INVITED PAPER

Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing

This article conducts a comprehensive survey of the research efforts on edge intelligence. It provides an overview of the architectures, frameworks, and emerging key technologies for deep learning model toward training and inference at the network edge.

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ABSTRACT | With the breakthroughs in deep learning, the recent years have witnessed a booming of artificial intelligence (AI) applications and services, spanning from personal assistant to recommendation systems to video/audio surveillance. More recently, with the proliferation of mobile computing and Internet of Things (IoT), billions of mobile and IoT devices are connected to the Internet, generating zillions bytes of data at the network edge. Driving by this trend, there is an urgent need to push the AI frontiers to the network edge so as to fully unleash the potential of the edge big data. To meet this demand, edge computing, an emerging paradigm that pushes computing tasks and services from the network core to the network edge, has been widely recognized as a promising solution. The resulted new interdiscipline, edge AI or edge intelligence (EI), is beginning to receive a tremendous amount of interest. However, research on EI is still in its infancy stage, and a dedicated venue for exchanging the recent advances of EI is highly desired by both the computer system and AI communities. To this end, we conduct a comprehensive survey of the recent research efforts on EI. Specifically, we first review the background and motivation for AI running at the network edge. We then provide an overview of the overarching architectures, frameworks, and emerging key technologies for deep learning model toward training/inference at the network edge. Finally, we discuss future research opportunities on EI. We believe that this survey will elicit escalating attentions, stimulate fruitful discussions, and inspire further research ideas on EI.

KEYWORDS | Artificial intelligence, deep learning, edge computing, edge intelligence.

I. INTRODUCTION

We are living in an unprecedented booming era of artificial intelligence (AI). Driving by the recent advancements of algorithm, computing power, and big data, deep learning [1]—the most dazzling sector of AI—has made substantial breakthroughs in a wide spectrum of fields, ranging from computer vision, speech recognition, and natural language processing to chess playing (e.g., AlphaGo) and robotics [2]. Benefiting from these breakthroughs, a set of intelligent applications, as exemplified by intelligent personal assistants, personalized shopping recommendation, video surveillance, and smart home appliances have quickly ascended to the spotlight and gained enormous popularity. It is widely recognized that these intelligent applications are significantly enriching people's

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lifestyle, improving human productivity, and enhancing social efficiency.

As a key driver that boosts AI development, big data have recently gone through a radical shift of data source from the megascale cloud datacenters to the increasingly widespread end devices, e.g., mobile devices and Internet-of-Things (IoT) devices. Traditionally, big data, such as online shopping records, social media contents, and business informatics, were mainly born and stored at megascale datacenters. However, with the proliferation of mobile computing and IoT, the trend is reversing now. Specifically, Cisco estimates that nearly 850 ZB will be generated by all people, machines, and things at the network edge by 2021 [3]. In sharp contrast, the global datacenter traffic will only reach 20.6 ZB by 2021. Clearly, via bringing the huge volumes of data to AI, the edge ecosystem will present many novel application scenarios for AI and fuel the continuous booming of AI.

Pushing the AI frontier to the edge ecosystem that resides at the last mile of the Internet, however, is highly nontrivial, due to the concerns on performance, cost, and privacy. Toward this goal, the conventional wisdom is to transport the data bulks from the IoT devices to the cloud datacenters for analytics [4]. However, when moving a tremendous amount of data across the wide area network (WAN), both monetary cost and transmission delay can be prohibitively high, and the privacy leakage can also be a major concern [5]. An alternative is on-device analytics that run AI applications on the device to process the IoT data locally, which, however, may suffer from poor performance and energy efficiency. This is because many AI applications require high computational power that greatly outweighs the capacity of resource- and energy-constrained IoT devices.

To address the above-mentioned challenges, edge computing [6] has recently been proposed, which pushes cloud services from the network core to the network edges that are in closer proximity to IoT devices and data sources. As shown in Fig. 1, here an edge node can be nearby end-device connectable by device-to-device (D2D) communications [7], a server attached to an access point (e.g., WiFi, router, and base station), a network gateway, or even a microdatacenter available for use by nearby devices. While edge nodes can be varied in size: ranging from a credit-card-sized computer to a microdatacenter with several server racks, physical proximity to the information-generation sources is the most crucial characteristic emphasized by edge computing. Essentially, the physical proximity between the computing and information-generation sources promises several benefits compared to the traditional cloud-based computing paradigm, including low latency, energy efficiency, privacy protection, reduced bandwidth consumption, on-premises, and context awareness [6], [8].

Indeed, the marriage of edge computing and AI has given rise to a new research area, namely, "edge intelligence (EI)" or "edge AI" [9], [10]. Instead of entirely relying on the cloud, EI makes the most of the widespread edge resources to gain AI insight. Notably, EI has garnered much attention from both the industry and academia. For example, the celebrated Gartner hype cycle has incorporated EI as an emerging technology that will reach a plateau of productivity in the following five to ten years [11]. Major enterprises, including Google, Microsoft, Intel, and IBM, have put forth pilot projects to demonstrate the advantages of edge computing in paving the last mile of AI. These efforts have boosted a wide spectrum of AI applications, spanning from live video analytics [12], cognitive assistance [13] to precision agriculture, smart home [14], and Industrial Internet of Things (IIoT) [15].

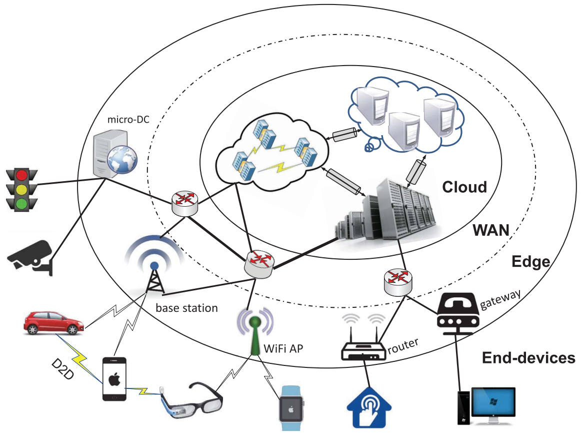

Fig. 1. ***Illustration of edge computing.***

Notably, research and practice on this emerging interdiscipline—EI—are still in a very early stage. There is, in general, a lack of venue dedicated for summarizing, discussing, and disseminating the recent advances of EI, in both industrial and academia. To bridge this gap, in this paper, we conduct a comprehensive and concrete survey of the recent research efforts on EI. Specifically, we will first review the background of AI. We will then discuss the motivation, definition, and rating of EI. Next, we will further review and taxonomically summarize the emerging computing architectures and enabling technologies for EI model training and inference. Finally, we will discuss some open research challenges and opportunities for EI. This paper is organized as follows.

