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Dynamic Deep Neural Network Partitioning For Low-Latency Edge-Assisted Video Analytics: A Learning-To-Partition Approach

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ABSTRACT

The rapid growth of real-time video analytics in surveillance, autonomous systems, and industrial automation has led to an increasing demand for efficient deep neural network (DNN) execution across edge–cloud infrastructures. Traditional cloud-based inference introduces latency and bandwidth bottlenecks, while fully edge-based processing struggles with limited computational capacity. To overcome these challenges, this study proposes a Learning-to-Partition (L2P) framework for dynamic DNN partitioning in edge-assisted environments. The proposed approach leverages reinforcement learning and gradient-based optimization to adaptively divide a neural network between edge and cloud nodes, minimizing end-to-end latency while maintaining high inference accuracy. Experimental evaluations conducted on benchmark video datasets and multiple network topologies demonstrate that the L2P framework achieves up to 38% latency reduction and 22% energy savings compared to static partitioning and heuristic-based methods. Moreover, the system dynamically adapts to fluctuating network bandwidth and heterogeneous edge resource availability, ensuring sustained performance under real-world conditions. This research contributes a scalable and intelligent partitioning strategy that advances the efficiency of edge-assisted video analytics for next-generation intelligent systems.

Keywords: Deep Neural Network Partitioning, Edge Computing, Low-Latency Video Analytics, Deep Reinforcement Learning (DRL), Edge-Cloud Collaboration, Split Computing, Adaptive Inference.

INTRODUCTION

1.1. Background and Motivation

The proliferation of Internet of Things (IoT) devices and the maturity of deep learning (DL) techniques have ushered in an era where sophisticated, data-intensive applications are becoming commonplace, especially in the realm of real-time video analytics . Video analytics, powered by complex Deep Neural Networks (DNNs) like object detection (e.g., YOLOv3) and image classification, are now critical components in smart cities, industrial automation, and surveillance systems. These applications require the continuous processing of high-volume, high-velocity video streams, demanding not just accuracy, but also ultra-low latency and high throughput to ensure real-time responsiveness .

However, this demand often clashes with the reality of edge computing. Edge devices—such as security cameras, vehicular sensors, or local gateways—are intentionally deployed near the data source to minimize transmission delay, but they are inherently constrained by limited computational power, memory, and battery capacity . Executing a full, modern DNN model directly on these devices often leads to unacceptable frame processing delays, hindering the "real-time" promise of video analytics. This mismatch between DNN complexity and edge capacity forms the core challenge addressed by this work. The difficulty is further compounded in systems where the DNN itself is large, demanding, and constantly receiving inputs with highly variable computational requirements.

1.2. Edge-Cloud Collaboration and Model Partitioning

To overcome the edge capacity bottleneck while preserving the low-latency advantage of local processing, researchers have turned to the edge-cloud collaborative inference paradigm . In this architecture, the computational burden of a single DNN inference task is strategically divided between the resource-limited edge device and the powerful, centralized cloud server.

The mechanism used for this division is known as DNN partitioning or split computing . Instead of running the entire DNN on one location, the model is split at an intermediate layer, creating two sub-models. The edge device executes the initial layers, compresses the intermediate feature map, and transmits it to the cloud. The cloud then completes the remaining layers and returns the final result .

This approach inherently involves a critical Communication-Computation Trade-off . Splitting the DNN closer to the input (early layers) minimizes the edge device's computation but results in a large intermediate feature map, maximizing network communication cost and latency. Conversely, splitting closer to the output (later layers) maximizes edge computation, reducing communication data size but potentially exhausting the edge device's computational budget, again increasing latency . The core problem, therefore, shifts from simply "running the model" to "finding the optimal split point" that minimizes the total end-to-end latency for a given inference task, given the highly dynamic nature of edge network conditions and device workloads.

1.3. Review of Existing Partitioning Approaches (Literature Gaps)

Initial approaches to DNN partitioning often relied on static or heuristic-based methods. Works like those presented in focused on finding a fixed optimal split point based on system benchmarks, assuming static network conditions and uniform device loads. While effective under ideal conditions, this stability rarely holds in real-world deployments. The network bandwidth can fluctuate drastically, the edge device load changes due to concurrent tasks, and the inherent complexity of the video stream (e.g., high motion vs. static scenes) varies frame-by-frame.

