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Draft Version

Deep Learning-Driven Edge Video Analytics: A Survey

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Abstract—Video, as a key driver in the global explosion of digital information, can create tremendous benefits for human society. Governments and enterprises are deploying innumerable cameras for a variety of applications, e.g., law enforcement, emergency management, traffic control, and security surveillance, all facilitated by video analytics (VA). This trend is spurred by the rapid advancement of deep learning (DL), which enables more precise models for object classification, detection, and tracking. Meanwhile, with the proliferation of Internet-connected devices, massive amounts of data are generated daily, overwhelming the cloud. Edge computing, an emerging paradigm that moves workloads and services from the network core to the network edge, has been widely recognized as a promising solution. The resulting new intersection, edge video analytics (EVA), begins to attract widespread attention. Nevertheless, only a few loosely-related surveys exist on this topic. A dedicated venue for collecting and summarizing the latest advances of EVA is highly desired by the community. Besides, the basic concepts of EVA (e.g., definition, architectures, etc.) are ambiguous and neglected by these surveys due to the rapid development of this domain. A thorough clarification is needed to facilitate a consensus on these concepts. To fill in these gaps, we conduct a comprehensive survey of the recent efforts on EVA. In this paper, we first review the fundamentals of edge computing, followed by an overview of VA. The EVA system and its enabling techniques are discussed next. In addition, we introduce prevalent frameworks and datasets to aid future researchers in the development of EVA systems. Finally, we discuss existing challenges and foresee future research directions. We believe this survey will help readers comprehend the relationship between VA and edge computing, and spark new ideas on EVA.

Index Terms—Video analytics, edge computing, computer vision, deep learning.

I. INTRODUCTION

CAMERAS are in every corner of our cities in this information-centric era. According to a 2019 report by the Information Handling Services (IHS), one surveillance camera is installed for every 8 people on the planet nowadays, with mature markets (e.g., China and the United States) having one camera for 4 people [1]. As predicted by LDV Capital, the number of cameras (including various types of cameras) in the world will reach 45 billion by 2022, experiencing an increase of 216% in the past five years [2]. This trend poses a great challenge for humans to discover useful information from explosive video data. It is beyond human capacity to make sense of what is happening in all video feeds manually. Video analytics is a technique that can automatically and efficiently recognize objects and identify interesting events in unstructured video data. It can drive a large number of applications with wide-ranging impacts on our society. Examples of such applications include security surveillance in public and

private venues, assisted and autonomous driving and consumer applications including digital assistants for real-time decision-making.

Early-stage video analytics is based on conventional image processing techniques, which mainly rely on human expertise and empirical knowledge, and thus are not robust to changes in lighting conditions, viewing angles, weather conditions, etc. Deep learning, as a research hot spot in the past decades, has made striking breakthroughs in many fields, specifically, compute vision (CV). Advanced CV technologies, e.g., object classification, detection, and tracking, enable extracting more accurate information and insights from video feeds. The resulting insights can help people make smarter and faster decisions.

However, many DL-driven applications are compute-intensive, thus not friendly to resource-constrained Internet-of-Things (IoT) devices. The conventional wisdom is to offload all workloads from devices to the cloud via wide area networks (WANs), where powerful data centers are located. This computing paradigm, known as cloud computing, suffers from high service delays due to long geographical distances and potential network congestion. According to a report by the International Data Corporation (IDC), worldwide data will reach 175 zettabytes (ZB) by 2025, 51% of which will be created by IoT devices [3]. Digesting such massive data in the cloud incurs excessive delays, making such solutions inadequate for mission-critical applications, e.g., security surveillance [4] and autonomous driving [5], where the safety of citizens and customers can be compromised if responses arrive too late.

Edge computing, a rising computing paradigm, has recently been recognized as a viable alternative to cloud computing. It is a distributed architecture that reduces latency by hosting applications and computing resources at locations geographically closer to the data source. Simply put, edge computing alleviates data transferring latency by processing data in local edge nodes rather than in a remote cloud. Here, an edge node can vary in size, ranging from tiny processing units co-located with IoT devices, to IT infrastructures in the physical proximity of base stations (BSs). These nodes, distributed at the network edge, can significantly alleviate the workloads and traffic congestions of the cloud, thereby reducing the service delay and improving the quality of experience (QoE) of users.

Obviously, edge computing is an extension of cloud computing by pushing centralized workloads to the network edge. Instead of entirely relying on the cloud, edge computing, a flexible computing paradigm leveraging both edge and cloud capabilities effectively, is gaining traction in building VA systems. Therefore, we are now witnessing the convergence of video analytics and edge computing, namely, *edge video*

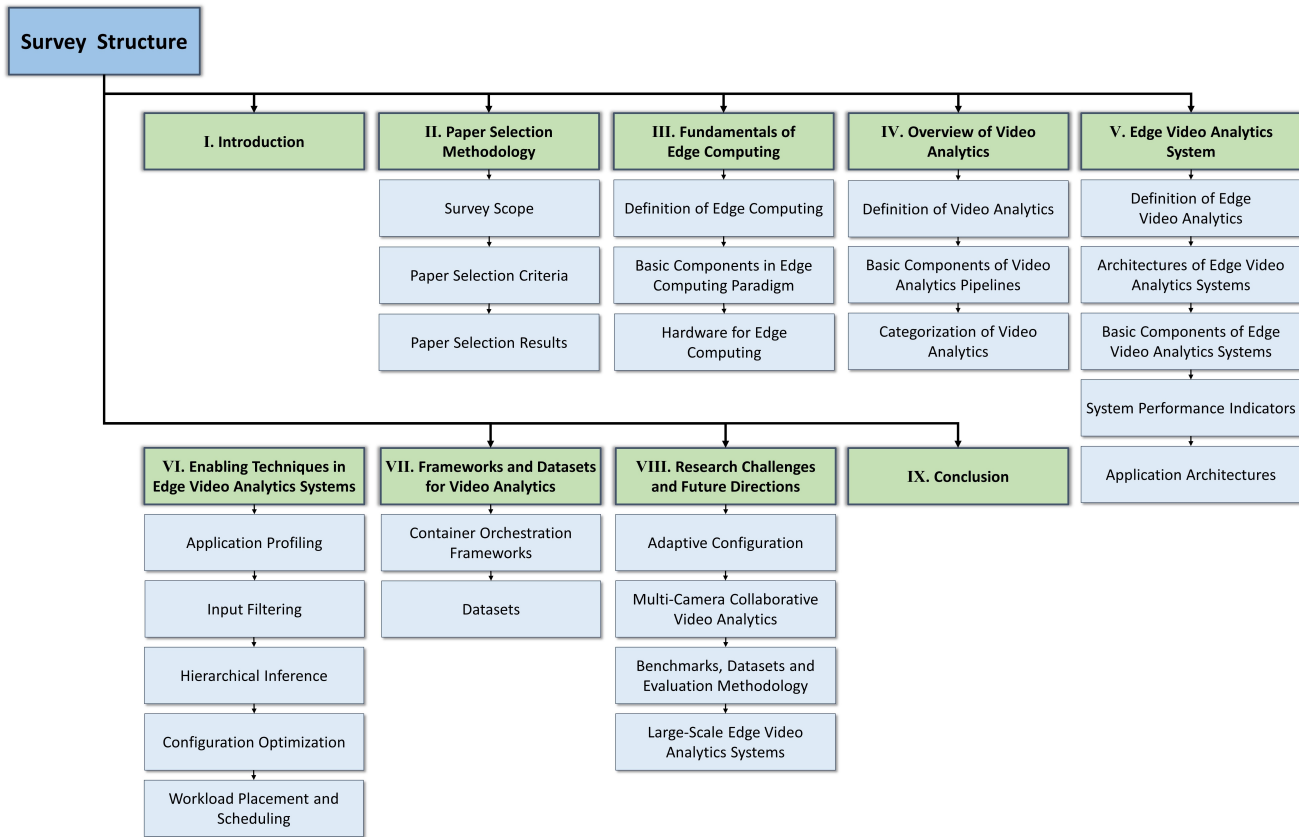


Fig. 1. Organization of the survey paper.

analytics. Major service providers, e.g., Microsoft, Google, Amazon, are providing customized VA services to drive a variety of VA applications.

Overall, EVA has gained widespread attention in academia and industry in the past decade. However, we find that there is a lack of comprehensive and up-to-date surveys to review the development of EVA. The most relevant surveys are [6]–[10]. References [6]–[9] focus more on a broader topic: edge intelligence (EI), including edge training and inference, but less on the convergence of VA and edge computing. Reference [10] focuses on EVA, but the discussion is limited to VA applications associated with public safety. In addition, these studies do not include the latest progress of EVA from 2020 to the present. To fill in these gaps, in this paper, we conduct a comprehensive survey on EVA. The survey structure is shown in Fig. 1. The remainder of the paper is organized as follows:

- 1) Section II describes the survey scope, paper selection criterion and results.
- 2) Section III reviews the fundamentals of edge computing, including its definition, basic components and common hardware.
- 3) Section IV provides an overview of VA, including its definition, basic components and categorization.
- 4) Section V explores EVA systems, including the definition of EVA, system architectures, basic system components, system performance indicators and application architectures.
- 5) Section VI discusses five enabling techniques in optimiza-

tion EVA systems: performance profiling, input filtering, hierarchical inference, configuration optimization, and workload placement and scheduling.

- 6) Section VII introduces mainstream container orchestration frameworks, and widely-adopted datasets.
- 7) Section VIII highlights existing challenges and foresees future research directions.

II. PAPER SELECTION METHODOLOGY

This section covers the survey scope, paper selection criteria and results.

A. Survey Scope

This survey focuses on the system aspects of EVA via surveying related research papers on the topics of VA and edge computing. The discussions are limited on real-time EVA systems built on computer vision modules (e.g., object classification, object detection, object tracking, etc.) and techniques which can improve the accuracy-latency tradeoff of the systems. The computer vision models used in video analytics pipelines although briefly touched, are not the focus of this survey. Privacy preservation [11], training stage optimization [12]–[17], and memory and energy efficiency [18]–[20], recognized as other challenges in video analytics, are outside the scope of this survey as well.

B. Paper Selection Criteria

To ensure comprehensive coverage of research papers on edge video analytics across different research areas, we first collected papers using the tool *Collected Papers*, starting from several top-cited representative papers: [21]–[25]. Then we applied keyword matching to search papers in the edge computing domain from Google Scholar. We focus on the most recent papers published from 2018 to the present, to reflect the most recent development in this field. The keywords used are listed as follows: video analytics, vision analytics, video processing, video surveillance, stream processing, and stream analytics.

Furthermore, we manually browsed publications in top-tier conferences on relevant subject areas (i.e., USENIX ATC, SenSys, INFOCOM, SIGCOMM, MobiCom, SEC, NSDI, OSDI) and the corresponding workshops in the past five years to avoid the limitations of keyword matching.

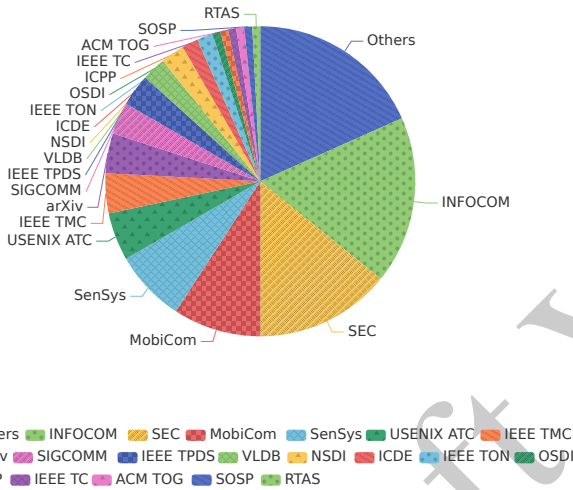


Fig. 2. The venue distribution of the papers included in this survey.

C. Paper Selection Results

We started from 1426 papers collected from Google Scholar, DBLP, IEEE/ACM digital library and arXiv based on the aforementioned criteria. In the first round of screening, we eliminated 834 papers whose titles lacked sufficient relevance. Next, we removed 389 papers which were not published in top-tier conferences or journals (i.e. ranked as A or A* according to CORE [26]), except for those with over 100 citations. In the final round, we manually reviewed the abstracts of the remaining papers to ensure that their topics match the survey scope. After three rounds of screening, we were left with 120 papers. All of them cover themes related to video analytics, computer vision, and edge computing topics. Fig. 2 shows the distribution of papers published in different research venues. Here, “Others” includes papers published in the venues not named. For unpublished papers in arXiv, we define them as the “arXiv” category.

According to Fig. 2, it can be observed that conference papers account for a larger proportion than journal papers, suggesting that conferences are preferred by most researchers

to share their latest results in this domain. Among these conferences, INFOCOM accounts for the largest percentage, followed by SEC, MobiCom, and SenSys. It is important to note that SEC is an unranked conference based on CORE, but given its influence in the edge computing community and the context of this paper, we consider it an important venue on this topic.

In addition, we conducted a statistical analysis on the number of publications on EVA from 2018 to the present, by searching papers using the aforementioned keywords on Google Scholar. The results are shown in Fig. 3a. We can find that the EVA domain experienced a rapid increase of 179% in the number of publications from 2018 to 2021. A slight drop of 18% can be seen in 2022, as the latest papers may not yet be included in Google Scholar as of the writing of this paper. Fig. 3b shows the distribution of the papers included in this survey that were published between 2018 and 2022. It can be observed that the overall trend is consistent with the trend in Fig. 3a.