1) Section II gives an overview of the basic concepts of AI, with a focus on deep learning—the most popular sector of AI.
2) Section III discusses the motivation, definition, and rating of EI.
3) Section IV reviews the architectures, enabling techniques, systems, and frameworks for training EI models.
4) Section V reviews the architectures, enabling techniques, systems, and frameworks for EI model inference.
5) Section VI discusses future directions and challenges of EI.

For this survey, we hope it can elicit escalating attentions, stimulate fruitful discussions, and inspire further research ideas on EI.

II. PRIMER ON ARTIFICIAL INTELLIGENCE

In this section, we review the concepts, models, and methods for AI, with a particular focus on deep learning—the most popular sector of AI.

A. Artificial Intelligence

While AI has recently ascended to the spotlight and gained tremendous attention, it is not a new term and it was first coined in 1956. Simply put, AI is an approach to build intelligent machines capable of carrying out tasks as humans do. This is obviously a very broad definition, and it can refer from Apple Siri to Google AlphaGo and too powerful technologies yet to be invented. In simulating human intelligence, AI systems typically demonstrate at least some of the following behaviors associated with human intelligence: planning, learning, reasoning, problem-solving, knowledge representation, perception, motion, and manipulation and, to a lesser extent, social intelligence, and creativity. During the past 60 year's development, AI has experienced rise, fall, and again rise and fall. The latest rise of AI after 2010s was partially due to the breakthroughs made by deep learning, a method that has achieved human-level accuracy in some interesting areas.

B. Deep Learning and Deep Neural Networks

Machine learning (ML) is an effective method to achieve the goal of AI. Many ML methodologies as exemplified by decision tree, K-means clustering, and Bayesian network have been developed to train the machine to make classifications and predictions, based on the data obtained from the real world. Among the existing ML methods, deep learning, by leveraging artificial neural networks (ANNs) [16] to learn the deep representation of the data, has resulted in an amazing performance in multiple tasks, including image classification, face recognition, and so on. Since the ANN adopted by deep learning model typically consists of a series of layers, the model is called a deep neural network (DNN). As shown in Fig. 2, each layer of a DNN is composed of neurons that are able to generate the nonlinear outputs based on the data from the input of the neuron.

The neurons in the input layer receive the data and propagate them to the middle layer (also known as the hidden layer). Then, the neurons in the middle layer generate the weighted sums of the input data and output the weighted sums using the specific activation functions (e.g., tanh), and the outputs are then propagated to the output layer. The final results are presented at the output layer. With more complex and abstract layers than a typical model, DNNs are able to learn the high-level features, enabling high precision inference in tasks. Fig. 3 presents three popular structures of DNNs: multilayer perceptrons (MLPs), convolution neural networks (CNNs), and recurrent neural networks (RNNs).

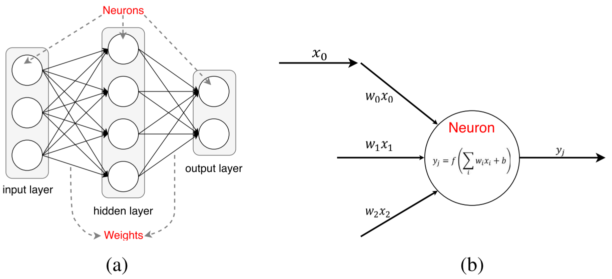

Fig. 2. ***Standard composition of DL model. (a) Layers in a DL model. (b) Architecture of a neuron.***

MLP models are the most basic DNN, which is composed of a series of fully connected layers [17]. Different from fully connected layers in MLPs, in CNN models, the convolution layers extract the simple features from input by executing convolution operations. Applying various convolutional filters, CNN models can capture the high-level representation of the input data, making it most popular for computer vision tasks, e.g., image classification (e.g., AlexNet [18], VGG network [19], ResNet [20], and MobileNet [21]) and object detection (e.g., Fast R-CNN [22], YOLO [23], and SSD [24]). RNN models are another type of DNNs, which use sequential data feeding. As shown in Fig. 3(c), the basic unit of RNN is called cell, and further, each cell consists of layers and a series of cells enables the sequential processing of RNN models. RNN models are widely used in the task of natural language processing, e.g., language modeling, machine translation, question answering, and document classification.

Deep learning represents the state-of-the-art AI technology as well as a highly resource-demanding workload that naturally suits for edge computing. Therefore, due to space limitation, in the remaining of this paper, we will focus on the interaction between deep learning and edge computing. We believe that the techniques discussed can also have meaningful implications for other AI models and methods, i.e., stochastic gradient descent (SGD) is a popular training method for many AI/ML algorithms (e.g., k-means, support vector machine, and lasso regression) [25], and the optimization techniques of SGD training introduced in this paper can be also deployed on other AI models training process.

C. From Deep Learning to Model Training and Inference

For each neuron in a DNN layer, it has a vector of weights associated with the input data size of the layer. Needless to say, the weights in a deep learning model need to be optimized through a training process.