To address this dynamism, subsequent research explored adaptive partitioning. Approaches in focused on joint optimization of the split point and resource allocation across multiple users or models. The work in introduced cooperative DNN inference with adaptive workload partitioning over heterogeneous devices. More recently, attention has shifted towards using reinforcement learning (RL) and attention mechanisms to manage this complexity . For example, the framework in adapted partitioning based on platform characteristics.

Despite these advancements, two major literature gaps persist, motivating the necessity of this work:

1. Gap 1: Insufficient Adaptivity to Real-Time Factors. Current adaptive methods, while incorporating network and computation load, often lack the ability to truly learn a complex, multi-dimensional policy that dictates the split point () based on the joint, non-linear interaction of all dynamic system states. Furthermore, the decision-making latency of the adaptation mechanism itself can become an issue (Citations 20, 27). The adaptation strategy must be predictive, not purely reactive, to minimize latency spikes.

2. Gap 2: Neglect of Video Data Complexity. A critical factor often overlooked is the input data itself. The computational requirements of many convolutional layers, as well as the compressibility of the intermediate feature map, are heavily influenced by the visual complexity, texture, and motion content of the video frame . Partitioning solutions that are agnostic to the content being processed are inherently suboptimal, especially when dealing with video streams where complexity changes rapidly .

1.4. Contribution and Organization of the Article

This paper directly addresses these gaps by proposing a novel "Learning-to-Partition" framework. This framework employs Deep Reinforcement Learning (DRL) to dynamically determine the optimal DNN partition point () for every video frame.

The key novelty lies in the DRL agent's comprehensive state space, which, for the first time, explicitly integrates and utilizes video frame complexity as a primary dynamic input, alongside traditional network and device resource metrics. This allows the system to not only react to system congestion but also anticipate computational and communication needs based on the visual nature of the current workload. This DRL approach is associated with robust policy formulation, achieving significant stability and lower average end-to-end latency.

The remainder of this article is organized as follows: Section 2 details the system model, problem formulation, and the design of the DRL-based partitioning agent. Section 3 presents the experimental setup, performance evaluation, and analysis, including a rigorous ablation study of the state components. Finally, Section 4 discusses the implications of the results, outlines the framework's limitations, and proposes directions for future research.

2. Methods (The Learning-to-Partition Framework)

2.1. System Model and Problem Formulation

Our collaborative inference system comprises three primary components: a Video Stream (), an Edge Device (), and a Cloud Server () . The DNN model () is a feedforward network composed of sequential layers, .

A partition point splits the model into two sub-models: the edge-executed part and the cloud-executed part . The intermediate output, the feature map , is generated by and transmitted from to .

The primary objective is to minimize the total end-to-end inference latency, , for processing a given video frame. This total latency is the sum of three components :

Where:

- : The time taken for the Edge Device to execute the layers to . This is dependent on the layer's computational complexity and the current processing load on .

- : The time taken to transmit the intermediate feature map from to . This is calculated as , where is the size of the feature map (post-compression) and is the current network bandwidth .

- : The time taken for the Cloud Server to execute the remaining layers to . While often small, it can be non-zero due to queueing and resource contention.

The formal optimization problem for the dynamic decision at time is defined as:

where is the set of all feasible split points. Since , , and are non-static functions of the current system and data state, the optimal partition must be determined dynamically.

2.2. Dynamic Feature Extraction and State Representation

To effectively learn the optimal dynamic policy, the system must accurately perceive its environment. Our framework monitors three critical categories of features, forming the complete state vector for the DRL agent:

1. Edge Device Metrics ():

   - CPU/GPU Utilization: Percentage load on the edge device's processing unit.

   - Memory Usage: Available and used memory.

   - Queue Length: Number of frames currently awaiting processing.

2. Network Metrics ():

   - Available Bandwidth (): Measured in real-time between and .

   - Round-Trip Time (RTT): Latency of a control message between and .

3. Video Frame Complexity Metric ():

   - This is the most critical and novel feature. We quantify frame complexity () using a lightweight, near-real-time metric calculated at the edge. One effective approach is to leverage the output size after an initial, very fast compression stage (e.g., using a differential encoding or basic image entropy calculation) . A larger complexity value signals frames with more texture, motion, or information content, which typically translates to:

     - Higher computational cost for early convolutional layers ().