We also did a statistical analysis on the appearance frequency of the keywords of the 120 papers selected to understand the subject topics of these papers. According to Fig. 4, unsurprisingly we can see that “edge computing” has the highest frequency, followed by “video analytics” and “deep neural networks”. These statistics are consistent with the keywords we use, and reflect the key of this survey, namely, DL-driven edge video analytics. Other keywords show related domains (e.g., “object detection”, “deep learning”, “computer vision”, “reinforcement learning”, “Internet of Things”, “augmented reality”, etc.), computing paradigms (e.g., “mobile computing”, “edge computing”, etc.), and key techniques (e.g., “scheduling”, “task offloading”, “computation offloading”, etc.).

III. FUNDAMENTALS OF EDGE COMPUTING

After a protracted period of development, edge computing has become the next evolution of cloud computing and has started to attract widespread attention [27], [28]. In this section, we introduce the fundamentals of edge computing.

A. Definition of Edge Computing

The earliest definition of edge computing was proposed in 2014 by Karim Arabi, the former vice president of research and development at Qualcomm as follows:

“All computing outside the cloud that happens at the edge of networks, and more specifically in applications where real-time processing of data is required.”

Karim Arabi believed that cloud computing and edge computing should have distinct purposes: cloud computing focuses on processing big data while edge computing focuses on handling “instant data”, i.e., data generated by sensors or users in real-time.

The concept of “edge” sprang up even earlier, and it can be traced back to the 1990s when Akamai Technologies introduced content delivery networks (CDNs) to improve web performance by placing nodes at locations geographically closer to the end user [29]. These nodes cached web content (e.g.,

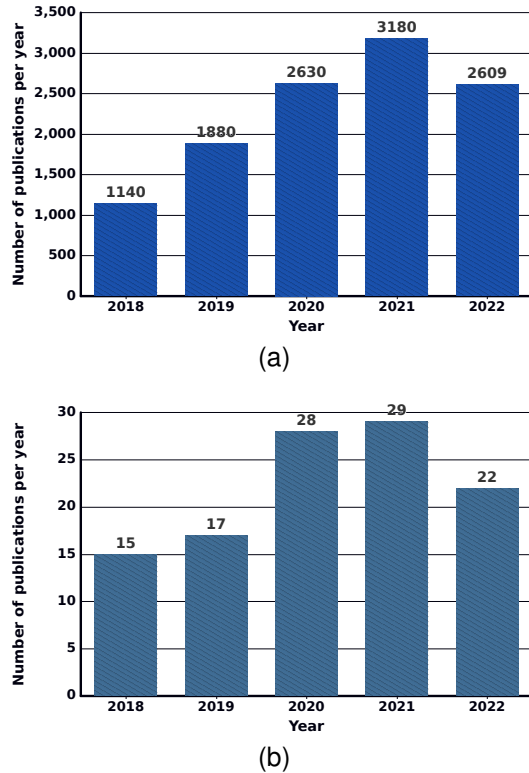


Fig. 3. A statistical analysis on the number of publications on EVA. (a) Number of publications on EVA per year from 2018 to 2022. The numbers are from Google Scholar using the aforementioned keywords. (b) The distribution of the papers included in this survey that were published between 2018 and 2022.

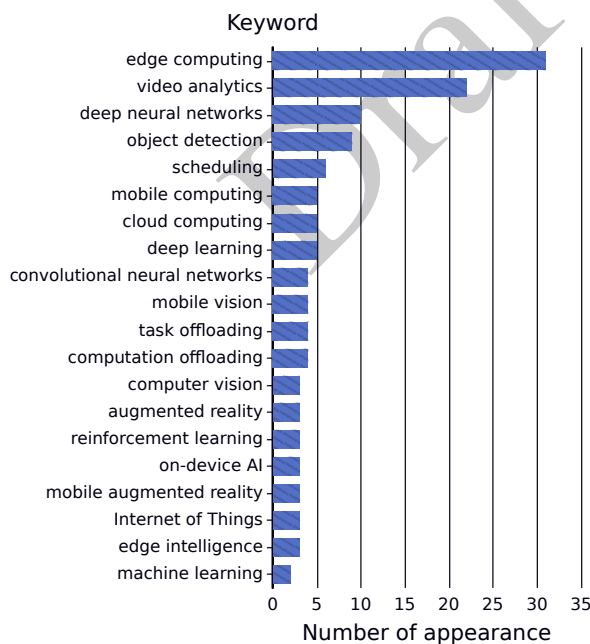


Fig. 4. A statistical analysis on the appearance frequency of the keywords of the 120 papers in this survey. Only the top 20 keywords are listed.

images and videos), accelerating visual content delivery and improving users' visual experience. In 2006, cloud computing emerged with the release of Amazon's Elastic Compute Cloud (EC2) service, and clouds quickly became the most popular infrastructure for companies to run their businesses [29]. Since then, three paradigms, namely, *Cloudlet Computing*, *Fog Computing*, and *Multi-Access (Mobile) Edge Computing (MEC)*, symbolizing the early stage of edge computing began to emerge [29], [30]:

1) *Cloudlet Computing*: The concept of cloudlet was originally proposed by Carnegie Mellon University in 2009 [31]. A cloudlet is defined as a trusted, resource-rich computing infrastructure (e.g., a computer, a cluster of computers) that is well-connected to the Internet and can be accessed by nearby mobile devices via wireless local area networks (WLANs) [31]. The key motivation of cloudlet is to improve the interactive performance of mobile applications, particularly those with rigorous requirements on end-to-end latency and jitter, such as language translation and facial recognition [31]. To guarantee users' QoE, such applications require a response time on the order of milliseconds, which is highly difficult to achieve over WANs. Owing to the physical proximity and high communication speed of WLANs, cloudlets can provide highly responsive cloud services to mobile users and hence complement the three-tier hierarchy, i.e., end-cloudlet-cloud. The concept of micro data center (MDC) was first proposed by Microsoft in 2015 [32], and the idea is similar to cloudlet [6], [33], [34]. Now, these two terms are almost equivalent.

2) *Fog Computing*: The term "fog computing" was first coined by Cisco in 2012, with the purpose of dealing with a huge number of IoT devices and massive data volumes for latency-sensitive applications [35]. Extended from cloud computing, this new paradigm includes a three-tier architecture: end-fog-cloud, with the fog layer located between the cloud and end layers. The fog has cloud-like properties (e.g., sufficient resources, geographical distribution, heterogeneity, scalability, elasticity, etc.) and can provide the lowest-possible service latency as it is aware of its logical location and closer to the "ground", i.e., IoT devices [35], [36].

3) *Multi-Access (Mobile) Edge Computing*: Mobile edge computing was initiated by the European Telecommunication Standards Institute (ETSI) to provide IT and cloud computing capabilities at the edge of the cellular network [37]–[39]. By placing MEC servers in the proximity of cellular base stations, MEC can improve the user experience by processing user requests at the network edge with lower latency, location-awareness and network context-related services (e.g., local points-of-interest, businesses and events) [37], as well as alleviate the load on the core network. Currently, the terminology "MEC" has been extended by ETSI from mobile edge computing to multi-access Edge Computing by accommodating wireless communication technologies (e.g., Wi-Fi) [6].

B. Basic Components in Edge Computing Paradigm

Due to the rapid development of edge computing, the community has not yet reached a consensus on standard definitions, architectures, and protocols of edge computing [6].

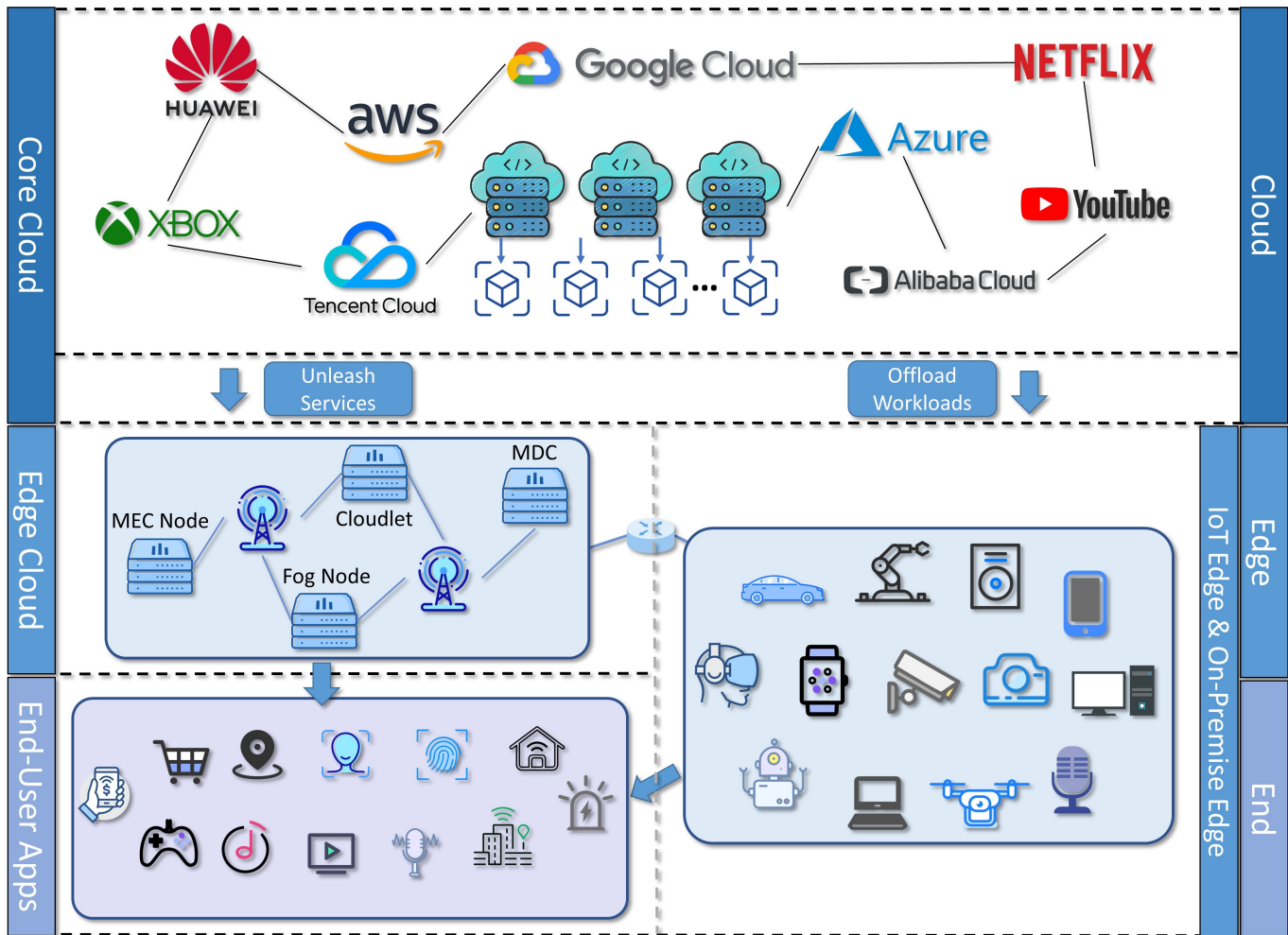


Fig. 5. Illustration of Edge Computing.

The boundaries between cloudlet, MDC, fog, MEC and edge are blurred [29]. Reference [6] simply uses the term “edge” to represent all of them. We follow this approach and divide the edge computing paradigm into three layers, as illustrated in Fig. 5:

1) *End*: In the context of edge computing, an end device is a source device in a networked system, which generates data by interacting with users (e.g., mobile phones, laptops, etc.) or sensing environments (e.g., cameras, sensors, etc.). Considering that modern end devices usually carry computing capacities, they are able to process workloads locally without offloading them to remote servers. For example, Tesla enables autonomous driving by leveraging on-board processing units to analyze data from sensors and cameras surrounding the car. AWS DeepLens, which is the world’s first DL-enabled video camera can host DL applications such as face detection and activity recognition on cameras. Therefore, modern end devices contain both the end part which generates data and the edge part which processes data from the end part.

2) *Edge*: An edge device can be any processing unit that is in close proximity to end devices and capable of processing data generated from them. Based on the scale, we divide edge into three categories, i.e., IoT edge, on-premise edge and edge

cloud. Notably, both IoT edge and on-premise edge overlap with the end, since they are usually located on users’ premises, generate data and process data locally. The description of these three categories are presented as follows:

- *IoT Edge*: IoT Edge covers almost any device that 1) can communicate with remote entities via local area networks (LANs) or WANs, and 2) has limited computation and storage capabilities to process data locally. As shown in Fig. 5, representative examples of IoT edge include mobile phones, smart cameras, smart vehicles, etc.
- *On-Premise Edge*: On-premise edge is dedicated computation, network and storage infrastructure residing on user premises, for example, a retail store, shopping mall, university campus, corporate building, or manufacturing plant. The infrastructure is intended for private use, and can provide various services to authenticated users (e.g., employees, students) within the LAN, including data processing, data storage, network routing, privacy and security preservation, application hosting, etc. The edge devices can take many forms, ranging from a single computer to a data center housing multiple racks of servers.
- *Edge Cloud*: While cloud computing excels in resource-intensive data processing and workloads like machine learn-

ing model training, its latency can be problematic for some latency-sensitive workloads as data must travel all the way to a remote data center and back again. To allow real-time service responses, cloud service providers are extending their services from the network core to the network edge by placing vast and highly-distributed edge clouds closer to local users, with software to deliver services in a way that is similar to using public cloud services. One use of the edge cloud is the delivery of visual content. Streaming services, cloud gaming, augmented reality and other visual workloads are growing dramatically. Computing services hosted on edge clouds can help cope with these visual workloads at locations closer to the customers, resulting in reduced latency and enhanced customer experiences. Therefore, the edge cloud can be viewed as an extension and complement to the core cloud [34], [40].