In a training process for a deep learning model, the values of weights in the model are often randomly assigned initially. Then, the output of the last layer represents the task result, and a loss function is set to evaluate the correctness of the results by calculating the error rate (e.g.,

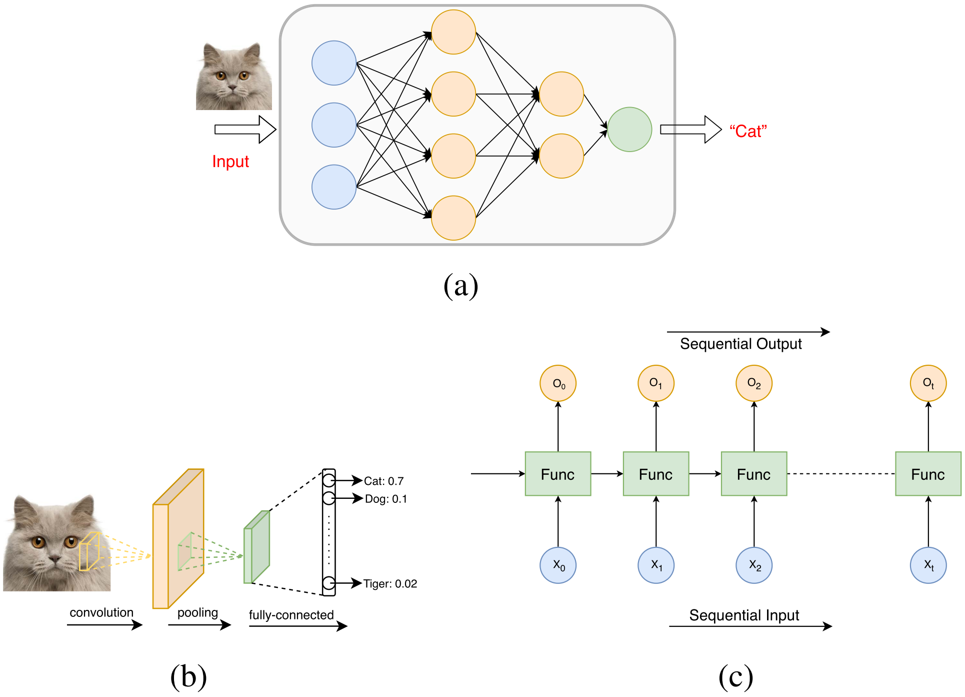

Fig. 3. ***Three typical structures of DL models. (a) MLPs. (b) CNNs. (c) RNNs.***

root-mean-squared error) between the results and the true label. To adjust the weights of each neuron in the model, an optimization algorithm, such as SGD [25], is used and the gradient of the loss function is calculated. Leveraging the backpropagation mechanism [26], [27], the error rate is propagated back across the whole neural network, and the weights are updated based on the gradient and the learning rate. By feeding a large number of training samples and repeating this process until the error rate is below a predefined threshold, a deep learning model with high precision is obtained.

DNN model inference happens after training. For instance, for an image classification task, with the feeding of a large number of training samples, the DNN is trained to learn how to recognize an image, and then, inference takes real-world images as inputs and quickly draws the predictions/classifications of them. The training procedure consists of the feed-forward process and the backpropagation process. Note that the inference involves the feedforward process only, i.e., the input from the real world is passed through the whole neural network and the model outputs the prediction.

D. Popular Deep Learning Models

For a better understanding of the deep learning and their applications, in this section, we give an overview of various popular deep learning models.

1) Convolution Neural Network: For image classification, as the first CNN to win the ImageNet Challenge in 2012, AlexNet [18] consists of five convolution layers and three fully connected layers. AlexNet requires 61 million weights and 724 million MACs (multiply-add computation) to classify the image with a size of 227 × 227. To achieve higher accuracy, VGG-16 [19] is trained to a deeper structure of 16 layers consisting of 13 convolution layers and three fully connected layers, requiring 138 million weights and 15.5G MACs to classify the image with a size of 224 × 224. To improve accuracy while reducing the computation of DNN inference, GoogleNet [28] introduces an inception module composed of different sized filters. GoogleNet achieves a better accuracy performance than VGG-16, while only requiring seven million weights and 1.43G MACs to process the image with the same size. ResNet [20], the state-of-the-art effort, uses the "shortcut" structure to reach a human-level accuracy with a top-5 error rate below 5%. The "shortcut" module is used to solve the gradient vanishing problem during the training process, making it possible to train a DNN model with deeper structure. CNN is typically employed in computer vision. Given a series of images or video from the real world, with the utilization of CNN, the AI system learns to automatically extract the features of these inputs to complete a specific task, e.g., image classification, face authentication, and image semantic segmentation.

2) Recurrent Neural Network: For sequential input data, RNNs have been developed to address the time-series problem. The input of RNN consists of the current input and the previous samples. Each neuron in an RNN owns an internal memory that keeps the information of the computation from the previous samples. The training of RNN

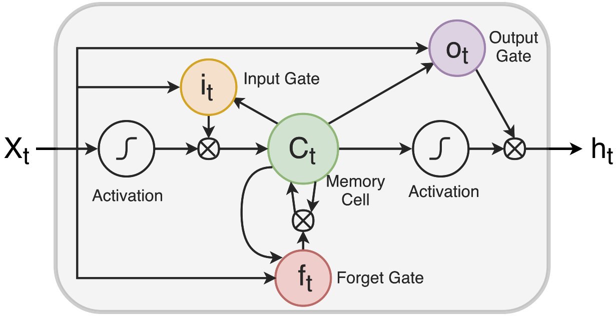

Fig. 4. ***Structure of an LSTM memory cell.***

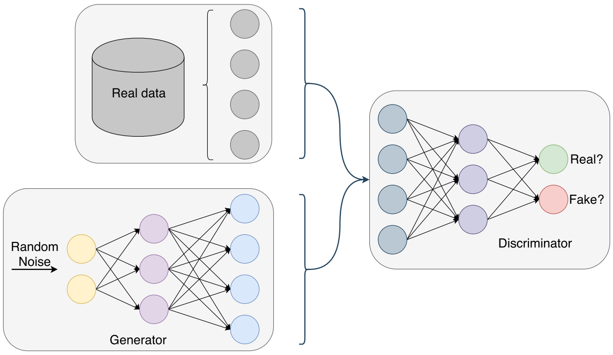

Fig. 5. ***Composition of a GAN.***

is based on backpropagation through time (BPTT) [29]. Long short-term memory (LSTM) [30] is an extended version of RNNs. In LSTM, the gate is used to represents the basic unit of a neuron. As shown in Fig. 4, each neuron in LSTM is called memory cell and includes a multiplicative forget gate, input gate, and output gate. These gates are used to control the access to memory cells and to prevent them from perturbation by irrelevant inputs. Information is added or removed through the gate to the memory cell. Gates are different neural networks that determine what information is allowed on the memory cell. The forget gate can learn what information is kept or forgotten during training. RNN has been widely used in natural language processing due to the superiority of processing the data with an input length that is not fixed. The task of the AI here is to build a system that can comprehend natural language spoken by humans, e.g., natural language modeling, word embedding, and machine translation.

