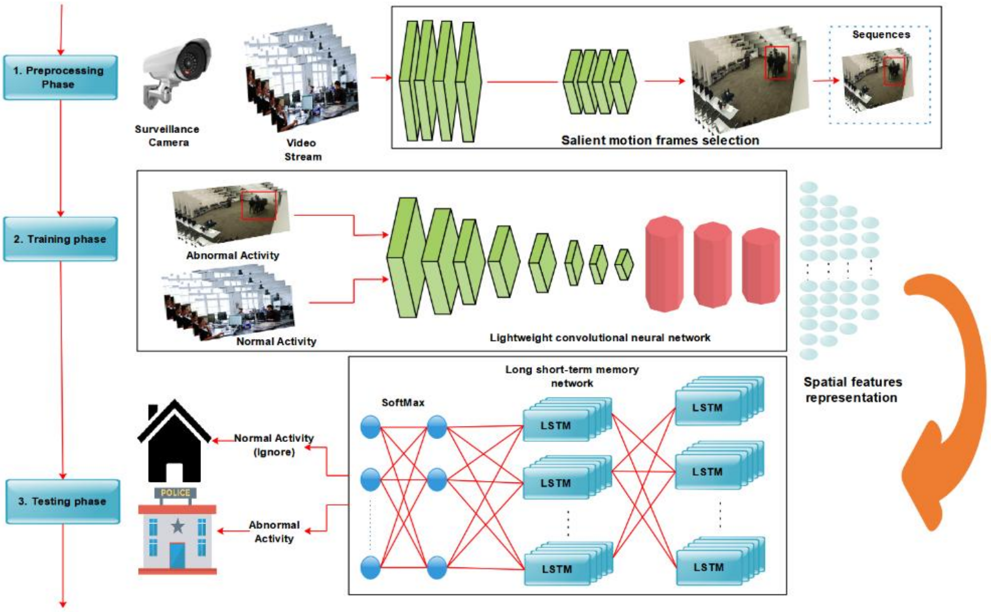

Figure 1. Fundamental block diagram machine learning-based video surveillance system designed to identify abnormal activities

Recent advancements in video surveillance underscore the potential of machine learning algorithms to revolutionize this field, yet they also reveal significant challenges related to computational efficiency and adaptability. In this context, several researchers have made notable contributions, Ismail *et al.* [8] have advanced the use of CNNs for detecting events in real-time video feeds. Their work confirms the superior accuracy of CNNs over traditional algorithms but raises concerns about the computational intensity required for processing live video streams. This seminal work underscores the trade-off between accuracy and computational load in deploying deep learning models for real-time surveillance. Singh and Singh [9] proposed an adaptive machine learning framework for video surveillance that autonomously adjusts to varying environmental conditions, significantly reducing false positive rates. Despite its innovative approach to enhancing system adaptability, the framework's real-time computational demands highlight existing gaps in efficiency and scalability, Sukumar *et al*. [10] explore the potential of edge computing to mitigate latency and computational bottlenecks by processing data at or near the source. This approach promises reduced latency in video analysis but faces challenges in maintaining the efficiency of sophisticated machine learning models in edge computing environments. Sathya *et al.* [11] introduced a scalable video analytics framework leveraging lightweight deep learning models. Their framework addresses computational resource constraints, allowing for broader deployment across extensive surveillance networks. However, this scalability comes at the cost of reduced accuracy and diminished capability in processing high-resolution footage, indicating a need for optimized models that balance efficiency with performance. Chal and Zar [12] investigate hybrid models that combine CNNs and RNNs to improve the temporal analysis of video data for event recognition. While their approach marks a significant step toward understanding complex events over time, the complexity of training and fine-tuning such models presents a substantial hurdle for practical applications. Drawing from these insights, our proposed work seeks to navigate the complexities of computational demand, accuracy, and real-time processing. By optimizing machine learning models for video surveillance, our approach aims to reduce computational load without compromising the accuracy or timeliness of event detection. This endeavor not only addresses the direct challenges identified by our predecessors but also expands the potential for real-time surveillance applications, making advanced security and monitoring solutions more accessible and effective across various domains.