The three types of edge have their own advantages and disadvantages. IoT edges can deliver the fastest responses since they are co-located with the data source, but constrained by their limited resources, they cannot handle heavy workloads. On-premise edges have more resources than IoT edges, and can produce rapid responses due to their proximity to the data source, but they require separate setup and configuration for each location and device, along with staff to manage it. Provisioned by major cloud service providers, edge clouds typically have near-infinite resources, and require no installation and maintenance cost, but because they are farther away and need to be accessed by WAN, the latency can be higher than IoT edge and on-premise edge.

3) *Cloud*: cloud, or core cloud, refers to remote large-scale data centers with powerful computing capabilities and massive storage space that can provision a large number of scalable and elastic virtual machines (VMs). Based on the definition of the National Institute of Standards and Technology (NIST) [41], a core cloud has five essential characteristics: 1) on-demand self-service, 2) broad network access, 3) resource pooling, 4) rapid elasticity and 5) measured service. A core cloud is a controller and orchestrator of all distributed edge clouds, while the edge clouds inherit all the characteristics of the core cloud.

C. Hardware for Edge Computing

In this section, we discuss some potential enabling hardware for deep learning workloads at edge, i.e., general-purpose processing units and customized AI chips.

1) *Central Processing Unit*: The central processing unit (CPU) is the standard and general-purpose processor used in many devices. Compared to field programmable gate arrays (FPGAs) and graphics processing units (GPUs), the architecture of CPUs has a limited number of cores optimized for sequential serial processing. For example, the Intel Core i9-13900K has 24 cores, AMD Ryzen 9 7950X has 16 cores, while the latest GPU Nvidia GeForce GTX 4090 has 16384 cores. The limited number of cores diminishes the effectiveness to run an AI algorithm, where large amounts of data need to be processed in parallel. The architecture of FPGAs and GPUs is designed with the intensive parallel processing capabilities required for performing multiple tasks quickly and

simultaneously. Therefore, FPGA and GPU processors can execute an AI algorithm significantly faster than a CPU. On the other hand, CPUs do offer some pricing advantages, especially when performing some small-scale training tasks with tiny models and limited datasets. Another benefit of CPUs is low power consumption. Compared to GPUs, CPUs can provide better energy efficiency. This is important since some edge devices operate without a power connection and are sensitive to battery life, e.g., mobile phones. Since mobile devices are the most widespread edge devices, CPUs dedicated to mobile devices, namely, mobile CPUs have been developed and integrated with mobile GPUs on system-on-chips (SoCs), e.g., Qualcomm Snapdragon, Samsung Exynos, HUAWEI Kirin, etc. Mobile CPUs can offer moderate computing capabilities while consuming less power.

2) *Graphics Processing Unit*: GPUs were originally developed to address the demands of real-time high-resolution 3D graphics compute-intensive tasks. By 2012, GPUs had evolved into highly parallel multi-core systems allowing efficient manipulation of large blocks of data. Thousands of cores and their parallel structure makes them more efficient than CPUs for algorithms that process large blocks of data in parallel. In addition, Nvidia created Compute Unified Device Architecture (CUDA), a parallel computing platform and programming model, which can dramatically increase the speed of deep learning training and inference. Therefore, GPUs are well suited for AI workloads and have become the most widespread devices for deep learning tasks, which can operate on various devices, e.g., IoT, mobile and embedded devices. However, high performance comes at the expense of energy consumption and heat. Heat can create durability issues for the hardware, degrade performance and restrict types of operating environments. Additional costs are also required for the power supply and cooling systems.

3) *Field Programmable Gate Array*: FPGAs are types of integrated circuits with programmable hardware fabric. In contrast to CPUs and GPUs, the functioning circuitry inside an FPGA processor is not hard etched. Benefited from the reprogrammable and reconfigurable architecture, FPGAs deliver key advantages to the ever-changing AI landscape. First, developers are able to build a neural network from scratch and structure the FPGA to best match application needs. The FPGA can be reprogrammed even after manufacturing to incorporate additional capabilities, e.g., an image processing module, without having to replace the application with new hardware. Second, developers are allowed to design, test and update new algorithms quite efficiently, which provides competitive benefits in less time to market and cost savings by eliminating the need to develop and release new hardware. Third, FPGAs can host multiple functions in parallel and assign parts of the chip for specific functions, which significantly enhances operation and energy efficiency. This reduces latency and, more importantly, can reduce power consumption compared to a GPU design. Overall, FPGAs deliver a combination of speed, programmability and flexibility that translates into performance efficiencies. Compared to GPUs, FPGAs are advantageous in execution speed, power consumption and the ability to update AI algorithms and

add new capabilities. FPGAs have faced increased use as AI hardware accelerators at edge, and a representative example is Microsoft’s so-termed “Project Catapult” [42], where FPGAs are employed to provide ultra-fast inference at edge.

4) *Application Specific Integrated Circuit*: An application specific integrated circuit (ASIC) is an integrated circuit chip customized for a particular use. While GPUs and FPGAs perform better than CPUs for AI-related tasks, more efficiency can be gained with a more specific design via ASICs, but at the cost of a high investment of time and finances. Unlike FPGAs, ASICs cannot be reprogrammed and modified after production. Hence, for smaller designs or lower production volumes, FPGAs may be more cost-effective than an ASIC design. In large production runs, ASICs can be a better choice because people do not have to pay for functionality they do not need. Recently, ASICs have been widely adopted by major enterprises to benefit respective edge AI businesses. Tensor Processing Unit (TPU) [43] was first announced by Google in 2016. The chip was specifically designed for Google’s TensorFlow framework to accelerate machine learning (ML) applications. In July 2018, Google announced the Edge TPU [44], a purpose-built ASIC chip designed to run ML models for edge computing. Other companies such as IBM, HUAWEI, Cambricon Technologies and Horizon Robotics are all designing their own AI ASICs, e.g., IBM TrueNorth (Neural Processing Unit, NPU) [45], Huawei Ascend AI chips (NPU), Cambricon chips (NPU), Horizon Sunrise and Journey (Brain Processing Unit, BPU), Intel Movidius (Vision Processing Unit, VPU).

Overall, each form of hardware is suited for a particular kind of workload, and using them together in heterogeneous computing applications provides all of the functionality that complex use cases require. When combined, they can also balance workloads, boost different AI inference performances, and build the most effective and efficient configurations [46].

IV. OVERVIEW OF VIDEO ANALYTICS

In this section, we begin by clarifying the definition of VA, since the terminology has different meanings in different contexts. We then introduce the basic components of a video analytics pipeline (VAP), followed by a taxonomy for VA.

A. Definition of Video Analytics

Video analytics is a technology that can extract useful information from videos, via detecting patterns, behaviours and events related to objects, faces, postures, etc. A VAP is composed of multiple video processing modules, which can vary across applications. For instance, the pipeline of a vehicle counting application (Fig. 6a) consists of a video decoder, followed by a foreground object tracker, an object classifier and a directional counter. In contrast, for a license recognition application, the pipeline (Fig. 6b) may consist of a video decoder, a motion detector, a plate detector and a character recognition module. Therefore, the components of a VAP are *application-dependent*.

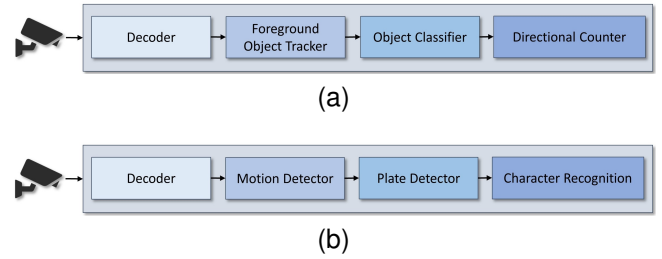


Fig. 6. Two examples of VAPs. (a) The pipeline of a vehicle counting application, including decoder, foreground object tracker, object classifier and directional counter. (b) The pipeline of a license plate recognition application, including decoder, motion detector, plate detector and character recognition.

B. Basic Components of Video Analytics Pipelines

Computer vision plays a crucial role in VA, as VAPs are built upon CV modules. Note that the CV modules mentioned here and throughout the remainder of this paper, refer to DL-driven CV modules. Despite diverse application requirements, several CV techniques are commonly used in VAPs, as discussed below.

1) *Video Decoding*: Cameras stream encoded videos based on live streaming protocols, such as real-time messaging protocol (RTMP), real-time transport protocol (RTP), real-time streaming protocol (RTSP), secure reliable video transport (SRT), web real-time communication (WebRTC), HTTP live streaming (HLS), and dynamic adaptive streaming over HTTP (MPEG-DASH). The prevalent video encoding formats include advanced video coding (H.264), high-efficiency video coding (H.265), versatile video coding (H.266), etc. Video decoding is the process of decoding or uncompressing an encoded video into a series of frames in real-time.

2) *Pre-processing*: We define all operations between video decoding and subsequent image processing procedures as pre-processing operations, including image resizing, cropping, denoising [47], super-resolution [47], enhancement [48], etc. In general, these operations aim to improve the quality of an image and can therefore benefit the following procedures. For instance, an image captured by a drone camera at night can be enhanced by brightness augmentation and motion blur restoration for further process. Another way is to directly remove those frames with high distortions, as done in [49], considering that they are not likely to bring satisfactory analytics quality. As reported by [50], pre-processing processes can be a bottleneck in many VA systems on modern hardware.

3) *Object Classification*: Generally, classification maps an object into one of a finite set of classes. Traditionally, this is done by comparing the measured features of a new object with those of known objects and determining whether the new object belongs to a particular category of objects [51]. With the success of DL techniques, convolutional neural network (CNN)-based classifiers (e.g., ResNet [52], MobileNet [53], etc.) are often utilized to predict the class of target objects.

4) *Object Detection*: When humans look at an image or a video, we can locate and recognize objects of interest within a matter of milliseconds. Object detection is a CV technique for locating and recognizing objects in images or videos. Nowadays, object detection algorithms typically leverage deep

neural networks (DNNs) to achieve high accuracy and can be classified into two categories: two-stage and one-stage [54].

- *Two-stage*: A two-stage object detector first extracts regions (i.e., local areas of a image) that potentially contain objects, and then makes a separate prediction for each of these regions. An early approach is to leverage background subtraction to detect regions with motion and apply a CNN-based classifier to label them. Faster region-based convolutional neural network (RCNN) [55] represents a state-of-the-art (SOTA) two-stage detectors, which exploit a region proposal network (RPN) to generate region proposals and performs classification for these regions separately.
- *One-stage*: A one-stage object detector, on the other hand, simply applies a single DNN model to conduct end-to-end object localization and recognition. Both tasks are cast as an unified regression problem. The most widely-known one-stage detectors are the Yolo family [56]–[58] and the SSD family [59]. In general, one-stage detectors are much faster but less accurate than two-stage ones.

The types of objects of interest can vary across applications. In traffic monitoring applications, we are concerned with road users, such as pedestrians and vehicles [60], [61], while in retail surveillance applications [62], [63], customers and merchandise need to be detected. Other interesting objects in VA domain include plants [64], animals [65], faces [66], postures [67], activities [68], flames [69], smoke [70], etc.

5) *Object Tracking*: Multi-Object Tracking (MOT) is the process of locating moving objects and estimating the trajectory for each of them from a video sequence. MOT is commonly divided into two steps: object detection and object association [71]. First, objects are detected in each frame of the sequence. Second, the detections are matched to form complete trajectories. This is called the tracking-by-detection paradigm [72], a mainstream tracking paradigm leveraged by recent works.

The aforementioned components need to be customized in practice based on the requirements of the target applications. Users can specify additional attributes or constraints for relevant objects, e.g., counting the customers within a time period, detecting hazardous behaviours in public space, querying specific objects (e.g., a man dressed in blue), etc. The final results will be aggregated to answer user queries based on custom rules (so-called *business logic*).

C. Categorization of Video Analytics

Video analytics can be divided into multiple categories based on different perspectives, e.g., the latency requirements of applications, the number of cameras, and if the camera is moving. In this section, we present a taxonomy for video analytics, i.e. live or retrospective, single-camera or multi-camera, and stationary or non-stationary.

1) *Live or Retrospective*: Based on the latency requirements, VA can be divided into two categories: live video analytics (LVA) and retrospective video analytics (RVA). LVA requires real-time responses, which means that all processes should be finished within the deadline (i.e., a relatively short time period) [73], [74]. For instance, if the video is streamed at

30 frames per second (FPS), it means that each frame should be processed within 33 milliseconds; otherwise, the deadline will be missed, and the next frame will be stored in the buffer, waiting to be processed. Autonomous driving and cloud gaming are good examples of LVA applications. Obviously, they are latency-sensitive; each frame matters and needs to be processed in time. If the deadline is missed, users' QoE and even their safety could be compromised. On the other hand, RVA deals with retrospective queries on already stored videos [75]–[85]. Imagine that the local police are searching for a suspect with a black T-shirt and white hat. They issue a query such as “a man with a black T-shirt and white hat” for the system to quickly search the database of recorded surveillance videos for a subject matching the query description. In contrast to LVA, which prioritizes real-time latency, RVA emphasizes the rapid retrieval of historical video data.

2) *Single-Camera or Multi-Camera*: According to the number of cameras, VA can be categorized into single-camera-based and multi-camera-based VA. Plainly, single-camera-based VA applications deliver services depending on the data from a single camera, e.g., facial recognition. On the contrary, multi-camera-based applications leverage multiple cameras, e.g. retail store surveillance. These cameras can be situated in the same location with overlapping fields of view (FoVs) [86], [87] or distributed in different locations without overlapping FoVs [21], [68]. Cross-camera collaborations and correlations can be utilized to enhance overall accuracy and efficiency [21], [86], [88], [89]. Currently, the multi-camera setting is mostly exploited in tracking applications [63], as targets can frequently get lost by a single camera because of occlusions, causing great challenges in object re-identification (Re-ID) and object association. With multiple cameras, the lost targets are more likely to be captured by other cameras since every camera has different angles of view, thereby improving tracking accuracy.