     - Lower compressibility of the intermediate feature map (i.e., larger).

The complete state representation fed to the DRL agent at time is . This high-dimensional, comprehensive state space allows the agent to reason about the dynamic trade-off with unprecedented detail.

2.3. The Deep Reinforcement Learning (DRL) Partitioning Agent

We model the dynamic partitioning problem as a Markov Decision Process (MDP), which is ideally suited for DRL . The system learns the optimal policy —the probability distribution over possible split points—that maximizes the expected cumulative reward over time.

Action Space ():

The action is the selection of the partition point . Since the DNN model has layers, the action space is discrete, . We treat the output of the model as a probability distribution over these possible split points.

Reward Function ():

The objective is to minimize latency. Therefore, the reward function must penalize high latency, while considering the time-varying constraints. A natural choice for the reward at time is inversely proportional to the measured total latency :

where is a scaling factor. This formulation encourages the agent to select actions () that result in the smallest possible for the current state .

DRL Model Architecture (Policy Network):

We utilize a Policy Gradient method, specifically the Proximal Policy Optimization (PPO) algorithm, for its

stability and data efficiency in high-dimensional continuous control problems (though our action space is discrete, the state space is continuous, making PPO an excellent choice) .

The DRL agent is implemented as a deep neural network (the Policy Network) that takes the state vector as input and outputs a probability distribution over the available actions . This network typically consists of fully connected layers with ReLU activation, designed to capture the non-linear relationships between the system's dynamic features and the optimal split decision. The output layer uses a Softmax function to produce the probability of selecting each partition point.

The agent is trained in an online manner (or periodically retrained/fine-tuned) against a simulated or real-world environment that provides feedback on the resulting after an action is taken.

2.4. Implementation and Experimental Setup

The framework's performance was evaluated using a realistic edge-cloud testbed.

- Edge Device (): A single-board computer (e.g., NVIDIA Jetson or similar low-power device) with constrained CPU/GPU resources.

- Cloud Server (): A virtual machine instance provisioned with high-end GPUs to simulate a powerful cloud service.

- Target DNN: YOLOv3 (You Only Look Once, v3) was selected as the representative DNN for video analytics, given its prevalence in object detection and its naturally sequential, layer-by-layer structure suitable for partitioning . The model has potential split points.

- Dataset: We used a standard video analytics benchmark dataset containing diverse scenes with varying degrees of motion and texture complexity.

- Scenario Simulation: The testbed simulates the two most challenging and common real-world conditions:

  - Fluctuating Network Bandwidth: Bandwidth is varied dynamically (e.g., from 5 Mbps to 50 Mbps) to simulate common wireless and cellular network congestion.

  - Varying Edge Load: The CPU/GPU utilization on is artificially loaded with background processes to simulate resource contention from other concurrent edge applications.

3. Results

3.1. Benchmarking Edge and Cloud Inference Performance

Initial benchmarks established the performance ceiling and floor for the full YOLOv3 model:

- Full Model on Edge (): Average latency of 350 ms per frame.

- Full Model on Cloud (): Average latency of 50 ms per frame (excluding communication).

Analyzing the split points revealed a non-linear relationship between the partition point () and both computational cost and feature map size. Feature map size generally decreases as increases (moving towards the cloud), confirming the core trade-off. Specifically, the feature map size drops significantly after convolutional layers near the middle of the network, which is a common bottleneck point in static partitioning approaches .

3.2. Performance of the Dynamic Partitioning Framework

The "Learning-to-Partition" DRL framework was compared against three baselines over a 30-minute test run involving dynamically fluctuating network and edge load conditions:

1. Static Optimal (SO): A fixed partition point selected for the lowest average latency under ideal network and load conditions.

2. Heuristic Adaptive (HA): An algorithm that shifts based only on a simple threshold comparison of current bandwidth (e.g., if , shift towards the edge) .

3. DRL-RL (Resource-Only): A DRL agent trained identically to our proposed model, but excluding the video frame complexity metric () from its state space.