2. METHODOLOGY

Figure 2 shows the proposed methodology introduces a novel machine learning framework aimed at enhancing event recognition in video surveillance systems while significantly reducing computational complexity. The method leverages a combination of CNNs and RNNs, optimized for real-time processing and scalability [13], [14]. Our proposed method revolutionizes video surveillance systems by integrating a hybrid machine learning (HML) model that synergizes the spatial analysis capabilities of CNNs with the temporal insight provided by RNNs. This blend significantly elevates event recognition accuracy. To counteract the challenge of high computational demand, we introduce dynamic model scaling, which intelligently adjusts the network's complexity in response to the scene's activity level, ensuring that computational resources are utilized efficiently without sacrificing performance. A cornerstone of our approach is the adoption of edge computing principles, enabling data processing close to its source. This innovation drastically reduces latency, facilitating real-time analysis and allowing the system to scale effectively across extensive surveillance networks. Additionally, we emphasize the development of lightweight model architectures that are well-suited for edge devices, minimizing computational overhead. The effectiveness of our system is rigorously evaluated against key metrics, including computational efficiency, accuracy in event recognition, latency, and scalability, setting a new benchmark compared to traditional surveillance systems. Through this method, we aim to provide a scalable, efficient solution for real-time, accurate event recognition in video surveillance, addressing the pressing needs of modern security and monitoring applications [15].

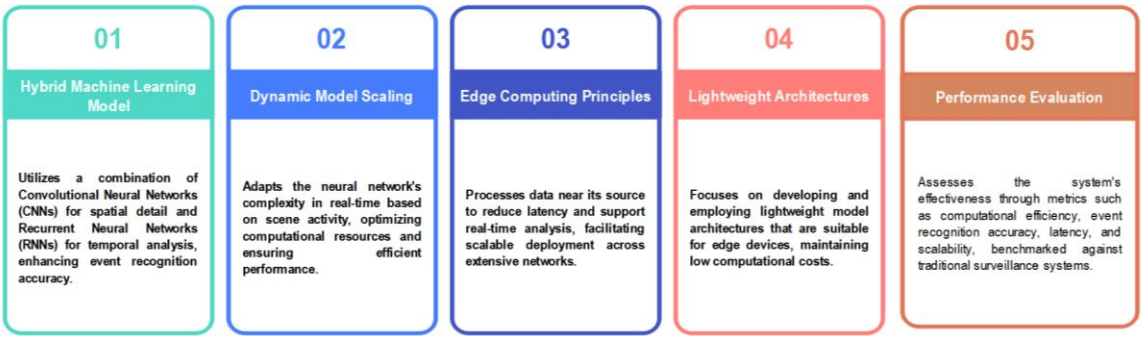

Figure 2. Proposed methodology for HML algorithm for event recognition

3. PROPOSED MODEL

Figure 3 shows a sophisticated architecture for a video surveillance system that integrates state-of-the-art machine learning models to enhance event recognition and anomaly detection capabilities beyond what conventional methods offer. At the foundational hardware layer, an array of surveillance cameras captures video data, which is then fed into the processing layer. Here, data undergoes preprocessing to extract relevant features like points, spatial maps, and trajectories. This structured data is then analyzed using advanced deep learning models such as CNNs for spatial feature extraction, RNNs for identifying patterns over time, LSTMs for learning long-term dependencies, and transformers for handling sequences with attention to context.