3) *Continuous or Event-based*: Generally, continuous VA processes each frame without specific objectives. Whether the videos are recorded depends on the scenarios. For security surveillance applications, all frames need to be processed, and all objects appearing in the video frame need to be detected or tracked. The results will be stored as metadata along with raw video data, waiting for future retrieval. For retail traffic analysis applications, raw video data is not important and not necessarily stored; only the unique characteristics of customers obtained from these videos are helpful for retailers to make marketing decisions. On the contrary, in event-based VA, the process is triggered only when a pre-defined event is detected. The event in question could originate from the processing of the video signal itself (e.g., when motion is detected) or from an independent source (e.g., a door sensor signals that the door has been opened). It could also stem from a user's request (so-called *live query*), for instance, recording all video clips that contain a red truck from now on. Note that these two categories are not mutually exclusive, and sometimes they can be combined together. For suspicious action detection applications, continuous monitoring is necessary due to security concerns, and when a target event, i.e. suspicious behaviour, is detected, an alert will be triggered and the corresponding video clip will

be recorded.

4) *Stationary or Non-Stationary*: Stationary cameras such as surveillance cameras and traffic cameras usually have perfect parameter configuration (brightness, contrast, colour-saturation, sharpness, etc.), mounting height, and shot angle based on the environment where the cameras are working. But for non-stationary cameras such as body-worn, drone and dash cameras, surrounding objects, environments and shot angles constantly change. It is necessary to take precautions to prevent these variables from interfering with performance. Consequently, pre-processing techniques, e.g., image enhancement, noise reduction, motion blur elimination, should be utilized to guarantee the quality of video frames before further processing. In addition, it is difficult for moving cameras to offload workloads due to network bandwidth fluctuations caused by unstable network environments. For real-time processing, computations are mainly performed locally on cameras or co-located processing units (e.g., in-vehicle chips). To this end, lightweight pipeline designs and model-level optimization techniques targeting energy, memory, and storage efficiency (e.g., model compression [90]–[92], scaling [73], [93], merging [19], etc.) can be considered.

V. EDGE VIDEO ANALYTICS SYSTEM

Large-scale real-time VA is becoming the “killer app” for edge computing [94]. First, the latency requirements for video processing can be stringent when the output of the analytics is used to interact with humans (e.g., cloud gaming, augmented reality) or to actuate some mission-critical systems (e.g., security alert, traffic light, etc.). Second, transmitting high-definition videos requires substantial bandwidth (e.g., 5 Mbps or even 25 Mbps for 4K video) [94]. Streaming a large number of video feeds directly to the cloud is not always feasible since the available uplink bandwidth is often limited when the cameras are connected wirelessly, e.g. via cellular data networks inside vehicles. Finally, the model inference is compute-intensive and naively performing inferences on cameras is inefficient as their computing capabilities are limited. We are likely to be stuck in the dilemma where using heavy DNNs can guarantee the accuracy requirements but miss the latency requirements, and vice versa for lightweight DNNs. Because of high data volume, resource demands, and latency requirements, cameras are the most challenging “things” in the Internet of Things. Tapping into the convergence of edge computing and video analytics presents potential system challenges. In this section, we first clarify the definition of EVA. Then, we go through system aspects, including system architectures, basic system components, system performance indicators, and application architectures.

A. Definition of Edge Video Analytics

To the best of our knowledge, no paper has provided a clear definition of EVA so far. Therefore, the definition remains vague and no consensus has yet been reached in this domain. In [8], Zhou et al. define edge intelligence, as the convergence of edge computing and artificial intelligence (AI) that fully exploits the available data and resources across the hierarchy

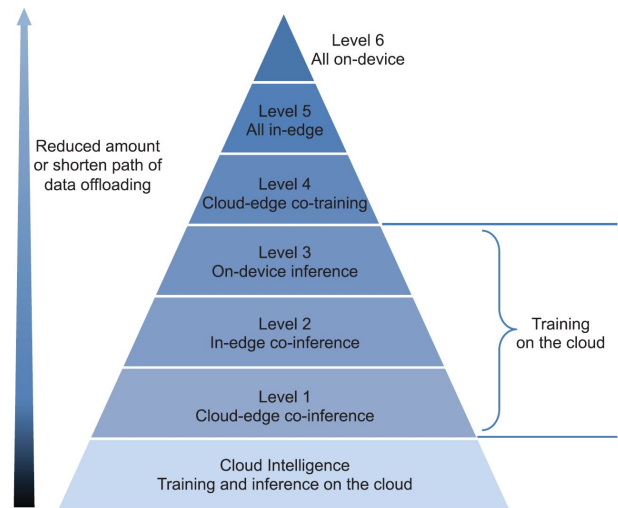


Fig. 7. Six-level rating for edge intelligence [8].

of end, edge and cloud to optimize the overall performance. Specifically, the authors rate EI into six levels, as shown in Fig. 7. Since the scope of this study does not cover model training, We only concentrate on levels 1 to 3, where training is done on the cloud.

Since EVA is a subset of EI. We can define EVA, similar to EI, namely, a paradigm that leverages the hierarchy of end, edge and cloud to maximize the performance of VA applications. An EVA system should be designed to function across a wide spectrum of deployments, which can vary from distributed analytics in a hybrid edge and cloud (level 1), to analytics across on-premise edges and IoT edges (level 2), to even hosting all analytics on IoT edges (level 3).

B. Architectures of Edge Video Analytics Systems

In this section, we introduce four architectures of EVA systems, i.e., 1) pure-IoT edge, 2) IoT edge + on-premises edge, 3) IoT edge + edge cloud, and 4) IoT edge + on-premise edge + edge cloud, which are illustrated in Fig. 8. The characteristics of each architecture are described as follows:

1) *Pure-IoT Edge*: This architecture only includes IoT edge, namely, IoT devices such as mobile phones, smart cameras, smart vehicles, etc. As stated earlier, an IoT edge can be divided into an end part and an edge part. The end component collects data from the surrounding world, whereas the edge component performs computations locally on devices. Since IoT devices are resource-poor, they can only support small-scale computation. To further enhance the accuracy and accelerate the computation, multiple IoT Edge can form a tiny cluster and collaborate with each other to share information and resources [95], [96].

2) *IoT Edge + On-Premise Edge*: Since on-premise edges are close to IoT edges and are sometimes wired together, the communication overhead is minor. As a result, workloads can be offloaded from the IoT edge to the on-premise edge. This offloading can either be full or partial, depending on the application architecture and what tradeoff needs to be hit

between accuracy and latency. In addition, heavier neural network models can be considered as more computational power is available at the on-premise edge. The size of on-premise edges can vary from single device (e.g., a single computer) to multiple devices (e.g., a computer cluster). Hence, in multi-device cases, workload placement is a major concern.

3) *IoT Edge + Edge Cloud*: Edge cloud is another option for workload offloading. As edge clouds are only accessible via WANs and are not adjacent to IoT edges like on-premise edges, communication latency is much higher. However, as a cloud, edge cloud outperforms on-premises edge in terms of its scalability and elasticity. Edge clouds can easily cope with dynamic loads by increasing or shrinking the amount of the physical resources provisioned to VMs, which can significantly increase resource utilization.

4) *IoT Edge + On-Premise Edge + Edge Cloud*: This architecture is becoming prevailing recently and recognized as the only feasible approach to meeting the strict real-time requirements of large-scale live video analytics by Microsoft. [94]. By pooling heterogeneous resources across different hierarchies and taking into account their respective strengths, we have more opportunities to hit the best tradeoff between accuracy and resource consumption.

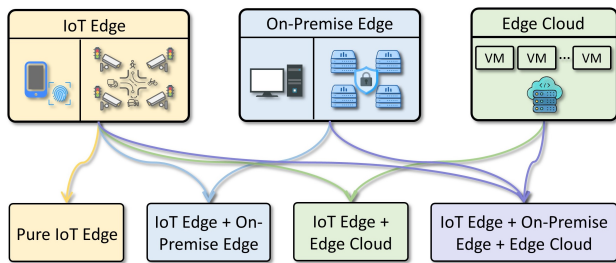


Fig. 8. An overview of the architectures of EVA systems, including pure IoT edge, IoT edge + on-premise edge, IoT edge + edge cloud, and IoT edge + on-premise + edge cloud.

C. Basic Components of Edge Video Analytics Systems

Generally, as shown in Fig. 9, an EVA system is composed of four building blocks: 1) pipeline optimizer, 2) resource manager, 3) executor, and 4) video storage. Applications are implemented based on these system components.

1) *Pipeline Optimizer*: A video pipeline optimizer converts high-level video queries to video-processing pipelines composed of several vision modules. Each module implements predefined interfaces to receive and process events (or data) and then sends its results downstream. Each module has its associated implementation and configurable parameters (also called *knobs*) [21]–[23]. For instance, object detection can be implemented in two approaches: a) CNN-based approaches, such as Yolo; or b) traditional CV approaches, such as background subtraction. Tunable parameters include frame resolution, frame rate, model and other internal algorithmic parameters. A particular combination of implementations and knob settings is called a *configuration*. Different configurations can have different performance-resource tradeoffs.

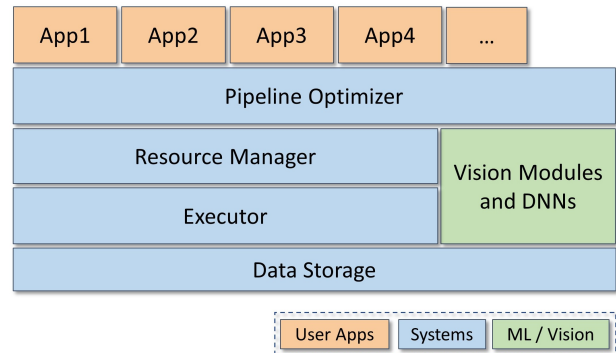


Fig. 9. Basic components of edge video analytics systems. The system is composed of: pipeline optimizer, resource manager, executor and data storage. Applications are implemented based on the system components

To estimate the resource consumption and execution performance of each module, a profiler can be employed by the pipeline optimizer. Application profiling is a popular technique to improve program performance based on its behaviour. It can capture program behaviour from previous runs to guide optimization decisions for future runs [97]. Specifically, for each vision module in the pipeline, a profiler collects the execution information (e.g., accuracy, latency, energy consumption, etc.), based on prepared representative datasets or the initial fractions of videos [22], [23]. The pipeline and its generated profiles are then submitted to the resource manager, where optimization decisions are made.

2) *Resource Manager*: A service level agreement (SLA) defines the level of service that users expect from a service provider, laying out the metrics to measure the service, as well as remedies or penalties to be applied if the agreed service levels are not achieved [98], [99]. With the objective of minimizing resource consumption and maintaining SLAs, a resource manager determines the best configurations and placements for all pipeline modules by jointly considering the availability of resources and pipeline profiles [22], [23].

3) *Executor*: The pipeline will then be executed by a suitable executor, or a group of executors if the pipeline is partitioned. The executors can be co-located (i.e. centralized in a data center) [23] or distributed (e.g., across remote devices) [22]. An agent is located with the executors to continuously observe their working status. Any underutilization or overutilization of resources will be reported to the resource manager.

4) *Data Storage*: Finally, raw video data will be optionally stored and the corresponding processing results will be stored as *metadata* for users' future retrospective queries. Metadata is defined as the data that can provide information about one or more aspects of raw video data [100], [101]; it is used to summarize fundamental information about data, which can facilitate the tracking and manipulation of specific data. The reason why metadata is essential for VA is that machines or computers cannot “watch” videos and interpret them like a human, and metadata can make them “machine understandable” by using absolute and measurable “identifiers” such as time, location, movement, identity, size, gender, age, color, etc. These “identifiers” allows a rapid retrieval of video clips

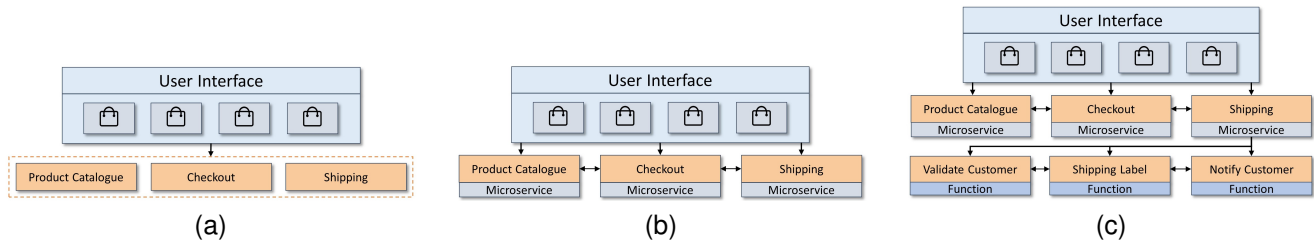


Fig. 10. Three types of application architectures. (a) Monolithic architecture. (b) Microservices architecture. (c) Serverless microservices architecture.

containing significant changes, suspicious trends or specific events without re-processing the entire video data [102]. This vastly increases the efficiency of RVA, whose goal is to perform a quick retrieval of relevant video data based on users' queries.

D. System Performance Indicators

Measuring the performance of a system is crucial since it determines the quality of service (QoS) delivered to users. Ensuring a certain level of system performance is the key enabler for SLA fulfillment. The following metrics have been widely adopted to measure the performance of an EVA system.