3) Generative Adversarial Network: As shown in Fig. 5, generative adversarial networks (GANs) [31] consists of two main components, namely, the generative and discriminator networks (i.e., generator and discriminator). The generator is responsible for generating new data after it learns the data distribution from a training data set of real data. The discriminator is in charge of classifying the real data from the fake data generated by the generator. GAN is often deployed in image generation, image transformation, image synthesis, image superresolution, and other applications.

4) Deep Reinforcement Learning: Deep reinforcement learning (DRL) is composed of DNNs and RL. As illustrated in Fig. 6, the goal of DRL is to create an intelligent agent that can perform efficient policies to maximize the rewards of long-term tasks with controllable actions. The typical application of DRL is to solve various scheduling problems, such as decision problems in games, rate selection of video transmission, and so on.

In the DRL approach, the RL searches for the optimal policy of actions over states from the environment, and the DNN is in charge of representing a large number of states and approximating the action values to estimate the quality of the action in the given states. The reward is a function to represent the distance between the predefined requirement and the performance of an action. Through continuous learning, the agent of DRL model can be used for various tasks, e.g., gaming [32].

III. EDGE INTELLIGENCE

The marriage of edge computing and AI gives the birth of EI. In this section, we discuss the motivation, benefits, and definition of EI.

A. Motivation and Benefits of Edge Intelligence

The fusion of AI and edge computing is natural since there is a clear intersection between them. Specifically, edge computing aims at coordinating a multitude of collaborative edge devices and servers to process the generated data in proximity, and AI strives for simulating intelligent human behavior in devices/machines by learning from data. Besides enjoying the general benefits of edge computing (e.g., low latency and reduced bandwidth consumption), pushing AI to the edge further benefits each other in the following aspects.

1) Data Generated at the Network Edge Need AI to Fully Unlock Their Potential: As a result of the proliferation of the skyrocketing number and types of mobile and IoT devices, large volumes of multimodal data (e.g., audio, picture, and video) of physical surroundings are continuously sensed at the device side. In this context, AI will be functionally necessary due to its ability to quickly analyze those huge data

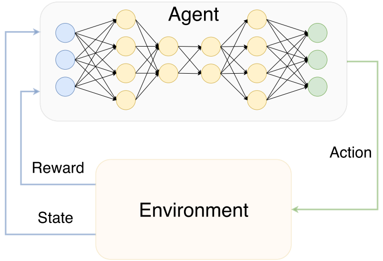

Fig. 6. ***Concept of a DRL model.***

volumes and extract insights from them for high-quality decision making. As one of the most popular AI techniques, deep learning brings the ability to automatically identify patterns and detect anomalies in the data sensed by the edge device, as exemplified by population distribution, traffic flow, humidity, temperature, pressure, and air quality. The insights extracted from the sensed data are then fed to the real-time predictive decision-making (e.g., public transportation planning, traffic control, and driving alert) in response to the fast-changing environments, increasing the operational efficiency. As forecast by Gartner [33], more than 80% of enterprise IoT projects will include an AI component by 2022, up from only 10% today.

2) Edge Computing Is Able to Prosper AI With Richer Data and Application Scenarios: It is widely recognized that the driving force behind the recent booming of deep learning is fourfold: algorithm, hardware, data, and application scenarios. While the effect of algorithm and hardware on the development of deep learning is intuitive, the role of data and application scenarios has been mostly overlooked. Specifically, to improve the performance of a deep learning algorithm, the most commonly adopted approach is to refine the DNN with more layers of neurons. By doing this, we need to learn more parameters in the DNN and so does the data required for training increase. This definitely demonstrates the importance of data on the development of AI. Having recognized the importance of data, the next problem is where are the data from. Traditionally, data are mostly born and stored in the megascale datacenters. Nevertheless, with the rapid development of IoT, the trend is reversing now. According to Cisco's report [3], in the near future, massive IoT data will be generated at the edge side. If these data are processed by AI algorithms at the cloud data center, it will consume a lot of bandwidth resources and bring great pressure to the cloud data center. To address these challenges, edge computing is proposed to achieve low-latency data processing by sinking the computing capability from the cloud data center to the edge side, i.e., data generation source, which may enable AI processing with high performance.

While edge computing and AI complement each other from a technical perspective, their application and popularization are also mutually beneficial.

3) AI Democratization Requires Edge Computing as a Key Infrastructure: AI technologies have witnessed great success in many digital products or services in our daily life, e.g., online shopping, service recommendation, video surveillance, smart home devices, and so on. AI is also a key driving force behind emerging innovative frontiers, such as self-driving cars, intelligent finance, cancer diagnosis, and medicine discovery. Beyond the above-mentioned examples, to enable a richer set of applications and push the boundaries of what is possible, AI democratization or ubiquitous AI [34] has been declared by major IT companies, with the vision of "making AI for every person and every organization at everywhere." To this end, AI should go "closer" to the people, data, and end devices. Clearly, edge computing is more competent than cloud computing in achieving this goal. First, compared to the cloud datacenter, edge servers are in closer proximity to people, data source, and devices. Second, compared to cloud computing, edge computing is also more affordable and accessible. Finally, edge computing has the potential to provide more diverse application scenarios of AI than cloud computing. Due to these advantages, edge computing is naturally a key enabler for ubiquitous AI.

4) Edge Computing Can Be Popularized With AI Applications: During the early development of edge computing, there has always been the concern in the cloud computing community with which high-demand applications edge computing could take to the next level that cloud computing could not, and what are the killer applications of edge computing. To clear up the doubt, Microsoft has conducted continuous exploration on what kinds should be moved from the cloud to the edge since 2009 [35], ranging from voice command recognition, AR/VR, and interactive cloud gaming [36] to real-time video analytics. By comparison, real-time video analytics is envisioned to be a killer application for edge computing [12], [37], [38]. As an emerging application built on top of computer vision, real-time video analytics continuously pulls high-definition videos from surveillance cameras and requires high computation, high bandwidth, high privacy, and low latency to analyze the videos. The one viable approach that can meet these strict requirements is edge computing. Looking back to the above evolution of edge computing, it can be foreseen that novel AI applications emerged from the sectors such as IIoT, intelligent robots, smart cities, and smart home will play a crucial role in the popularization of edge computing. This is mainly due to the fact that many mobile and IoT related AI applications represent a family of practical applications that are computation- and energy-intensive, privacy- and delay- sensitive, and thus naturally align well with edge computing.