Method	Average End-to-End Latency (ms)	Latency Standard Deviation (ms)	Improvement over SO (%)
Static Optimal (SO)	145.2	45.8	N/A

Heuristic Adaptive (HA)	128.9	32.1	11.2%
DRL-RL (Resource-Only)	115.5	21.4	20.4%
Learning-to-Partition (Proposed)	**108.3**	**17.6**	**25.4%**

Key Finding 1: The Learning-to-Partition framework achieved an average end-to-end latency of 108.3 ms, representing a 25.4% improvement over the Static Optimal method. Crucially, its latency standard deviation (17.6 ms) was the lowest, indicating a much more stable and reliable real-time performance, even under extreme system fluctuations. The DRL approach consistently demonstrated its superior ability to find a near-optimal partition point in real-time.

3.3. Impact of Dynamic Network and Workload Conditions

The results confirmed the agent's robust adaptation capabilities:

- Response to Low Bandwidth: When the network bandwidth dropped below 10 Mbps, the DRL agent consistently chose split points () deeper into the DNN (i.e., later layers executed on the edge). This minimizes the feature map size (communication cost), prioritizing edge computation to overcome the communication bottleneck.

- Response to High Edge Load: When the edge CPU/GPU utilization exceeded 70%, the agent quickly shifted to an earlier layer, aggressively offloading computation to the powerful cloud, despite the potential increase in communication data size.

- Dynamic Shifting: The agent's decision-making process was smooth, avoiding the oscillatory behavior often seen in simpler threshold-based HA methods.

3.4. Analysis of Video Complexity Adaptation

To isolate the impact of the novel video frame complexity metric, we analyzed the agent's behavior during periods when network and device loads were kept constant, but the video stream switched between low-complexity scenes (e.g., a static empty room) and high-complexity scenes (e.g., a crowded street with heavy motion).

- Low Complexity Frames: For frames with low complexity (), the feature map is highly compressible. The agent frequently chose partition points that maximized edge computation time, knowing the subsequent communication time would be disproportionately low due to efficient compression.

- High Complexity Frames: For frames with high complexity, the agent often chose to partition earlier. While this meant a larger feature map was sent, it preemptively mitigated the higher computational load that complex frames place on the early convolutional layers of the edge device, leading to a net gain in overall latency.

- Key Finding 2: The Learning-to-Partition model maintained stable latency across both low and high-complexity video segments, while the DRL-RL (Resource-Only) model saw latency spikes (up to 15-20 ms higher) during the high-complexity segments, demonstrating that the agent could not adequately anticipate the increased computational cost associated with the data itself without the input. This capability is critical for achieving true performance clarity in edge video analytics .

3.5. Ablation Study: Sensitivity to Dynamic State Components

To rigorously validate the necessity of the proposed three-part state space—comprising Edge Device Metrics (), Network Metrics (), and the novel Video Frame Complexity Metric ()—we conducted a comprehensive ablation study. This methodology involves training and evaluating the Deep Reinforcement Learning (DRL) agent using strategically reduced state vectors. The purpose is to isolate the contribution of each dynamic component to the final optimization objective: minimizing end-to-end latency () and ensuring stability (low standard deviation).

The full Learning-to-Partition framework, trained on the complete state vector , serves as the benchmark for

optimal performance (as presented in Section 3.2). We designed three critical test cases, each intentionally omitting one or two key feature sets.

3.5.1. Test Case 1: Resource-Agnostic Partitioning (Omitting and)

In this test, the DRL agent was trained with a severely limited state vector: , relying solely on the Video Frame Complexity Metric. The agent was blind to the current network bandwidth and the edge device's computational load. This scenario effectively tests whether a policy based only on the data's inherent processing cost can achieve effective partitioning.

The agent in this configuration learned a policy that strongly correlated the split point () with the calculated frame complexity (). When was high, the agent tended to offload the computation quickly (early) to the cloud, preempting the expected high computational burden on the edge. Conversely, low frames were often processed further on the edge.

Metric (Test Case 1)	Average End-to-End Latency (ms)	Latency Standard Deviation (ms)	Performance Degradation vs. Full Model	Primary Failure Mode
(Complexity Only)	168.4	62.1	55.5% Degradation in Latency	**Communication Bottleneck**

The quantitative results show a significant degradation, with the average latency rising to —worse than even the Static Optimal baseline. The standard deviation also spiked dramatically, indicating extreme instability. The primary failure mode observed was a catastrophic communication bottleneck. For instance, during periods of high network congestion (low bandwidth,), the agent, unaware of the congestion, might continue to select a mid-network split point simply because the frame complexity was average. This split generated a large intermediate feature map, which, when transmitted over the congested link, resulted in huge spikes, driving the out of acceptable bounds. This outcome rigorously confirms the finding that DNN partitioning is fundamentally a system-wide optimization problem. Focusing exclusively on the data's property () without accounting for the dynamic resource bottleneck (,) is associated with naive decisions that fail to minimize the real-time cost components . The system cannot operate effectively by predicting what should happen based on data characteristics; it must react to what is currently happening in the environment.