1) *Accuracy*: We use the term “accuracy” to denote the metric that measures the analytics quality of an EVA system. Higher accuracy means that the system can bring more reliable results. This is crucial for applications like security surveillance, where unreliable analytics results could potentially trigger a false alarm. There are two types of measures. The first is to directly measure application-level metrics, which can vary across applications. For instance, for vehicle counting applications, the accuracy may refer to the ratio of the estimated vehicles counts to the real vehicle counts within a period. The second is to use task-level metrics, e.g. top-1 or top-5 accuracy for object classification tasks [103], mean average precision (MAP) for object detection tasks [54], multiple object tracking accuracy (MOTA) for MOT tasks [104], etc. Most works in this survey utilize the second one, since 1) their solutions are general and can be applied to any application containing the proposed modules and 2) the task-level metrics can more or less reflect the application performances [21].

2) *Latency*: End-to-end latency refers to the actual amount of time spent on completing the entire pipeline, including execution time and data transmission time [105]. For real-time applications (e.g., autonomous driving, cloud gaming, etc.), the latency requirement is really stringent (e.g., less than 30ms). Latency can be affected by many factors, i.e., internal factor: the arithmetic power of executors (i.e., CPUs, GPUs, FPGAs, ASICs) and external factor: the resource availability (i.e. computation and network) of executors. We consider resource availability an external factor because it can change based on the emergence of external workloads. Variants based on latency are also introduced for different evaluation purposes, e.g. deadline missing rate [73] and latency service level objective (SLO) missing rate [106].

3) *Throughput*: Originally, throughput was a measure of how many units of information a system can process in a

given amount of time. In the VA domain, it is introduced to quantify how many frames an EVA system can process in a certain amount of time, and determine if the system can achieve real-time processing. Live EVA systems need to process streaming video frames in a continuous manner, and having a high throughput is essential to keeping up with the incoming video streams. For a single-executor EVA system, throughput is almost equivalent to latency, while for a multi-executor EVA system, throughput can quantify the computing power of the entire system [106]. Typically, throughput is modelled as “the number of requests (or frames) processed per second” [107], but it can vary based on specific systems. For instance, in Distream [106], throughput is measured as “the number of inference processed per second (IPS)”, while in CEVAS [108] throughput represents the ratio of the analysis frame rate to the frame rate of the video stream (e.g., for a video stream with a frame rate of 10 FPS, a throughput of 50% indicates that the video stream is analyzed at 5 FPS).

E. Application Architectures

As shown in Fig. 10, applications are implemented based on the system components. The design of an application is highly dependent on the application requirements, e.g. scalability, flexibility, etc., and specific systems, e.g., the number of executors, the resource availability, etc. To optimize the application performance and alleviate the future maintenance difficulty, the application architectures have experienced several evolutions: from monolithic architectures to microservices architectures, and finally to serverless microservices architectures.

1) *Monolithic Architecture*: Traditionally, all application processes are tightly coupled and run as a single service, i.e., the *monolithic architecture* [109], [110]. This means that if one process of the application experiences a spike in demand, the entire architecture needs to be scaled, i.e., provision a VM to host a new application instance. Adding or improving the features of a monolithic application becomes more complex as its code base grows. This complexity makes it difficult to implement new ideas. The monolithic architecture also adds risk for application availability because the dependency and coupling among processes amplify the impact of a single process failure.

2) *Microservices Architecture*: With the microservices architecture, an application can be built with a collection of loosely-coupled fine-grained *microservices* [109]–[112]. These microservices are built for business capabilities, and each of them has different functionality. They communicate with

each other via well-defined and lightweight application programming interfaces (APIs). Each of them can be separately updated, deployed, and scaled to meet demands for specific functionalities of an application since they are independently run. Take an e-commerce application as an example; each microservice focuses on a single business capability (e.g., product catalogue, checkout, shipping), as shown in Fig. 10b. Each of them can be an independent service written in different programming languages, deployed in different infrastructures, and managed by different operation teams. In general, a microservice is a around-the-clock service, which means it is able to run 24/7 on a continuous basis.

3) *Serverless Microservices Architecture*: Nowadays, microservices architecture is usually combined with another emerging architecture, i.e., serverless architecture [113], [114]. The resulting architecture, *serverless microservices architecture* [115] is widely adopted in commercial solutions. In the serverless architecture, the unit of execution is not just a small service, but a function, which can be smaller than services (e.g., a few lines of code) [114]. Functions are oriented towards code efficiency; they are not long-term [114], unlike microservices. They only start running when there is a specific condition or input [114]. In other words, serverless architecture is event-driven. The most obvious advantage is that resource utilization will be significantly improved since functions are short-term and run on demand. In a serverless microservices architecture, a microservice can work in a serverless manner by being developed as a set of event-driven functions. As shown in Fig. 10c, the “shipping” microservice is divided into three serverless functions: validate customer, shipping label and notify customer.

VI. ENABLING TECHNIQUES IN EDGE VIDEO ANALYTICS SYSTEMS

In this section, we introduce key enabling technologies to realize SLAs of EVA systems.

A. Application Profiling

The performance of an application is determined by many factors, such as configurations and workload placements. As explained in Section V-C, different configurations can bring different resource-accuracy tradeoffs. Choosing a good configuration can minimize resource demands while maintaining analytics quality. Workload placement is another important problem in edge computing since the application performance can vary a lot based on the resource availability of executors. Application profiling gathers information regarding the program characteristics during execution, and is a popular technique to reason about the dynamic behaviour of a program [97]. The profiling information, or short as profile, can then be used to optimize configuration and placement decisions. In general, profiling can be done either offline or online.

1) *Offline Profiling*: To get an accurate profile, a natural approach is to do a one-time but exhaustive offline profiling. A profiler executes instrumented tasks multiple times with different inputs and configurations on all possible executors and outputs metrics such as accuracy, execution time, resource

demand, memory footprint, input or output data size, etc. The datasets used in profiling tasks need to be representative of target application scenarios. Typically, the initial fraction (usually several minutes) of videos is labelled by detectors with “golden” configurations [21]–[23], which can be computationally expensive but are known to produce high-quality results, and then be utilized for profiling. The profiling cost can be prohibitive since the search space tends to grow exponentially with the number of parameters (e.g., configurations, placements, etc.). For instance, VideoEdge [22] considers a search space of 1800 combinations from five resolutions, five frame rates, three object detector implementations, four tracker types and six placements for trackers. Similarly, VideoStorm [23] considers a search space of 414 combinations, and it takes 20 CPU-days to generate the profile for a 10-minute video. The situation is even worse for lengthier videos. Even though parallelism [23], [25] has been exploited to accelerate profiling, the high resource demand for exhaustive profiling remains a challenge. To alleviate this problem, VideoEdge [22] merges common components among multiple configurations and caches intermediate results. For instance, assume that both components in the pipeline $A \rightarrow B$ have two implementations: A_1, A_2 and B_1, B_2 . Four implementation plans have to be profiled: B_1A_1, B_1A_2, B_2A_1 and B_2A_2 . If profiling is done natively, B_1 and B_2 will run twice on the same video data. So, merging common components B_1 and B_2 and caching their results can avoid redundant runs. Another way to reduce profiling cost is to sub-sample the configuration space. ApproxDet [116] only profiles 20% of the configurations, at the cost of generating a less accurate profile [25].

The inability to capture varying visual characteristics in real scenes is another problem of offline profiling. As a result, the decision may fail to account for the intrinsic resource-accuracy tradeoffs, leading to either resource wastage from unnecessarily expensive configurations or SLA violations. Take vehicle detection as an example, a configuration with low resolution (e.g., 480p) and frame rate (e.g., 5 FPS) is sufficient to retain acceptable accuracy if cars are moving slowly, e.g., at a traffic stop. This configuration may fail if cars move fast. A promising solution to this problem is content-aware profiling, which incorporates content features as additional dimensions of the profile. Then, a prediction model is trained based on the profile and used to estimate the performance online. In this way, the model can adapt at runtime since the video characteristics are involved in the prediction. Various content features are considered in different approaches. ApproxNet [117] uses edge values to measure the frame complexity and ApproxDet [116] uses the number of objects, their sizes and moving speeds to characterize their moving patterns. CEVAS [108] quantifies video content dynamics by self-defined metrics: average number of objects per frame and average number of unique objects per frame.

2) *Online Profiling*: One weakness of the aforementioned approaches in incorporating scene dynamics in offline profiling is that the selection of features highly relies on domain expertise. Moreover, it is hard to ensure the generalizability of such handcrafted and low-level features [118]. They may perform well for specific scenarios but not for others. Designing good

and universal content features is a challenging task. Recently, online profiling has become a popular alternative. Different from offline profiling, which is done once or infrequently (e.g., once a day [21]), online profiling updates the profile periodically (e.g., every few seconds or minutes [21]) during video streaming. The main challenge of online profiling is how to reduce the overhead of periodic profiling. As mentioned earlier, naively performing a one-time profiling can take a large amount of time, let alone periodic ones. To mitigate this challenge, Chameleon [21] first does full online profiling to exhaustively profile all configurations and generate several candidate configurations. Then, by leveraging cross-camera correlation and video content consistency, the candidate configurations are shared and propagated both spatially and temporally. Thus, the significant cost of full profiling can be amortized. Knob independence (i.e., for a given knob, the relationship between its resource and accuracy is independent of the values of the other knobs) is also leveraged to reduce the search space from exponential to linear. Notably, this solution is coarse-grained and relies on setting a pre-fixed time interval for profiling. Alternatively, techniques like scene understanding can be used to detect scene changes, predict the need for re-profiling and trigger a fresh profiling, thus saving the profiling cost even further. However, existing studies regarding this aspect are scant. AWStream [25] considers a combination of offline profiling and online profiling. Online profiling is used to gradually refine the bootstrap profile obtained offline. To speed up, AWStream only profiles a subset of configurations, which are pareto-optimal (i.e., the ones on pareto boundary). Only when more resources are available, a full profiling is triggered to update the current profile.

B. Input Filtering

Input filtering aims to remove redundant computation, and thus save resource consumption. The type and extent of redundant computation can vary across application scenarios; it can refer to stationary or irrelevant frames [118]–[121], redundant inferences [118], [122], uninformative or duplicated regions [86], [123], etc. Input filtering is realized by several techniques discussed in detail next.

1) *Pixel-Level Difference Detector*: Glimpse [119] applies a pixel-level frame difference detector to detect scene changes. Only when the number of “significantly different pixels” between two consecutive frames exceeds a threshold will the current frame, called the trigger frame, be sent to an edge server for assistance. ApproxNet [117] also utilizes a scene change detector to initiate the succeeding frame complexity estimator, but unlike Glimpse, it utilizes changes in the colour histogram (R channel) of pixels. Similarly, ClouSeg [124] proposes a two-level thresholding method based on pixel deviation, where the lower threshold is for selecting useful frames and the higher one is for key frames (i.e., the most useful frames). The heavy inference will only be imposed on key frames. Notably, instead of using pre-defined thresholds that may fail due to dynamic video content, CloudSeg adapts the thresholds according to network conditions and application requirements. Reducto [125] is an extension of CloudSeg. It

dynamically adapts filtering configurations (i.e., the feature type of the difference detector and the filtering threshold) for different queries and videos by efficiently coordinating with the server. Specifically, Reducto selects the best feature type using offline server profiling, and predicts the filtering threshold with a lightweight regression model. Periodical retraining is also considered in case the model is outdated.

2) *Binary Classifier*: Binary classifiers can be utilized in input filtering to determine redundant frames and frames to be retrained. FilterForward [121] identifies the most relevant video clips to the applications using microclassifiers. Wang et al. [126] proposes a cascaded filter composed of two classifiers: EarlyDiscard and Just-in-time-Learning (JITL). EarlyDiscard is a customized CNN classifier for selecting mission-specific video frames, while JITL, which is periodically trained based on the frames reported by the EarlyDiscard filter, is used to verify and further eliminate wrong results. FFS-VA [127] presents a similar multi-stage filtering method, which exploits a difference detector, a CNN classifier, and an object detector to progressively eliminate background frames, non-relevant frames and frames with few target objects.

3) *Inference Result Caching*: There is much redundancy when performing inferences on continuous video streams, as the inference results of previous frames can be reused. DeepCache [122] finds that only a small portion of contents change in consecutive frames. Hence, it caches the inference results of previous frames, and identifies redundant blocks using block-wise matching. The inference results of these blocks are then reused over time. InFi [118] proposes an end-to-end learnable input filter, which can predict the redundancy score of the input and perform filtering in two manners: SKIP and REUSE. SKIP aims to filter irrelevant frames (i.e., frames without target objects), and REUSE attempts to filter frames whose results can reuse the previously cached inference results. Due to end-to-end learnability, InFi can perform robust filtering in a workload-agnostic manner. Notably, InFi also provides a generic formalization of the input filtering problem and a theoretical filterability analysis.

4) *Spatial Filtering Mask*: Different from the above approaches, which eliminate temporal redundancy, spatial filtering aims to remove spatial redundancy, i.e., duplicated regions across cameras. A representative work is CrossRoI [86], which exploits the intrinsic physical correlations of cross-camera viewing fields to avoid duplicated computation for the same objects. Specifically, CrossRoI operates in two distinct phases: an online phase and an offline phase. In the offline phase, it establishes the cross-camera correlation and generates corresponding a RoI mask for each camera. In the online phase, cameras only keep data in these regions covered by the RoI masks and run a specialized RoI-based object detector to reduce inference time. It is worth noting that the spatial filtering is orthogonal to the temporal filtering, so the two can be combined together to achieve further computation savings.