Due to the superiority and necessity of running AI application on the edge, edge AI has recently received great attention. In December 2017, in a white paper, "A Berkeley View of Systems Challenges for AI" [39] published by the University of California Berkeley, the cloud–edge AI system is envisioned as an important research direction to achieve the goal of mission-critical and personalized AI. In August 2018, edge AI emerges in the Gartner Hype Cycle for the first time [40]. According to Gartners prediction, edge AI is still in the innovation trigger phase, and it will reach a plateau of productivity in the following five to ten years. In the industry, many pilot projects have also been carried out toward edge AI. Specifically, on the edge AI service platform, the traditional cloud providers, such as Google, Amazon, and Microsoft, have launched service platforms to bring the intelligence to the edge, through enabling end devices to run ML inferences with pretrained models locally. On edge AI chips, various high-end chips designated for running ML models have been made commercially available on the market, as exemplified by Google Edge TPU, Intel Nervana NNP, and Huawei Ascend 910 and Ascend 310.

B. Scope and Rating of Edge Intelligence

While the term edge AI or EI is brand new, explorations and practices in this direction have begun early. As aforementioned, in 2009, to demonstrate the benefits of edge computing, Microsoft has built an edge-based prototype to support mobile voice command recognition, an AI application. Albeit the early begin of exploration, there is still not a formal definition for EI.

Currently, most organizations [41], [42] and presses [43] refer to EI as the paradigm of running AI algorithms locally on an end device, with data (sensor data or signals) that are created on the device. While this represents the current most common approach (e.g., with high-end AI chips) toward EI in the real world, it is crucial to note that this definition greatly narrows down the solution scope of EI. Running computation intensive algorithms as exemplified by DNN models locally is very resource-intensive, requiring high-end processors to be equipped in the device. Such a stringent requirement not only increases the cost of EI but is also incompatible and unfriendly to existing legacy end devices that have limited computing capacities.

In this paper, we submit that the scope of EI should not be restricted to running AI models solely on the edge server or device. In fact, as demonstrated by a dozen recent studies, for DNN models, running them with edge-cloud synergy can reduce both the end-to-end latency and energy consumption when compared to the local execution approach. Due to these practical advantages, we believe that such collaborative hierarchy should be integrated into the design of efficient EI solutions. Furthermore, existing thoughts on EI mainly focus on the inference phase (i.e., running the AI model), assuming that the training of the AI model is performed in the power cloud datacenters since the resource consumption of the training phase significantly overweights the inference phase. However, this means that the enormous amount of training data should be shipped from devices or edges to the cloud, incurring prohibitive communication overhead as well as the concern on data privacy.

Instead, we believe that EI should be the paradigm that fully exploits the available data and resources across the hierarchy of end devices, edge nodes, and cloud datacenters to optimize the overall performance of training and inferencing a DNN model. This indicates that EI does not necessarily mean that the DNN model is fully trained or inferenced at the edge but can work in a cloud–edge-device coordination manner via data offloading. Specifically, according to the amount and path length of data offloading, we rate EI into six levels, as shown in Fig. 7. Specifically, the definition of various levels of EI is given as follows.

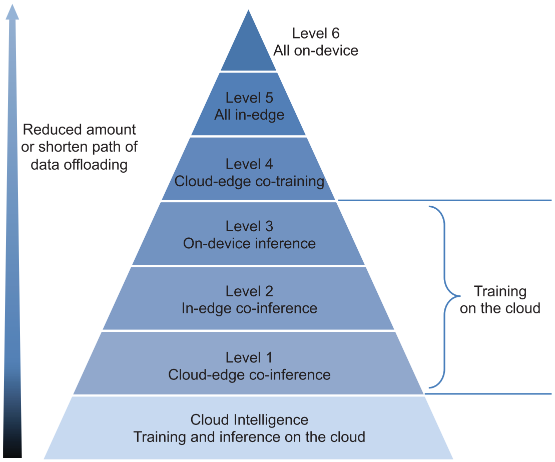
Reduced amount or shorten path of data offloading
Level 6 All on-device
Level 5 All in-edge
Level 4 Cloud-edge co-training
Level 3 On-device inference
Level 2 In-edge co-inference
Level 1 Cloud-edge co-inference
Cloud Intelligence Training and inference on the cloud
Training on the cloud

Fig. 7. ***Six-level rating for EI.***

1) *Cloud Intelligence:* Training and inferencing the DNN model fully in the cloud.
2) *Level 1—Cloud–Edge Coinference and Cloud Training:* Training the DNN model in the cloud, but inferencing the DNN model in an edge-cloud cooperation manner. Here edge-cloud cooperation means that data are partially offloaded to the cloud.
3) *Level 2—In-Edge Coinference and Cloud Training:* Training the DNN model in the cloud, but inferencing the DNN model in an in-edge manner. Here in-edge means that the model inference is carried out within the network edge, which can be realized by fully or partially offloading the data to the edge nodes or nearby devices (via D2D communication).
4) *Level 3—On-Device Inference and Cloud Training:* Training the DNN model in the cloud, but inferencing the DNN model in a fully local on-device manner. Here on-device means that no data would be offloaded.
5) *Level 4—Cloud–Edge Cotraining and Inference:* Training and inferencing the DNN model both in the edge-cloud cooperation manner.
6) *Level 5—All In-Edge:* Training and inferencing the DNN model both in the in-edge manner.
7) *Level 6—All On-Device:* Training and inferencing the DNN model both in the on-device manner.

As the level of EI goes higher, the amount and path length of data offloading reduce. As a result, the transmission latency of data offloading decreases, the data privacy increases, and the WAN bandwidth cost reduces. However, this is achieved at the cost of increased computational latency and energy consumption. This conflict indicates that there is no "best-level" in general; instead, the "best-level" EI is application-dependent and it should be determined by jointly considering multicriteria such as latency, energy efficiency, privacy, and WAN bandwidth cost. In the later sections, we will review enabling techniques as well as existing solutions for different levels of EI.