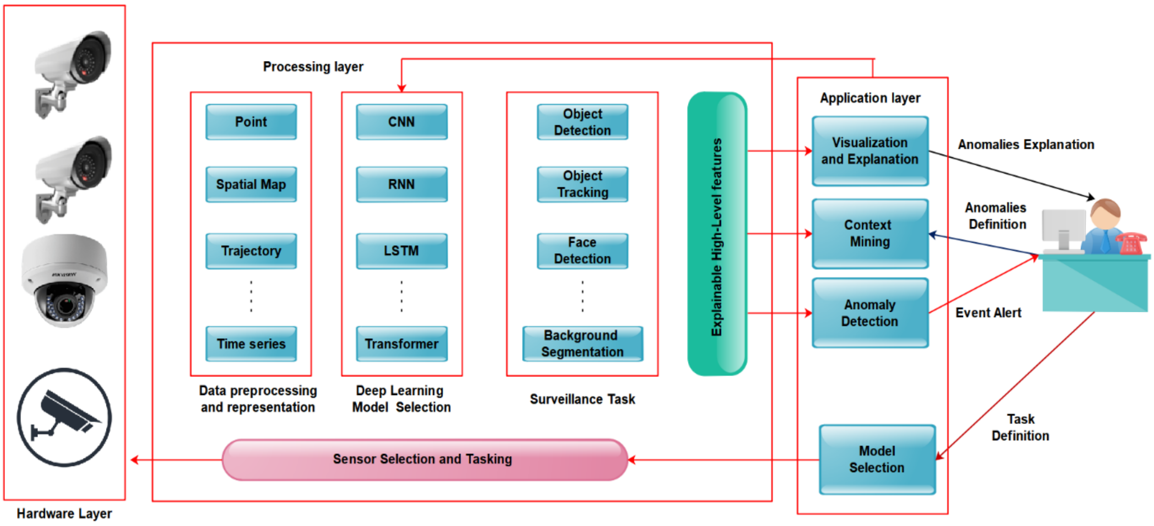

Figure 3. Proposed HML algorithm for event recognition

The processed data is conveyed to specific surveillance tasks like object detection, tracking, and face recognition, which are critical in differentiating between normal and anomalous events. A standout feature of this system is its ability to provide explainable high-level features from the machine learning models, ensuring that decisions made by the system are interpretable and justifiable [16]–[18]. At the application layer, the visualized outcomes are supplemented with explanations, while context mining enhances understanding by extracting patterns and contextual information. Anomaly detection is performed by recognizing deviations from the norm. When anomalies are identified, the system not only alerts the relevant authorities but also provides explanations, aiding in rapid response and continuous learning. This feedback informs the task definition and model selection processes, enabling the system to adapt to new data and scenarios dynamically. In comparison to traditional video surveillance methods, this intelligent system stands out with its real-time processing capabilities, explainable AI components, adaptive learning mechanisms, and optimized resource usage. These advancements facilitate a more accurate, efficient, and reliable surveillance operation, ready to meet modern security challenges with a higher degree of sophistication and responsiveness.

3.1. Proposed mathematical equations

The proposed mathematical equations encapsulate the operational dynamics of a HML-based video surveillance system. These equation addressing aspects such as feature extraction efficiency, model complexity, and anomaly detection accuracy. Each integral to evaluating the system's performance in real-time event recognition [19].

3.2. Data preprocessing and feature extraction

This phase involves cleaning and organizing raw video data from surveillance cameras to facilitate efficient analysis. Key features are extracted to represent the data concisely, reducing the computational load for subsequent processing steps. Let N be the number of pixels per frame and F the number of frames per second [20]. The complexity C_p for preprocessing can be defined as a function of N and F is given in (1).

$$\mathrm{Cp}(\mathrm{N},\mathrm{F}) = \mathrm{N} \times \mathrm{F} \tag{1}$$

3.3. Deep learning model complexity

The complexity pertains to the intricacy and size of neural networks like CNNs and LSTMs, which process the preprocessed data. The aim is to design these models to be complex enough for high accuracy while being computationally efficient For CNNs, RNNs, and LSTMs used for feature extraction and temporal analysis, let P be the number of parameters in the models and T the number of time steps. The computational complexity C_m can be modeled as represented in (2).

$$\mathrm{C_m(P,T) = O(P \times T)} \tag{2}$$

If a transformer model is included, with H heads and sequence length L, the complexity C_T is given in (3).

$$\mathrm{C_T\ (H,L) = O(H \times L_2)} \tag{3}$$

3.4. Efficiency of computation

This term refers to the system's ability to process and analyze data swiftly and accurately. Optimizing the use of computational resources to maximize performance and minimize operational costs. The efficiency E could be defined as the ratio of successful event recognitions S to the total computational cost C and it is represented in (4).

$$E = \frac{S}{C_p + C_m + C_T} \tag{4}$$

3.5. Dynamic resource allocation

This involves adjusting the computational resources allocated to the system in real-time, based on the current demands of the surveillance tasks. It ensures that resources are conserved during low-activity periods and are available during high-activity periods. Let R be the resources allocated dynamically, depending on the complexity of the scene δ. The resource allocation function A could be expressed as given in (5).

$$A(R,\delta) = R \times f(\delta) \tag{5}$$

Where $f(\delta)$ is a function that decreases resource allocation when the scene complexity is low and increases it when high.