C. Hierarchical Inference

It is known that DNN model inference is compute-intensive. Deeper network architectures bring higher accuracy and also

incur more computation overhead. Naively running a deep model on a video can waste resources, as not every frame is difficult and requires such a heavy model. A hierarchical architecture allows more flexibility in model inference, i.e., using a lightweight model to handle “easy” frames and a heavy model to handle challenging frames. Two techniques can be employed to enable hierarchical inference:

1) *Model Early Exit*: early exit first appeared in BranchyNet [128], a Dynamic DNN (DDNN) model proposed in 2016. In contrast to traditional DNNs, DDNNs [129], [130] are capable of performing conditional computations and selectively activating a subset of the network model, whereas traditional DNNs use the entire network in the computation even when a certain portion of the network is sufficient to make a good inference. BranchyNet supports the early inference of certain input samples using a multi-branch and multi-exit design. Like a traditional DNN classifier, the BranchyNet network architecture consists of a multi-layer network followed by a softmax layer for output predictions. However, in addition to the main network, a small network called branches is added to the outputs of different layers of the main network. These branches, similar to the main network are also followed by softmax layer. These outputs as well as that of the main network are called *exits*. The multi-exit approach implemented in BranchyNet is based on the observation that the earlier layers of the network can perform inference for most input samples accurately. With early exits, the average runtime can be reduced. Specifically, during the inference phase, BranchyNet computes the entropy of the softmax output at an exit. If the entropy of the input sample is larger than the given threshold, the sample is sent to the next exit for inference and the process continues till it reaches the final exit at the end of the main network; otherwise, the softmax output is taken as the model prediction.

Recently, several works have utilized the early exit technique and DDNNs to achieve low-latency and efficient VA on edge devices. ApproxNet [117] designs a DDNN classifier based on BranchyNet to perform multi-class object classification. The network architecture is composed of six *stacks* and each stack has four or six ResNet layers and a variable number of blocks from the original ResNet design. These stacks are connected to six exits, each of which consists of a spatial pyramid pooling (SPP) module, a fully connected (FC) layer, and a softmax layer. Via these exits, inference can terminate earlier without executing the entire network. Exits can be selected based on the resource availability on the device, the content characteristics and application requirements to achieve a desired tradeoff between accuracy and latency. In addition, switching exits is much faster than switching DNN models, as loading a new DNN model into memory is time-consuming (e.g., up to 1 second [21]). EdgeML [131] combines DDNN with partial offloading. In the offline stage, a DDNN model is constructed by inserting branches across the layers of the original DNN model, and then trained and fine-tuned. In the online stage, a deep reinforcement learning (DRL)-based optimizer is utilized to determine the optimal execution policy including the layer-wise partition point and

the threshold for the early exit of each branch, based on the available network bandwidth, input data characteristics, and the user’s latency and energy requirements. Then, the model is partitioned and separately executed by the edge and cloud. A similar problem is considered in MAMO [132], but it jointly considers the resource allocation of containers. One limitation of the aforementioned works is being input-agnostic, as the number and locations of exits are pre-determined based on heuristics or domain expertise. A bad setting can potentially diminish the benefit of early exit [133]. To address this issue, FlexDNN [133] proposes an input-aware architecture search scheme to find the optimal early exit insertion plan (i.e., the number and locations of exits) that balances the tradeoff between early exit rate and its computational overhead, based on the input data.

2) *Model Cascade*: The key idea of the model cascade is similar to model early exit, i.e., running models of different complexity on different frames, but the models are separated rather than integrated as in a DDNN. To be more specific, input frames are first processed by a small model and only when the results are not reliable (e.g., the results has a low confidence score [134], [135], or anomalies are detected [136], [137]), a heavier model will be invoked for further processing [137], [138]. Therefore, the small model acts like a soft “filter” and allows for efficient processing of live video streams by avoiding resource-intensive processing on easy frames (typically with less related information). Note that this is different from input filtering, where non-informative frames are eliminated. For example, Rocket [139] cascades a light and a heavy DNN object detector in the pipeline. Frames are processed at an edge server by the light detector unless the detection results are unreliable (i.e., the average confidence is lower than certain threshold), in which case they will then be sent to the cloud, where the heavy detector will be called for a second-round inference. SurveilEdge [4] utilizes a similar cascade architecture in an event-based EVA system, where two classifiers with different complexity are placed on the edge server and the cloud. Once a query is issued, a lightweight, context and query-specific (CQ-specific) CNN classifier is trained based on the context-specific training set and then deployed on the edge server to process the video stream and answer the query. At the same time, a highly-accurate CNN classifier is deployed on the cloud as a backup to handle the frames deemed challenging (based on pre-defined thresholds) by the edge classifier.

D. Configuration Optimization

As mentioned previously, a typical VAP involves several video processing components. Core components such as object tracking may have many implementation choices, but no single one is always the most accurate or efficient across all scenarios [22]. Each implementation can also have several tuning knobs like resolution and frame rate. Thus, a VAP can have thousands of configurations (i.e., the combinations of implementations and their knob values). The choice of configuration can impact the resource consumption and accuracy of an application [21]–[23], [140]. For instance, using a high frame resolution or

a complex DNN model in object detection enables accurate detection but also demands more computing resources. The “best” configuration can be the one with the lowest resource demand whose accuracy meets the application requirement or the one that maximizes accuracy subject to latency and resource constraints. A configuration is pareto-optimal if one cannot unilaterally improve one metric (e.g., accuracy) without degrading the other (e.g., latency). It is non-trivial to decide the best configuration for a VAP, since it varies over time, and characterizing the tradeoff between resource usage and performance is a challenging task in itself.

A large number of works consider adapting configurations at runtime. Knobs like video quality (e.g., resolution, frame rate, bitrate) [21]–[23], [25], [105], [141]–[150] and DNN model [21]–[23], [91], [116], [145], [150]–[153] are widely explored. In addition, camera configurations [154], e.g., brightness, contrast, colour-saturation, sharpness, etc. are shown to impact the analytics quality. Furthermore, internal algorithmic parameters like model input size, filter feature type, sampling interval, number of proposals, and down-sampling ratio [116] can impact efficiency-performance tradeoffs as well.

In general, configuration identification can be done *proactively* or *reactively*.

1) *Proactive*: Proactive approaches make configuration adaptation decisions based on real-time system status. Hence, they require precise information about the available network bandwidth (typically done with bandwidth probing), CPU or GPU resource availability, and the expected performance under the current condition (e.g., based on a complex performance model), all in real-time. Conventional proactive approaches have three steps: 1) probing available resources (e.g., compute and network resources), 2) estimating the performance of each configuration (e.g., accuracy and latency), and 3) solving an optimization problem to maximize a certain objective function (e.g., desired accuracy, latency) given the constraints (e.g., resource, energy budget) and obtain the optimal configuration. Specifically, compute resources can be quantified by the number of CPU cores [22], [23], CPU or GPU utilization rate [73], [155], [156], contention level [116], [117], etc.; network resources can be characterized by available bandwidth [22], [23]. Profiling techniques, as introduced previously, are utilized to obtain the execution performance of different configurations. However, regardless of offline or online profiling, the entire pipeline must be executed to obtain the final result, which is inefficient. To address this issue, DeepScale [105] proposes a surrogate-driven approach. By self-supervised learning, DeepScale can predict the heatmaps of different configurations (i.e., resolution) in an inference. The detection rate, which can be derived based on the heatmaps, is used as a surrogate to predict the performance of different configurations since the detection rate is highly correlated with the detection accuracy. By employing a cheap surrogate, expensive computations can be avoided since measuring the performance metric in real-time is difficult. Other proactive configuration adaption approaches differ in the objective function and constraints in the formation. For instance, VideoEdge [22] considers the joint decision of optimal configuration and workload placement by tackling a combinatorial problem. To efficiently solve the NP-hard

problems, a heuristic-based approach is employed to obtain an approximate (near-optimal) solution. Similarly, JCAB [145] jointly optimizes the configuration and bandwidth allocation, and the original combinatorial problem is transformed into a series of one-slot optimization problems, each of which is solved by leveraging the Markov approximation and the KKT condition. The solution is proven to achieve a close-to-optimal performance.

Recently, deep reinforcement learning, a powerful sequential decision tool, has been applied in proactive configuration adaption [20], [131], [143], [154], [157]–[161]. Generally, with the goal of getting the maximum accumulated rewards, a DRL agent starts from knowing nothing and gradually adjusts its actions (or policies) through trial-and-error interactions with the environment. The key challenge in DRL-based approach is how to define states, actions and rewards as the action space tends to be very large. For example, Cuttlefish associates the state space with the key factors that will affect the configuration choice, including bandwidth, moving velocity of objects, and historical configurations. The agent, trained with the asynchronous advantage actor critic (A3C) algorithm, takes these states as input and select the optimal action (configuration) in the action space. The reward function is carefully crafted by jointly considering three metrics that can directly reflect users’ QoE, i.e., detection latency, accuracy and fluency of video play. Similarly, Gemini [155] takes the estimated bandwidth, resource utilization (i.e., CPU and GPU), delay requirement, and frame rate as input, and formulate a multi-armed bandit problem to solve for the optimal CPU-GPU time partition of FPGA, and choice of video resolution and DNN model. The reward is defined as the uncertainty of prediction results since accuracy cannot be measured without ground truth.

2) *Reactive*: In contrast to proactive approaches, which can be viewed as open-loop solutions to configuration selection, reactive approaches adapt configurations based on the differences from performance targets in a close-looped manner. Nigade et al. [142] present a prototype model which guarantees strict SLO for VAPs by feedback control-based resolution adaptation. The absolute difference between the real latency from the last frame and the target latency serves as feedback. A threshold-based controller takes the feedback and decides the resolution for upcoming frames. Although the threshold is empirically set and thus is unlikely to work well in all scenarios, the work is among the first to demonstrate the value of reactive approaches. Reactive approaches do not require precise information about the available resources, which are highly dynamic and hard to obtain on time. There is no need to probe resource availability and explicitly model the relationship between performance and resources. But the simplicity comes at the cost of longer or lack of convergence and suboptimality.

E. Workload Placement and Scheduling

In an EVA system, users can submit their requests remotely. A request can take many forms based on the specific application: it could be a query issued by a user (i.e., event-based

VA) or a video feed continuously streamed from a camera (i.e., continuous VA). The service provider is responsible for fulfilling these requests and guaranteeing SLAs. To manage network, computation and storage resources efficiently, the service provider needs to determine the optimal devices to handle these requests. As mentioned in Section V-E, an application can be implemented in the microservices architecture, where each component of the pipeline can be implemented as a separate microservice to be deployed, scaled and updated independently. We call a running instance of an application a *job*, which consists of a set of *tasks*, each representing a running instance of a microservice. A proper workload placement strategy allows service providers to maximize resource utilization and, more importantly, their revenue. The microservices architecture enables more flexibility in workload placement.

1) *Job Offloading*: IoT edges usually have low compute capacities, and thus a natural solution is to offload workloads to an on-premise edge or an edge cloud. However, doing so naively such as offloading every frame, can incur considerable unnecessary overhead due to network latency. Furthermore, offloading and processing a frame without any object or any target object is a waste of network and computation resources. One promising solution is to leverage a filter to eliminate redundant frames before offloading [121], [126], [162]. Moreover, to reduce the communication overhead, frame compression or subsampling can be performed [163]. The key is to reduce the amount of transmitted video data during streaming to save bandwidth consumption without compromising accuracy. For instance, CloudSeg [124] and Runespoor [164] stream low-resolution videos, but a super-resolution procedure is applied on cloud to recover the original high-resolution frames. Similarly, DDS [165] continuously sends low-quality videos to an edge server, where an advanced DNN model is employed to determine regions that are likely to be missing. Based on the feedback from the server, the camera re-sends these regions with higher quality for further inference. In VPaaS [166], taking advantage of the negligible communication overhead between cameras and an edge server due to their physical proximity, high-quality videos are streaming to the edge server, where videos are compressed and sent to the cloud. The cloud runs a heavy model to extract object regions and then send these region coordinates back to the edge server for classification. The intuition behind this approach is that object localization can be done well on low-quality videos, but accurate classification requires high-quality input. Liu et al. [167] propose a dynamic video encoding technique, which divides each frame into blocks, and applies different encoding schemes to them. In particular, important blocks that are likely to contain objects are encoded with less compression while stronger compression is applied to the other blocks. What is in common among all the aforementioned works is that they treat the pipeline as one non-divisible job. When a frame is offloaded, an edge or cloud server will be responsible for the entire processing. Such approaches are called job offloading (or full offloading).

2) *Task Offloading*: In task offloading (or partial offloading),

a task is the smallest unit in offloading. This is beneficial since the components of a VAP can have heterogeneous resource demands. For example, background subtraction is CPU-intensive, while CNN-based object detection is GPU-intensive. Therefore, placing these two components on the same device may result in low execution efficiency since the target executor is not optimized for both. Partitioning the VAP into a collection of tasks allows more flexibility for the pipeline execution (e.g., distributing tasks to different executors). Distream [106] partitions a VAP among a cluster of multiple cameras and an edge server to maximize the throughput. CEVAS [108] and LEVEA [24] investigate partitioning for serverless pipelines, where each component is implemented as a stateless function and executed either on edge or in cloud. Lightweight serverless functions are a key enabler for rapid deployment and execution on both edge and cloud. More fine-grained partitioning is considered in several works [90], [131], [168]–[176] by splitting neural network layers. Inference terminates at a certain partition point, and the features of the intermediate layer are offloaded to another executor, which will finish the remaining inference. Compression techniques, e.g., lossy and lossless encoding [170], [177], DNN-based compression [178]–[181], can be used to compress the data and reduce the transmission time in conjunction with layer-wise partitioning. References [66], [182]–[184] represent another type of task offloading, i.e., spatial offloading, where an input frame or feature map is partitioned into smaller blocks for distributed processing. ADCNN [182] splits a frame into multiple blocks and offloads them to an edge cluster for parallel processing. Zhou et al. [185] and EdgeFlow [184] propose a similar approach, but they perform partition on the feature maps. In EdgeDuet [183], blocks containing medium and large objects are processed on IoT devices, while those containing small objects are offloaded to an edge server for accurate detection. Similarly in EagleEye [66], blocks containing large frontal faces are processed by lightweight face recognition models on the mobile device, while the rest of the blocks are sent to the cloud for heavy processing. Therefore, in spatial offloading, the processing of each block can be viewed as a task.