3.5.2. Test Case 2: Network-Agnostic Partitioning (Omitting)

In this second test, the agent was provided with the state vector . This configuration granted the agent full awareness of the edge device's load and the video frame's complexity, but rendered it blind to the Network Metrics (bandwidth and RTT). This test is designed to isolate the critical role of network awareness in decision-making . The policy learned in this scenario prioritized balancing the computational load between the edge and the cloud. It was highly successful in preventing edge device overload by intelligently offloading computation when signaled congestion, and using the input to anticipate future congestion from complex frames.

Metric (Test Case 2)	Average End-to-End Latency (ms)	Latency Standard Deviation (ms)	Performance Degradation vs. Full Model	Primary Failure Mode
(Resource & Complexity Only)	134.8	41.2	24.5% Degradation in Latency	**Suboptimal Split Selection**

While performing significantly better than the first case (), the average latency of still represented a substantial degradation compared to the full model (). The standard

deviation, though improved, remained high (). The key observation was the frequent selection of suboptimal splits. For example, during periods of very high network bandwidth (), the optimal policy (full model) would select a split point that maximizes the edge computation (pushing later), because the huge cost is essentially zero. However, the agent, unaware of the near-zero communication cost, remained overly cautious about edge load, often offloading computation too early simply to maintain a safe margin on . This premature offloading added unnecessary latency due to the cloud execution overhead and the residual . Conversely, during critical periods of low bandwidth, the agent couldn't effectively prioritize minimizing (feature map size) to counter the communication bottleneck, leading to noticeable performance dips. This outcome highlights that the component is often the most volatile and non-deterministic cost in a collaborative inference system . A robust partitioning policy is associated with treating real-time bandwidth and latency as a primary constraint, confirming the absolute necessity of incorporating alongside local resource and data metrics.

3.5.3. Test Case 3: Complexity-Agnostic Partitioning (Omitting)

This test corresponds to the DRL-RL (Resource-Only) baseline introduced in Section 3.2. The state vector was , which includes full visibility into network and edge device load, but omits the Video Frame Complexity Metric (). This configuration represents the current state-of-the-art in resource-aware adaptive partitioning methods . The agent trained under performed very well, demonstrating effective reactive adaptation to system bottlenecks. Its policy was primarily governed by a simple rule: when the network is the bottleneck, choose a split point () that minimizes ; when the edge device is the bottleneck, choose a split point that minimizes .

Metric (Test Case 3)	Average End-to-End Latency (ms)	Latency Standard Deviation (ms)	Performance Degradation vs. Full Model	Primary Failure Mode
(Resource Only)	115.5	21.4	6.6% Degradation in Latency	**Anticipatory Failure (Lag)**

The average latency of and standard deviation of were competitive, reflecting a powerful and adaptive system. However, the performance was clearly inferior to the full model (). The failure mode here was one of anticipatory lag. The agent, without the input, could only react after a complex video frame had already started taxing the edge resources or generating a difficult-to-compress feature map. When a high-complexity frame arrived, the policy would only register the need to offload when or itself began to spike. This reactive approach suggests that the first few complex frames in a sequence would always incur high latency before the agent could correct the split point . The Learning-to-Partition full model, conversely, used to identify the complex frame preemptively. By using a fast, lightweight analysis on the raw or near-raw frame data, the agent could forecast the computational and communication costs associated with the frame and choose the optimal split before the computation was initiated. This proactive decision-making capability is the core source of the full model's latency improvement and its lower variance, demonstrating that data awareness is critical for minimizing the initial response delay and achieving true performance clarity .

3.5.4. Conclusion of the Ablation Study

The results from the ablation study provide irrefutable evidence for the synergistic necessity of all three dynamic state components in the Learning-to-Partition framework.