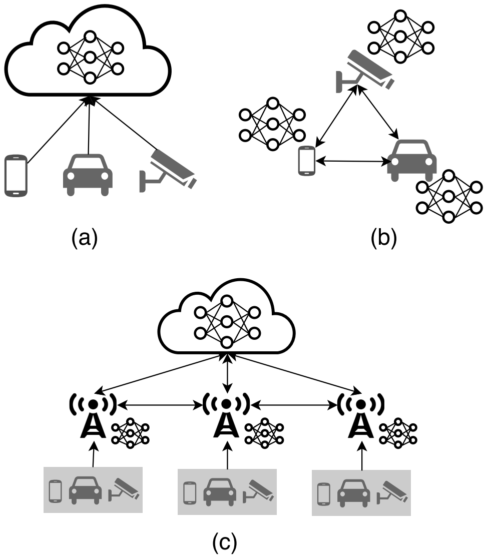

Fig. 8. *Architecture modes of distributed training. (a) Centralized. (b) Decentralized. (c) Hybrid.*

IV. EDGE INTELLIGENCE MODEL TRAINING

With the proliferation of mobile and IoT devices, data, which are essential for AI model training, are increasingly generated at the network edge. In this section, we focus on distributed training of DNN at the edge, including the architectures, key performance indicators, enabling techniques, and existing systems and frameworks.

A. Architectures

The architectures of distributed DNN training at the edge can be divided into three modes: centralized, decentralized, and hybrid (cloud–edge device). Fig. 8 shows the three architectures, illustrated in (a), (b), and (c), respectively. The cloud refers to the central datacenter, whereas the end devices are represented by mobile phones, cars, and surveillance cameras, which are also data sources. For the edge server, we use base stations as the legend.

1) Centralized: Fig. 8(a) describes a centralized DNN training, where the DNN model is trained in the cloud datacenter. The data for training are generated and gathered from distributed end devices such as mobile phones, cars, and surveillance cameras. Once the data are arrived, the cloud datacenter will perform DNN training using these data. Therefore, the system based on the centralized architecture can be identified in cloud intelligence, level 1, level 2, or ;evel 3 in Fig. 7 according to the specific inference mode that the system employs.

2) Decentralized: Under the decentralized mode as shown in Fig. 8(b), each computing node trains its own DNN model locally with local data, which preserves private information locally. To obtain the global DNN model by sharing local training improvement, nodes in the network will communicate with each other to exchange the local model updates. In this mode, the global DNN model can be trained without the intervention of the cloud datacenter, corresponding to the level 5 EI defined in Fig. 7.

3) Hybrid: The hybrid mode combines the centralized mode and the decentralized mode. As shown in Fig. 8(c), as the hub of the architecture, the edge servers may train the DNN model by either decentralized updates with each other or centralized training with the cloud datacenter; thus, the hybrid architecture covers level 4 and level 5 as shown in Fig. 7. The hybrid architecture is also called as cloud–edge device training due to the involved roles.

B. Key Performance Indicators

To better assess a distributed training method, there are six key performance indicators.

1) Training Loss: Essentially, the DNN training process solves an optimization problem that seeks to minimize the training loss. Since the training loss captures the gap between the learned (e.g., predicted) value and the labeled data, it indicates how well the trained DNN model fits the training data. Therefore, it is expected that the training loss can be minimized. Training loss is mainly affected by training samples and training methods.

2) Convergence: The convergence indicator is specialized for the decentralized methods. Intuitively, a decentralized method works only if the distributed training processes converge to a consensus, which is the training result of the method. The term convergence measures whether and how fast a decentralized method converges to such a consensus. Under the decentralized training mode, the convergence value depends on the way the gradient is synchronized and updated.

3) Privacy: When training the DNN model by using the data originated at a massive of end devices, the raw data or intermediate data should be transferred out of the end devices. Obviously, it is inevitable to deal with privacy issues in this scenario. To preserve privacy, it is expected that less privacy-sensitive data is transferred out of the end devices. Whether privacy protection is implemented depends on whether the raw data is offloaded to the edge.

4) Communication Cost: Training the DNN model is data-intensive since the raw data or intermediate data should be transferred across the nodes. Intuitively, this communication overhead increases the training latency, energy, and bandwidth consumption. Communication overhead is affected by the size of the original input data, the way of transmission, and the available bandwidth.

5) Latency: Arguably, latency is one of the most fundamental performance indicators of distributed DNN model training since it directly influences when the trained model is available for use. The latency of the distributed training process typically consists of the computation latency and the communication latency. The computation latency is tightly dependent on the capability of the edge nodes. The communication latency may vary from the size of transmitted raw or intermediate data and the bandwidth of network connection.

6) Energy Efficiency: When training the DNN model in a decentralized manner, both the computation and communication processes consume enormous energy. However, for most end devices, they are energy-constrained. As a result, it is highly desirable that the DNN model training is energy-efficient. Energy efficiency is mainly affected by the size of the target training model and resources of the used devices.

It is worth noting that the performance indicators, training loss and convergence, are common objectives, and thus they may not be explicitly claimed by some literature on DNN training.

C. Enabling Technologies

In this section, we review the enabling technologies for improving one or more of the aforementioned key performance indicators when training the EI model. Table 1 summarizes the highlights of each enabling technology.

1) Federated Learning: Federated learning is dedicated to optimizing privacy issue in the above-mentioned key performance indicators. Federated learning is an emerging yet promising approach to preserve privacy when training the DNN model based on data originated by multiple clients. Rather than aggregating the raw data to a centralized datacenter for training, federated learning [45] leaves the raw data distributed on the clients (e.g., mobile devices) and trains a shared model on the server by aggregating locally computed updates. The main challenges of federated learning are optimization and communication.