3) *Workload Scheduling*: Apart from offloading, workload scheduling is another important problem that needs to be considered, especially for a system with multiple devices or hosting multiple applications. A scheduler needs to account for a number of constraints, including latency requirements, resource availability, budgets, etc. Therefore, a scheduling problem is typically formulated as a constrained optimization problem. Based on where tasks are executed, we divide the scheduling problem into two categories: inter-device scheduling and intra-device scheduling.

Inter-device scheduling finds the optimal workload placement across different devices, and its objective is to maximize the analytics performance. Distream [106] and SurveilEdge [4] schedule tasks in an edge cluster by migrating tasks from busy devices to idle ones. Notably, Distream also exploits a long short-term memory network (LSTM) to predict potential incoming tasks in the near future and thus avoid placing tasks on the nodes that are going to be busy. Other works go beyond simply balancing workloads, and incorporate other

criteria, allowing the scheduler to have more choices based on the circumstances. VideoStorm [23] places new tasks and migrates existing tasks based on three rules: high utilization, load balancing and lag spreading. The device with the highest average of the three scores will be prioritized in placement. Similarly, LAVEA [24] introduces three task placement strategies, i.e., Shortest Transmission Time First (STTF), Shortest Queue Length First (SQLF) and Shortest Scheduling Latency First (SSLF). Based on the experiments, SSLF has a better overall performance among the three. VideoEdge [22] applies a greedy heuristic starts with assigning the configuration and placement with the lowest dominant resource demand (i.e., the maximum ratio of demand to capacity across all resources) to each VAP and greedily considers incremental improvements to the VAPs. The scheduler also considers merging common tasks from different applications on the same stream (e.g., two applications need to detect objects in input frames) to further avoid redundant computation. Similar merging approaches are also explored in [186], [187]. Nexus [188], on the other hand, focuses on shared models that operate on different inputs to increase the resource utilization of the underlying GPU hardware through batching.

Intra-device scheduling, also known as on-device scheduling, decides the granular and the order of tasks on a single device. It is a well-known problem in real-time systems. Compare to real-time scheduling, on-device scheduling of VA tasks often considers GPU and CPU resources, and takes into account “elasticity” in DL inference by selecting models of different complexity for different parts of the inputs. RT-mDL [73] considers a task scheduling problem in a resource-constrained edge device hosting different DL applications, each with respective deadline. This problem is common in multi-application systems such as autonomous driving [73], where a set of DL tasks with heterogeneous latency requirements (e.g., on-road collision detection, pedestrian tracking, driver speech recognition, etc.) need to be executed concurrently on a resource-limited on-board device. To minimize the overall deadline missing rate, RT-mDL proposes a priority-based task scheduler that divides a DL task into CPU and GPU subtasks and schedules them using separate CPU and GPU task queues, which substantially improve the GPU and CPU temporal utilization. To improve spatial utilization of GPU, the scheduler employs a GPU packing strategy to enable parallel execution of DL inferences with priority guarantee. Heimdall [189] considers a similar problem, i.e., dividing DNN tasks into units and orchestrate them between the GPU and CPU with priorities. Unlike RT-mDL, it allows inference tasks to be scheduled on CPUs. DNN-SAM [190] first splits a DNN task into two sub-tasks: 1) a mandatory sub-task dedicated for a critical portion (e.g., containing target objects) of each image and 2) an optional sub-task for processing a down-scaled image, then executes them independently, and finally merges their results as a single output. To achieve efficient and accurate detection performance, two priority-based scheduling algorithms with different optimization objectives (i.e., minimizing latency or maximizing accuracy) are utilized. DeepQuery [191] improves GPU utilization by co-locating delay-critical and delay-tolerant tasks on shared GPUs. The

future resource demand of delay-critical tasks is predicted. If more resources are required, the batch-size of delay-tolerant tasks will be reduced by the scheduler to release resources. REMIX [123] presents a different subtask division scheme, which adaptively partitions an input frame into multiple non-uniform blocks, and assign each block a proper object detector. Specifically, blocks with dense objects will be processed with an expensive object detector, while the others will be handled with a cheap detector or even ignored. The key idea is similar to the spatial offloading, i.e. spatially partitioning the inference task on the input frame into multiple subtasks, but they differ in that 1) the blocks in REMIX are non-uniform, and 2) REMIX schedules subtasks locally on the same device, rather than offloading them.

VII. FRAMEWORKS AND DATASETS FOR VIDEO ANALYTICS

In this section, we introduce existing open-source frameworks for managing EVA systems, and popular public datasets for VA applications.

A. Container Orchestration Frameworks

To enable microservices and serverless microservices architecture for applications, one good option is to use containers. Containerization is a new virtualization technique that significantly simplifies and speeds up the creation of isolated containers on VMs or physical machines. Different from VMs, which virtualize hardware to run multiple OS instances to host applications, containers encapsulate a lightweight virtualization runtime environment for applications on a single OS, as shown in Fig. 11. Containers present a consistent software environment, and one can encapsulate all dependencies of a target application as a deployable unit and run it on different devices, e.g., a laptop, bare metal server, a public cloud, etc.

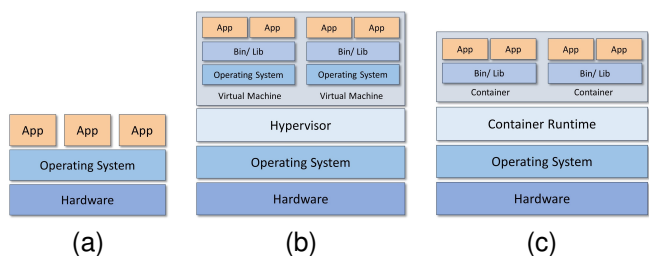


Fig. 11. Three ways to deploy an application. (a) Physical machine-based. (b) Virtual machine-based. (c) Container-based.

Many organizations use container orchestration frameworks to manage containers [192]. Orchestration is a way of automating the operational efforts required for managing containerized applications, such as scale-in, scale-out, networking, deployments of containers, etc. All of these operations mentioned above can also be done without an orchestrator if the containerized application to be managed is very small. But when it comes to large-scale applications with hundreds of microservices running thousands of containers, it becomes challenging to manage all these containers, and orchestrators come to rescue.

Here, we are going to introduce and compare four widely-adopted container orchestration frameworks:

1) *Kubernetes*: Kubernetes [193], [194], also known as K8s, is initially developed by Google and is currently managed by Cloud Native Computing Foundation (CNCF). According to the 2021 CNCF Annual Survey [192], 96% of organizations are using or evaluating K8s (up significantly from 83% in 2020 and 78% in 2019), and more than 5.6 million developers are currently using K8s. By far, K8s has been adopted by major cloud platforms, e.g., Google Kubernetes Engine (GKE), Amazon Elastic Kubernetes Services (EKS) and Microsoft Azure Kubernetes Services (AKS), etc.

In general, K8s manages the complete lifecycle of containerized applications in a cluster. It provides high availability, scalability, and predictability to containerized applications, and automates their deployment, management, and scaling. K8s also supports automated rollout & rollbacks, service discovery, storage orchestration, scaling, batch execution, etc.

However, K8s was initially designed to run in cloud environments. Before considering K8s as an orchestrator for EVA systems, there are some major technical challenges to overcome:

- *Limited Resource at Edge*: Vanilla K8s requires 2 CPUs (cores) and 2GB memory [195]. However, edge devices, such as IoT devices, often do not have enough hardware resources to support a complete base K8s deployment. This may limit the applicability in edge computing that contains resource-constrained devices but require features like high availability, scalability, and fault-tolerance to work in critical areas like surveillance in smart cities [195].
- *Edge Autonomy*: Vanilla K8s does not have a good support for offline independent operations of edge devices (also known as *edge autonomy* [196]). The control plane of a K8s cluster needs to frequently request status information from the nodes to schedule and manage the workloads properly throughout the cluster. Edge computing environments often have restricted connectivity to the Internet in terms of bandwidth and latency, and as a result, the control plane can not communicate to the edge nodes as much as it needs. Worse still, connectivity can be lost during network outages. The nodes can no longer function without access to the control plane.
- *Heterogeneous Device Management*: One important feature of edge computing is the distributivity and heterogeneity of edge devices. The devices and their hardware architectures, configurations and communication protocols can significantly vary across application scenarios. Vanilla K8s lacks support for heterogeneous device management and edge-to-edge communication.

Recently, lightweight K8s distributions have emerged to address the afore-mentioned challenges and facilitate K8s-based deployments in edge computing settings. Frameworks such as MicroK8s, K3s, KubeEdge provide K8s-compatible distributions by modifying and reorganizing essential components. They aim to simplify configuring, running, and maintaining clusters to enable deployments with low-end edge devices.

2) *MicroK8s*: MicroK8s [197] is a low-ops, minimal pro-

duction K8s developed by Canonical. It is an open-source framework for automating the deployment, scaling, and management of containerized applications. MicroK8s aims to solve the challenge of limited edge resources, and provides the functionality of core K8s components, in a small footprint of 564MB, scalable from a single node to a high-availability production cluster. By reducing the resource commitments required in order to run K8s, MicroK8s makes it possible to run K8s on low-end edge devices, which is beneficial for small-appliance IoT applications.

3) *K3s*: Rancher offers K3s [198] as a lightweight K8s distribution for edge environments, IoT devices, and even ARM devices like Raspberry Pi. It is fully compliant with K8s, contains all basic components by default, and targets a fast, simple, and efficient way to provide a highly available and fault-tolerant cluster to a set of nodes. The minimum hardware requirements of K3s are 1 CPU and 512 MB of memory, which makes it feasible for edge computing use cases.

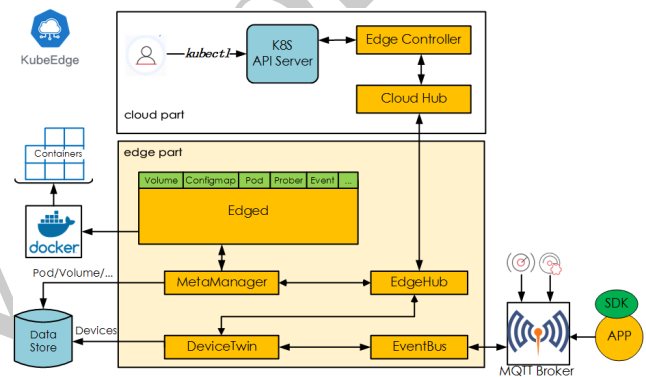


Fig. 12. The architecture of KubeEdge cluster [199].

4) *KubeEdge*: KubeEdge [196], [200], was first developed by Huawei, and later accepted as a CNCF sandbox project.

Unlike MicroK8s and K3s, which are simply lightweight K8s distributions, KubeEdge is specifically designed to build edge computing solutions by extending the cloud. As shown in Fig. 12, the KubeEdge architecture consists of cloud, edge, and device layers. In the cloud layer, the K8s API server represents an unchanged native Kubernetes control plane. The CloudCore contains EdgeController and DeviceController, which process data from the control plane, as well as Cloud Hub, which sends the data to EdgeHub at the edge. The edge layer enables application and device management. Specifically, Edged is for application management, whereas DeviceTwin and EventBus are for device management. DataStore facilitates local autonomy. In particular, when the data of an application or a device is distributed from the cloud through EdgeHub, the data is stored in a database before it is sent to Edged or the device. In this way, Edged can retrieve metadata from the database and the service recovers even when the edge is disconnected from the cloud or when the edge node restarts. For device connectivity, KubeEdge supports multiple communication protocols and uses MQTT as a common middleware layer. This helps in scaling the edge clusters with new nodes and devices efficiently. For AI workloads, KubeEdge provides

its own toolkit called *Sedna* to make deploying models from popular ML frameworks like Tensorflow and Pytorch easier.

Currently, KubeEdge is gaining popularity due to its lightweight feature (requiring only 66MB footprint and 30MB memory) [199] and flexible approach to making edge computing secure, reliable, and autonomous.

To summarize, although K8s is an industry leader in container management, competitors like K3s, MicroK8s and KubeEdge are viable alternatives in edge computing contexts with their respective strengths and weaknesses. For instance, K3s and MicroK8s are quite mature with extensive documentations and community support, but their functionalities are limited. KubeEdge is an attractive solution due to its features tailored for edge deployments, but still in its infancy. Hence, the best framework varies depending on the application requirements and technical competency.

B. Datasets

Many images or video datasets exist for CV tasks, such as ImageNet [103], Microsoft Common Objects in Context (COCO) [201], Canadian Institute for Advanced Research (CIFAR) [202], PASCAL Visual Object Classes (VOC) [203]. In this section, we limit the discussion to datasets that are widely adopted in 2D MOT tasks:

1) *MOTChallenge*: The goal of MOTChallenge is to provide benchmarks for MOT methods. Several variants were released each year, including MOT15 [204], MOT16 [205], MOT17 [205], MOT20 [206]. Each dataset includes video sequences captured in different places and under different conditions (e.g., camera motion, viewpoint, environment illumination, weather condition, etc.) and the corresponding annotations (e.g., box coordinates, object class, object id, etc.).