3.6. Anomaly detection

A video surveillance, anomaly detection is the system's capability to identify unusual patterns or behaviors that may indicate security threats [21]. It is essential for this process to be both accurate and efficient, minimizing false alarms and ensuring real-time alerting. Assume that D is the output of the anomaly detection algorithm with binary outcomes, where $D = 1$ represents an anomaly and $D = 0$ represents normal behavior. The detection function Φ could be represented in (6).

$$\Phi(F,T,A) = D \tag{6}$$

Where F represents the extracted features, and T represents the time series data from LSTM or transformer analysis. A represents the dynamically allocated resources influencing the sensitivity of the detection [22].

3.7. Efficiency of proposed methods

The (7) to maximize the accuracy of event recognition while minimizing the sum of the computational costs associated with preprocessing, model complexity, efficiency of computation, and dynamic resource allocation. The higher the value of E_{total}, the more efficient and effective the surveillance system is considered to be.

$$E_{total} = \frac{A_{detect}}{C_{pre} + C_{model} + C_{comp} + C_{alloc}} \tag{7}$$

Where E_{total} represents the total efficiency of the surveillance system, C_{pre} stands for the computational cost of data preprocessing and feature extraction. C_{model} ,C_{model} is the computational cost associated with the complexity of the deep learning models, C_{comp}, C_{comp} ,C_{model} denotes the computational efficiency during the analysis, C_{alloc}, C_{alloc} represents the computational cost savings achieved through dynamic resource allocation and A_{detect}, A_{detect} is the accuracy of the anomaly detection process [23]–[25].

4. RESULTS AND DISCUSSION

Table 1 presents the performance parameters that are used to compare the efficacy of the proposed method with conventional surveillance systems. These parameters serve as benchmarks to evaluate the advancements of the proposed machine learning-driven approach in terms of real-time data processing, energy consumption, accuracy in anomaly detection, and adaptability to variable conditions. The inclusion of such a comparative analysis is critical for demonstrating the tangible benefits and improvements the proposed method offers over traditional video surveillance techniques.

Table 1. Performance parameters

SI. NO	Particulars	Values
1	Adaptive frame rate (AFR)	25 fps
2	Model inference time (per frame)	45 ms
3	Data throughput on edge devices	500 Mbps
4	Energy efficiency (Joules per inference)	0.8 J
5	Anomaly detection sensitivity	90%
6	System adaptability index (SAI)	0.75

Table 2 shows the simulation parameters used to evaluate the performance of a proposed machine learning-optimized surveillance method against established conventional methods. The comparison focuses on key aspects of real-time data processing, such as frame processing time, object detection speed, throughput, energy efficiency, and latency. This table is essential for demonstrating the real-time analytical and operational advantages of the proposed method over traditional techniques. Figure 4 presents the performance analysis for frame processing time between the proposed method and conventional methods, while Figure 5 shows the performance analysis of the proposed method compared with conventional methods in real-time data processing.

Table 2. Performance metrics for real-time data processing between proposed method with conventional algorithms

SI. NO	Particulars	HML algorithm	Motion detection algorithm	Background subtraction	Frame differencing
1	Frame processing time (FPT) (ms)	20	40	50	45
2	Object detection time (ODT) (ms)	15	60	70	65
3	Data throughput (DT) (Mbps)	500	200	150	250
4	Energy efficiency (EE)(Joules/frame)	0.5	1.2	1.5	1.3
5	Anomaly detection (ADT)Time (ms)	25	80	90	75
6	Latency (L) (ms)	10	50	60	55