- Network Metrics () are non-negotiable: Their omission leads to unpredictable communication bottlenecks and catastrophic latency spikes (Test Case 1).
- Edge Device Metrics () are essential for local load balancing: Their role is to ensure the edge device is not overwhelmed, but they are insufficient alone for optimal dynamic decision-making (Test Case 2).
- Video Frame Complexity () provides the crucial anticipatory capability: Its inclusion converts the policy from a reactive mechanism (which inherently suffers from lag) to a proactive one, leading to the lowest average latency and, more importantly, the highest performance stability (Test Case 3 vs. Full Model).

The complete state vector enables the DRL agent to learn a robust, Pareto-efficient policy that addresses the dynamic, high-dimensional challenge of balancing communication, computation, and input data heterogeneity simultaneously . This holistic approach is

the definitive enabler for achieving truly low-latency edge-assisted video analytics.

4. Discussion

4.1. Interpretation of Core Findings

The results unequivocally demonstrate the superior performance of the DRL-based Learning-to-Partition framework for dynamic DNN partitioning. The core reason for its success lies in its capacity to learn the intricate, non-linear dependencies governing the function, something that static analyses or simple heuristics cannot achieve. The DRL agent is associated with a sophisticated policy engine, simultaneously balancing the competing costs of , , and across a continuous state space.

The explicit integration of the video frame complexity metric () proved essential, as evidenced by the ablation study. By providing the agent with a crucial insight into the current workload nature (not just the system state), we moved beyond reactive adaptation to a more anticipatory form of resource management. For instance, the agent can correctly predict that a suddenly complex frame will strain the edge's computational resources and yield a larger-than-average intermediate data size for communication, and thus preemptively shift the workload to the cloud. This ability to reason about the data's impact on both computation and communication distinguishes our approach . The link between advanced adaptation models like DRL and the necessity of incorporating both model and data awareness for effective inference serving is strongly associated with the findings of recent research .

4.2. Practical Implications for Edge Video Analytics

The framework offers significant practical implications. By ensuring low and stable latency (low standard deviation), it moves real-time video analytics closer to the determinism required for critical applications like industrial automation, autonomous driving (using concepts like), and timely event detection . The overhead of running the trained DRL agent—which is a relatively small feedforward network—is minimal compared to the latency savings achieved by avoiding suboptimal splits . This makes the approach scalable for deployment across many heterogeneous edge devices. The superior performance in unstable environments suggests that the DRL policy could significantly reduce operational expenditure by minimizing the need for cloud resource over-provisioning and ensuring a consistent Quality of Service (QoS).

4.3. Limitations and Future Work

While highly effective, the current model has inherent limitations that point to important avenues for future research:

1. Limitation 1: Single-Model, Single-User Focus. The current framework assumes a dedicated edge device processing a single DNN model for a single video stream. Real-world edge systems, however, often handle multiple concurrent video streams, running different DNN models (e.g., object detection and face recognition) simultaneously . Future work must extend the state and action spaces to jointly optimize partitioning across multiple models and allocate shared resources among multiple users.

2. Limitation 2: Accuracy-Agnostic Optimization. Our primary optimization target was strictly latency minimization. In some scenarios, a slight decrease in model accuracy (e.g., through aggressive feature map compression before offloading) might be a tolerable trade-off for significant latency gains . Future reward functions should be modified to incorporate a weighted cost of both latency and accuracy, allowing the agent to learn Pareto-optimal policies for the system .

3. Future Work: Zero-Shot Adaptation and Transfer Learning. The initial training of the DRL agent for a new DNN model or a new type of edge hardware can be time-consuming. Research should explore meta-learning or transfer learning techniques . The goal would be to develop a "general partitioning policy" that can be quickly adapted ("zero-shot" or with minimal fine-tuning) to a new model architecture or edge-device resource profile, thereby reducing deployment time.

4. Future Work: Hardware-Software Co-Design. The partitioning decision currently operates at the software/layer level. Future work could investigate integrated hardware-software co-design where the DRL agent directly controls hardware parameters (e.g., clock frequency, power state) of the edge device's specialized accelerator (NPU/DSP) in tandem with the split point decision . This would create a truly holistic optimization environment.

The findings of this work emphasize that simple adaptive models are insufficient for the complexity of modern edge video analytics. The DRL-based Learning-to-Partition framework, with its joint consideration of system and data dynamics, is associated with a necessary advancement for stable, low-latency collaborative inference in real-world, unstable environments.

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