2) *KITTI*: The dataset from Karlsruhe Institute of Technology and Toyota Technological Institute (KITTI) [207] is one of the most popular datasets in mobile robotics and autonomous driving. It consists of hours of traffic scenarios recorded with a variety of sensor modalities, including high-resolution RGB, grayscale stereo cameras, and a 3D laser scanner [207]. KITTI 2D tracking dataset is transformed from 3D data. It consists of 21 training sequences and 29 test sequences. Despite the fact that 8 different classes are labelled, only the classes “Car” and “Pedestrian” are evaluated in the benchmark, because there are not enough labelled instances for other classes.

3) *TAO*: Most MOT benchmarks (e.g. MOT, KITTI) focus on either people or vehicles, motivated by surveillance and self-driving applications. Moreover, they tend to include only a few dozen videos, captured in outdoor or road environments, which may limit the generalizability of models trained using these datasets. To bridge this gap, Tracking Any Object (TAO) [208] was proposed. It consists of 2,907 high-resolution videos that were captured in diverse environments with an average length of 30 seconds and contain annotations for 833 object categories [208]. Different from other datasets which have a limited vocabulary of categories, TAO focuses on diversity both in the category and visual domain distribution, resulting in a realistic benchmark for MOT tasks [208].

4) *BDD100K*: BDD100K [209] is a large-scale tracking dataset collected from diverse driving scenarios, covering New York, Berkeley, San Francisco Bay Area, and other regions in the US. It contains scenes in a wide variety of locations, weather conditions and day time periods, such as city streets, tunnels, highways, snowy, rainy, cloudy weather, etc. The BDD100K MOT dataset contains 2,000 fully annotated 40-second sequences at 5 FPS under different weather conditions, time of the day, and scene types [209]. The videos contain a total of 130.6K tracking identities and 3.3M objects.

5) *UAVDT*: UAVDT [210] is a large-scale challenging unmanned aviation vehicle (UAV) Detection and Tracking benchmark for object detection, single object tracking (SOT) and MOT from aerial videos. The objects of interest in this benchmark are vehicles, and it consists of 100 video sequences, which are selected from over 10 hours of videos taken with a UAV platform at a number of locations in urban areas, such as squares, arterial streets, toll stations, highways, crossings and T-junctions [210]. The videos are recorded at 30 FPS, with a resolution of 1080 × 540 pixels. The frames are manually annotated with bounding boxes and various attributes, e.g., weather condition, flying altitude, camera view, vehicle category, etc.

6) *UA-DETRAC*: UA-DETRAC [211] is a challenging real-world multi-object detection and multi-object tracking benchmark. It consists of 10 hours of videos captured with various illumination conditions and shooting angles at 24 different locations (e.g., urban highway, traffic crossings and T-junctions) in Beijing and Tianjin, China. The videos are recorded at 25 FPS, with a resolution of 960×540 pixels. More than 140K frames are manually annotated with 8250 vehicles and a total of 1.21M bounding boxes are labelled. UA-DETRAC is now a partner with AI City Challenge [212]–[216].

7) *MMPTRACK*: Multi-camera systems have widely been deployed in cluttered and crowded environments, where occlusions of the tracked objects often occur. Datasets for multi-camera multi-object tracking (MCMOT) are quite limited due to data collection and annotation challenges. Multi-camera Multiple People Tracking (MMPTRACK) dataset [217] contains around 9.6 hours of videos, with over half a million frame-wise annotations (e.g., per-frame bounding boxes, person identities, and camera calibration parameters) for each camera view. The annotations are done with the help of an auto-annotation system. The videos are recorded at 15 FPS in five diverse and challenging environment settings., e.g., cafe shop, industry, lobby, office, and retail [217]. This is by far the largest publicly available multi-camera multiple people tracking dataset [217].

VIII. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

Deep learning-driven edge video analytics is an active area intersecting with many fields, including video analytics, computer vision, deep learning, and edge computing. Despite significant research efforts, there are still some problems that have not been well addressed or are under-explored yet. In this section, we highlight these problems and outline potential research directions in EVA.

A. Adaptive Configuration

As mentioned in Section VI-A, periodic configuration update is necessary as a configuration can become stale with scene changes [21], [218]. An under-investigated aspect of existing configuration optimization methods is how often such configurations change. They all rely on a pre-fixed time interval for updating. For instance, in Chameleon [21], a fresh online profiling will be triggered every T seconds to update the configuration. Similarly, in DeepScale [105], the optimal resolution is updated every K frames. As reported in DeepScale, the setting of K has a significant impact on the accuracy-latency tradeoff. However, an ideal setting requires domain expertise and can vary depending on specific tasks. For parking surveillance, a large time interval is sufficient, while for traffic intersection monitoring, more frequent updates are needed since vehicle movement patterns can change at different times of the day. An improper setting can diminish the benefits brought by periodically updating.

Computer vision techniques can be used to extract features, therefore triggering updates. Take vehicle detection as an example. Low-level features like the number of vehicles, the average size of vehicles, and the average velocity of vehicles generated by an object detector can be used. However, such features may not be sufficient. In continuous videos, consecutive frames have negligible differences in these features, but the detection accuracy of frames can vary significantly due to factors like occlusions and camera parameters [219]. In addition, extracting these features accurately requires a reliable object detector and thus poses a chicken-egg problem—a full-fledged object detector with high computation complexity is needed to decide when to trigger profiling or configuration updates, but now the question becomes when to apply such a detector. One possible way out of the dilemma is to utilize cloud resources to decide the best configurations by trading off computation complexity (on edge) with communication complexity (over networks).

Prior knowledge is also useful in configuration updates. For example, at a traffic intersection, the prior knowledge could be the peak or off-peak hours on weekdays or weekends, the switching interval of traffic lights, and the vehicle movement patterns (e.g., direction, velocity, etc.) corresponding to the traffic signal. Updates can be simply triggered whenever the traffic signal changes or a rush hour begins. We observe that very few works take prior knowledge into consideration with the exception of Distream [106], where the data captured from a traffic intersection is employed to train a LSTM network to predict vehicle movement patterns in the near future. Note that prior knowledge can be used in conjunction with triggering mechanisms based on image features to improve the efficiency of adaptive configuration.

B. Multi-Camera Collaborative Video Analytics

The proliferation of on-camera computing resource has spurred the prospect of massive VA on the camera side. To deliver these promises, however, we must address the fundamental systems challenge of utilizing the on-camera resource in a large camera fleet to run VA applications at scale. Existing

multi-camera solutions solely focus on saving computation costs by sharing information across cameras [86], [220], or improving throughput by balancing workloads across cameras [106]. These solutions often work in isolation. We envision a holistic solution that transforms a group of networked cameras to a compute cluster, called a camera cluster, through which the following benefits can be realized [95]:

1) *Saving Computing Resources*: Different applications sometimes use the same set of vision models. This suggests one can share models, in addition to data, among these applications. For instance, object detection is a common building block in many applications. Instead of frequently loading or unloading DNN models into CPU or GPU memory, it is more efficient to leave the models loaded on specific cameras and route “data” to these devices for several reasons. First, loading a large DNN model into memory from external storage is time-consuming. As an example, loading a ResNet50 model to GPU takes about 10 seconds, which is 100× longer than using it to classify images (50 images per second). Second, many VAPs consist of a cascade of operations, where not all models need to be executed for each frame. Finally, pre-loaded DNNs can batch-process frames from multiple cameras together to further reduce computing costs.

2) *Resource Pooling*: By pooling the resources on cameras, one can process each video stream distributively in the cluster. This is beneficial in two aspects. First, application throughput can be improved if workloads are migrated from overloaded cameras to idle cameras, as cameras in the same cluster often have heterogeneous workloads. In Distream [106], the resources of a camera cluster and an edge server are pooled together, and workloads are balanced across cameras and also between the camera cluster and the edge server. Note that Distream employs a two-stage object detection process, where ROIs are first extracted and then fed into classifiers. The two-stage process makes it possible to improve throughput by load balancing despite increased network transfer time. Second, a camera cluster can run more complex and more accurate models than single-camera solutions. This can be accomplished by splitting a video stream into frame groups and processing them in parallel with multiple cameras. For example, if the current frame has not been finished before the arrival of the next frame (this is common when a heavier model is used), the next frame will be sent to another camera for processing.

3) *Improving Analytics Quality*: As a camera cluster offers direct access to the video streams of all cameras, one can improve video analytics quality by leveraging information from multiple video streams. Such collaboration has been widely used in MCMOT tasks. As each camera has limited FoVs, objects missed by one camera can potentially be captured by other cameras. By sharing intermediate outputs among the cluster, tracking performance can be improved. Even when cameras do not have overlapping FoVs, collaboration can still be beneficial. Consider a small-scale camera cluster with two cameras A and B, monitoring two different park lots of a shopping mall. They all connect to an edge server located in the mall. Even though the two cameras do not have

overlapping FoVs, they share the same type of target objects, i.e. vehicles, and similar video characteristics, i.e., vehicle movement patterns. This means that the optimal configuration for camera A is likely to perform well for camera B [21]. Moreover, the analytics quality can be further improved if the model is continuously trained with data from both A and B. Very few works consider this setting, and thus collaborative VA for non-overlapping cameras is a promising research direction.

C. Benchmarks, Datasets and Evaluation Methodology

The availability of large public datasets is the key driver of the advancement of ML models. In the VA domain, as discussed in Section VII-B, many datasets exist, but they primarily target training and evaluating individual building blocks of a VA pipeline, such as object classification detection and tracking. High-level application-level metrics are rarely included. Moreover, compared to single-camera VA, there are only a few datasets from multiple cameras in realistic settings. Existing evaluation methodologies for EVA are limited. First, most VA models are trained and tested on the same datasets. Their generalization to other datasets in different scenarios is seldom evaluated [221]. Second, realistic benchmarks on system aspects of VA, such as inference time, are rare. Researchers often report results from their specific setups, which are not necessarily reproducible by others. Instead of processing live camera streams, most works emulate streaming VA by “playing back” stored video clips from datasets. The incurred I/O time can be quite different. We also note that there is no distributed camera testbed that can be utilized to test and compare VAPs—an area concerted efforts are needed from the community.

D. Large-Scale Edge Video Analytics Systems

Despite the demand for large-scale VA, according to our survey, the majority of reported work considers small-scale deployment (e.g., a few IoT devices and one edge or cloud). To support large-scale VA across a variety of applications, infrastructure must be designed to support the following characteristics: geo-distribution [94], [222], to ensure analytics functionality across cameras, edges, private clusters, and public clouds (not just a central location); multi-tenancy [223], to capture and handle many queries per camera as well as queries across multiple cameras; and hardware heterogeneity [224], to flexibly manage a mix of processing capacities (in CPUs, GPUs, FPGAs, ASICs) and networks. Organizations managing cameras in a large geographical area can benefit from continuous VA on all of their live feeds, such as counting cars in all intersections for city-wide traffic planning.

As argued by Microsoft [94], large-scale LVA is the “killer app” of edge computing. A geographically distributed architecture of “public clouds-private edge clusters-cameras” is the only feasible approach to meeting the strict real-time requirements of large-scale LVA. Resource management (e.g., resource provisioning, resource scheduling, and resource monitoring) and across the hierarchy of “camera-edge-cloud” will pose significant challenges in such settings. The microservice

architecture is an attractive option when implementing large-scale EVA systems due to its several advantages. As introduced earlier, microservices provide long-term agility and enable better maintainability in complex, large, and highly-scalable systems by allowing the creation of applications based on many independently deployable services with granular, and autonomous lifecycles. Moreover, microservices can scale out independently, allowing one to scale only the functional area that requires additional processing power or network bandwidth to meet demand.

With serverless architecture, microservices are further decoupled into a series of stateless functions, which can be configured and invoked independently. The same function code can be executed by multiple function instances typically implemented by lightweight containers. Thanks to the lightweight nature of functions, they can scale up or down automatically in milliseconds, leading to rapid and flexible responses. This benefit enables serverless functions to scale and react to fine-grained input workload variations without the need for resource management and monitoring. Moreover, the pay-as-you-go pricing strategy of FaaS (Function-as-a-Service) can ensure no money is wasted on idle resources, thereby reaching high cost-efficiency.

We find the majority of work deploys applications in monolithic architecture, while only a small portion utilizes microservices and serverless microservices architectures. Further investigation is needed to utilize microservices and serverless microservices to efficiently place and execute VAPs on edge devices especially in multi-tenant use cases [225]–[230].

IX. CONCLUSION

Driving by the flourishing of VA and its stringent latency requirements, there is an imperative need to push the VA frontier from the remote cloud to the proximity of end users. To fulfill this trend, edge computing has been widely recognized as a promising solution to support computation-intensive DL-driven VA applications in resource-constrained environments. The convergence of VA and edge computing gives birth to the novel paradigm of EVA.

In this paper, we conducted a comprehensive survey of the recent research efforts on EVA. Specifically, we began by reviewing the basics of edge computing. We then provided an overview of VA, including its definition, components and typical applications. Next, we went through the definition, architectures, components, performance indicators, application architectures and enabling techniques of EVA systems. In addition, to bridge the gap between academia and industry, we introduced a number of frameworks that are widely used in the industry to manage the deployments of VA applications. We also collected various prominent MOT tracking datasets. Finally, we discussed the open challenges and future research directions on EVA. We hope this survey can reflect the recent progress in both academia and industry, evoke growing attention, stimulate wide discussions, and inspire further research ideas on EVA.

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