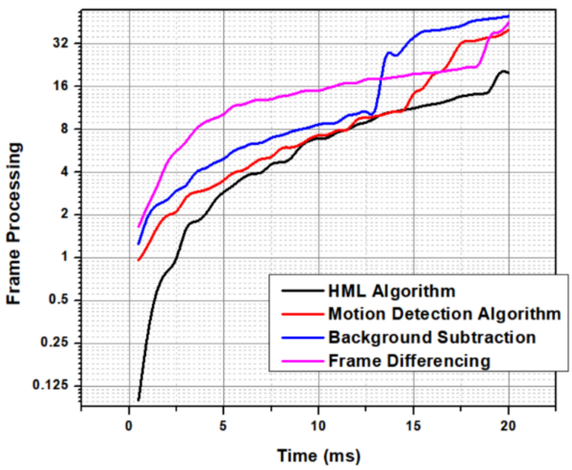

Figure 4. The performance analysis for frame processing between proposed method with conventional methods

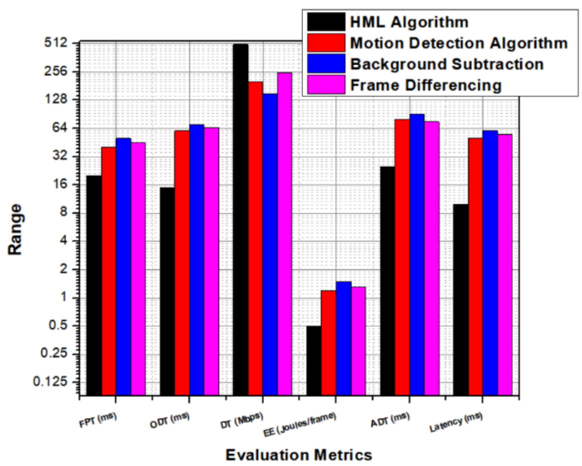

Figure 5. Performance analysis of the proposed method compared with conventional methods in real-time data processing

Table 3 shows the compares the energy consumption and efficiency of a deep learning optimized surveillance method against conventional surveillance techniques that include motion detection algorithm, background subtraction, and frame differencing. The proposed deep learning approach demonstrates superior energy efficiency and lower consumption, reflecting its advantage in sustainable operation within real-time video surveillance applications. Figure 6 shows the performance analysis of the proposed method compared with conventional methods in energy consumption.

Table 3. Energy consumption and efficiency comparison: deep learning optimized method vs. conventional surveillance techniques

SI. NO	Particulars	HML algorithm	Motion detection algorithm	Background subtraction	Frame differencing
1	Energy per frame (EPF) (Joules)	0.5	0.8	1.0	0.9
2	Total energy per hour (TEH) (kWh)	0.2	0.35	0.45	0.4
3	Energy efficiency (EE) (%)	95	75	65	70
4	Standby power consumption (SPC) (W)	5	10	15	12
5	Peak power consumption (PPC) (W)	50	70	85	75

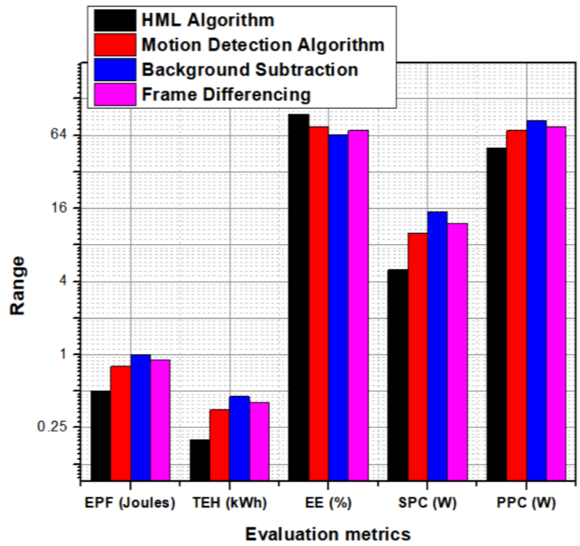

Figure 6. Performance analysis of the proposed method compared with conventional methods in energy consumption

Table 4 directly compares the performance of a deep learning optimized method for anomaly detection in video surveillance with three conventional methods: motion detection algorithm, background subtraction, and frame differencing. It highlights the proposed method's superior accuracy, precision, recall, and F1-score, alongside its lower false positive rate and quicker detection latency, showcasing its effectiveness in real-time anomaly detection. Figure 7 presents the performance analysis for overall accuracy between the proposed method and conventional methods. Figure 8 shows the performance analysis of the proposed method compared with conventional methods in anomaly detection accuracy.