For the optimization problem, the challenge is to optimize the gradient of a shared model by the distributed gradient updates on mobile devices. On this issue, federated learning adopts SGD. SGD updates the gradient over extremely small subsets (minibatch) of the whole data set, which is a simple but widely used gradient descent method. Shokri and Shmatikov [46] design a selective SGD (SSGD) protocol, allowing the clients to train independently on their own data sets and selectively share small subsets of their model's key parameters to the centralized aggregator. Since SGD is easy to be parallelized as well as asynchronously executed, SSGD targets both privacy and training loss. Specifically, while preserving client's own privacy, the training loss can be reduced by sharing the models among clients, comparing to training solely on their own inputs. A flaw of [46] is that it does not consider unbalanced and nonindependent identical distribution (non-IID) data. As an extension, McMahan *et al.* [45] advocate a decentralized approach, termed as federated learning, and present FedAvg method for federated learning with the DNN based on iterative model averaging. Here, the iterative model averaging means that the clients update the model locally with one-step SGD and then the server averages the resulting models with weights. The optimization in [45] emphasizes the properties of unbalanced and non-IID since the distributed data may come from various sources.

For the communication problem, it is the unreliable and unpredictable network that poses the challenge of communication efficiency. In federated learning, each client sends a full model or a full model update back to the server in a typical round. For large models, this step is likely to be the bottleneck due to the unreliable network connections. To decrease the number of rounds for training, McMahan *et al.* [45] propose to increase the computation of local updates on clients. However, it is impractical when the clients are under severe computation resources constraint. In response to this issue, Konečný *et al.* [47] propose to reduce communication cost with two new update schemes, namely, structured update and sketched update. In a structured update, the model directly learns an update from a restricted space parametrized using a smaller number of variables, e.g., either low-rank or a random mask. If using a sketched update, the model first learns a full model update and then compressed the update using a combination of quantization, random rotations, and subsampling before sending it to the server.

Though the federated learning technique exploits a new decentralized deep learning architecture, it is built upon a central server for aggregating local updates. Considering the scenario of training a DNN model over a fully decentralized network, i.e., a network without a central server, Lalitha *et al.* [48] propose a Bayesian-based distributed algorithm, in which each device updates its belief by aggregating information from its one-hop neighbors to train a model that best fits the observations over the entire network. Furthermore, with the emerging blockchain technique, Kim *et al.* [49] propose blockchain federated learning (BlockFL) with the devices model update exchanged and verified by leveraging blockchain. BlockFL also works for a fully decentralized network, where the ML model can be trained without any central coordination even when some devices lack their own training data samples.

2) Aggregation Frequency Control: This method focuses on the optimization of communication overhead during the DNN model training. On training deep learning model in edge computing environment, a commonly adopted idea (e.g., federated learning) is to train distributed models locally first and then aggregate updates centrally. In this case, the control of updates aggregation frequency significantly influences the communication overhead. Thus, the aggregation process, including aggregation content as well as aggregation frequency, should be controlled carefully.

Based on the above insight, Hsieh *et al.* [50] develop the Gaia system and the approximate synchronous

Table 1 Technologies for Distributed DNN Training at the Edge

Technology	Highlights	Related Work
Federated Learning	• Leave the training data distributed on the end devices • Train the shared model on the server by aggregating locally-computed updates • Preserve privacy	[44]–[49]
Aggregation Frequency Control	• Determine the best trade-off between local update and global parameter aggregation under a given resource budget • Intelligent communication control	[50]–[52]
Gradient Compression	• Gradient quantization by quantizing each element of gradient vectors to a finite-bit low precision value • Gradient sparsification by transmitting only some values of the gradient vectors	[53]–[57]
DNN Splitting	• Select a splitting point to reduce latency as much as possible • Preserve privacy	[58]–[61]
Knowledge Transfer Learning	• First train a base network (teacher network) on a base dataset and task and then transfer the learned features to a second target network (student network) to be trained on a target dataset and task • The transition from generality to specificity	[59], [60], [62]
Gossip Training	• Random gossip communication among devices • Full asynchronization and total decentralization • Preserve privacy	[63]–[66]

parallel (ASP) model for geodistributed DNN model training. The basic idea of Gaia is to decouple the communication within a datacenter from the communication between datacenters, enabling different communication and consistency models for each. To this end, the ASP model is developed to dynamically eliminate insignificant communication between datacenters, where the aggregation frequency is controlled by the preset significance threshold. However, Gaia focuses on geodistributed datacenters that are capacity-unlimited, making it is not generally applicable to edge computing nodes whose capacity is highly constrained.

To incorporate the capacity constraint of edge nodes, Wang *et al.* [51] propose a control algorithm that determines the best tradeoff between the local update and global parameter aggregation under a given resource budget. The algorithm is based on the convergence analysis of distributed gradient descent and can be applied to federated learning in edge computing with provable convergence. To implement federated learning in the capacity-limited edge computing environment, Nishio and Yonetani [52] study the client selection problem with resource constraints. In particular, an update aggregation protocol named FedCS is developed to allow the centralized server to aggregate as many client updates as possible and to accelerate performance improvement in ML models. An illustration of FedCS is shown in Fig. 9.

3) Gradient Compression: To reduce the communication overhead incurred by decentralized training, gradient compression is another intuitive approach to compress the model update (i.e., gradient information). To this end, gradient quantization and gradient sparsification have been advocated. Specifically, gradient quantization performs lossy compression of the gradient vectors by quantizing each of their elements to a finite-bit low precision value. Gradient sparsification reduces the communication overhead by transmitting part of the gradient vectors.

Lin *et al.* [53] observe that 99.9% of the gradient exchange in distributed SGD (DSGD) are redundant, which demonstrates the power of gradient compression. Based on this observation, Lin *et al.* propose deep gradient compression (DGC), which compresses the gradient by 270–600× for a wide range of CNNs and RNNs. To preserve accuracy during this compression, DGC employs four methods: momentum correction, local gradient clipping, momentum factor masking, and warm-up training.