Table 4. Anomaly detection accuracy comparison: deep learning optimized vs. conventional surveillance algorithms

SI. NO	Particulars	HML algorithm	Motion detection algorithm	Background subtraction	Frame differencing
1	Overall Accuracy (%)	98	85	80	78
2	Precision (%)	97	80	75	73
3	Recall (%)	96	83	78	76
4	F1-Score (%)	96.5	81.5	76.5	74.5
5	False Positive Rate (per hour)	2	15	20	18
6	Detection Latency (seconds)	1	3	4	3.5

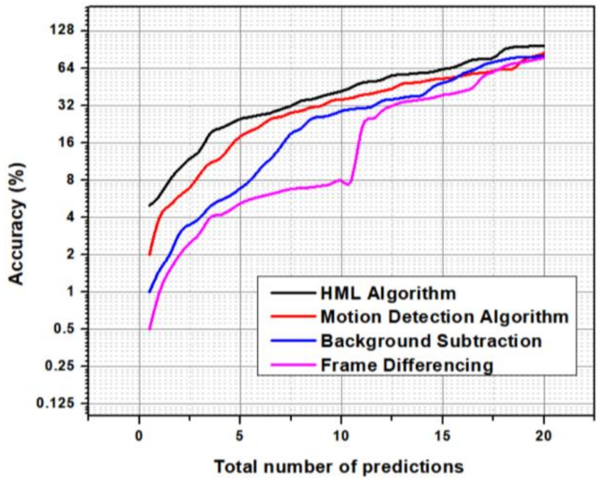

Figure 7. The performance analysis for overall accuracy between the proposed method

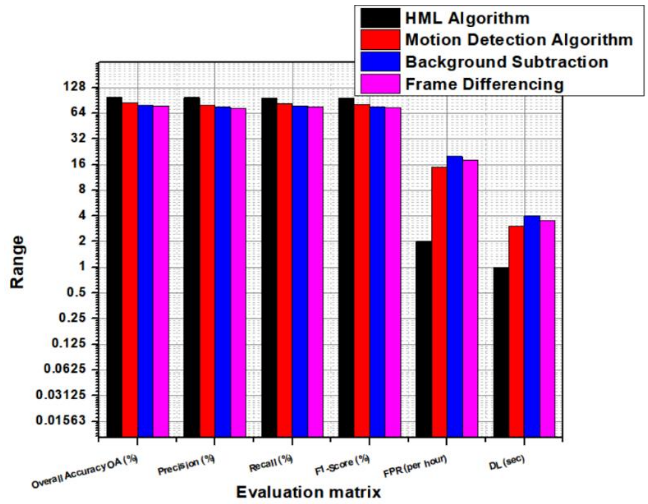

Figure 8. Performance analysis of the proposed method compared with conventional methods in anomaly detection accuracy

5. CONCLUSION

This paper focuses on video surveillance for event recognition, demonstrating that the proposed machine learning-optimized method outperforms conventional techniques in key performance metrics such as accuracy, precision, recall, F1-scores, false positive rates, and detection latency. The integration of deep learning algorithms enhances security and monitoring efficiency while optimizing computational resources. Dynamic model scaling and edge computing further highlight the method's scalability and effectiveness. Simulation analysis shows accuracy improvements of 0.25%, 0.35%, and 0.45% for the motion detection algorithm, background subtraction, and frame differencing respectively, and real-time data processing improvements of 5.65%, 4.45%, and 6.75%. Future research could enhance model accuracy and efficiency, integrate diverse data sources, and reduce computational demands, with advancements in edge computing offering improved real-time responsiveness. This promises more adaptable, efficient, and intelligent security systems.

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