Inspired by [53], Tao and Li [54] propose edge SGD (eSGD), a family of sparse schemes with both convergence and practical performance guarantees. To improve the first-order gradient-based optimization of stochastic

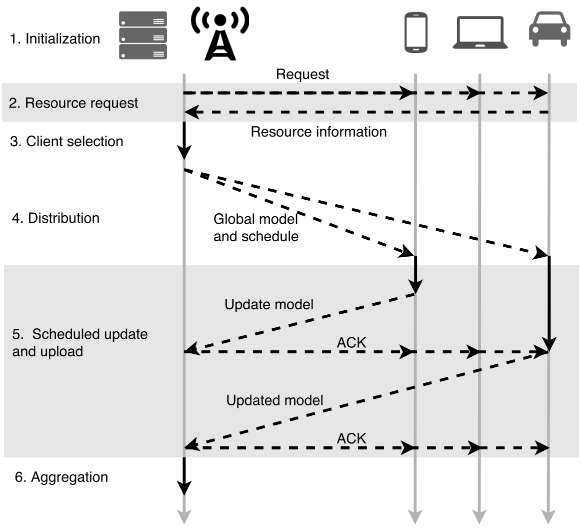

Fig. 9. ***Overview of the FedCS protocol.***

objective functions in edge computing, eSGD includes two mechanisms: 1) determine which gradient coordinates are important and only transmits these coordinates and 2) design momentum residual accumulation for tracking out-of-date residual gradient coordinates in order to avoid low convergence rate caused by sparse updates. A concise convergence analysis of sparsified SGD is given in [55], where SGD is analyzed with k-sparsification or compression (e.g., top-k or random-k). The analysis shows that this scheme converges at the same rate as vanilla SGD when equipped with error compensation (keeping track of accumulated errors in memory). In other words, communication can be reduced by a factor of the dimension of the problem (sometimes even more) while still converging at the same rate.

Quantizing the gradients to low-precision values can also reduce the communication bandwidth. In this regard, Tang *et al.* [56] develop a framework of compressed, decentralized training and propose two different algorithms, called extrapolation compression and difference compression, respectively. The analysis on the two algorithms proves that both converge at the rate of $O(1/\sqrt{nT})$, where n is the number of clients and T is the number of iterations, matching the convergence rate for full precision, centralized training. Amiri and Gunduz [57] implement DSGD at the wireless edge with the help of a remote parameter server and further develop DSGD in digital and analog schemes, respectively. Digital DSGD (D-DSGD) assumes that the clients operate on the boundary of the multiple-access channel (MAC) capacity region at each iteration of the DSGD algorithm and employs gradient quantization and error accumulation to transmit their gradient estimates within the bit budget allowed by the employed power allocation. In analog DSGD (A-DSGD), the clients first sparsify their gradient estimates with error accumulation and then project them to a lower dimensional space imposed by the available channel bandwidth. These projections are transmitted directly over the MAC without employing any digital code.

4) DNN Splitting: The aim of DNN splitting is to protect privacy. DNN splitting protects user privacy by transmitting partially processed data rather than transmitting raw data. To enable a privacy-preserving edge-based training of DNN models, DNN splitting is conducted between the end devices and the edge server. This is based on the important observation that a DNN model can be split inside between two successive layers with two partitions deployed on different locations without losing accuracy.

An inevitable problem on DNN splitting is how to select the splitting point such that distributed DNN training is still under the latency requirement. On this problem, Mao *et al.* [58] utilize the differentially private mechanism and partitions DNN after the first convolutional layer to minimize the cost of mobile devices. The proof in [58] guarantees that applying differentially private mechanism on activations is feasible for outsourcing training tasks to untrusted edge servers. Wang *et al.* [59] consider this problem across mobile devices and cloud datacenters. To benefit from the computation power of cloud datacenters without privacy risks, Wang *et al.* [59] design Arden (privAte infeRence framework based on Deep nEural Networks), a framework that partitions the DNN model with a lightweight privacy-preserving mechanism. By arbitrary data nullification and random noise addition, Arden achieves privacy protection. Considering the negative impact of private perturbation to the original data, Wang *et al.* [59] use a noisy training method to enhance the cloud-side network robustness to perturbed data.

Osia *et al.* [60] introduce a hybrid user-cloud framework on the privacy issue, which utilizes a private-feature extractor as its core component and breaking down large, complex deep models for cooperative, privacy-preserving analytics. In this framework, the feature extractor module is properly designed to output the private feature constrained to keep the primary information while discarding all the other sensitive information. Three different techniques are employed to make sensitive measures unpredictable: dimensionality reduction, noise addition, and Siamese fine-tuning.

When applying DNN splitting for privacy-preserving, it is remarkable that this technique also works for dealing with the tremendous computation of DNN. Exploiting the fact that edge computing usually involves a large number of devices, parallelization approaches are usually employed to manage DNN computation. DNN training in parallel includes two kinds of parallelism: data parallelism and model parallelism. However, data parallelism may bring heavy overhead of communication, while model parallelism usually leads to severe underutilization of computation resources. To address these problems, Harlap *et al.* [61] propose pipeline parallelism, an enhancement to model parallelism, where multiple minibatches are injected into the system at once to ensure efficient and concurrent use of computation resources. Based on pipeline parallelism, Harlap *et al.* [61] design PipeDream, a system that supports pipelined training and automatically determines how to systematically split a given model across the available computing nodes. PipeDream shows the advantage of reducing communication overhead and utilizing computing resource efficiently. The overview of PipeDream's automated mechanism is shown in Fig. 10.

5) Knowledge Transfer Learning: Knowledge transfer learning, or transfer learning for simplicity, is closely connected with DNN splitting technique. In transfer learning, for the purpose of reducing DNN model training energy cost on edge devices, we first train a base network (teacher network) on a base data set, and then, we repurpose the learned features, i.e., transfer them to the second target network (student network) to be trained on a target data set. This process will tend to work if the features are general (i.e., suitable to both base and target tasks)

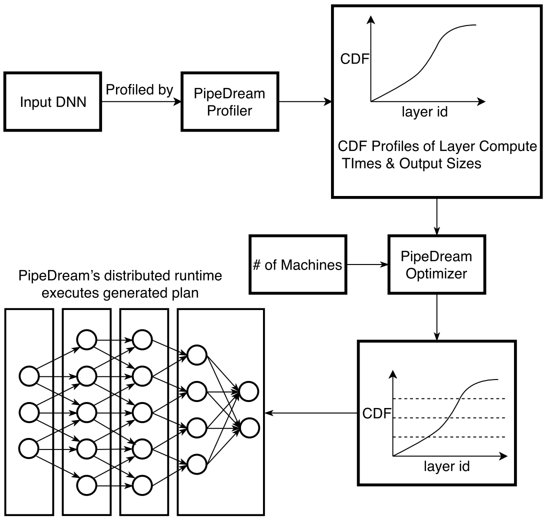
Input DNN
Profiled by
PipeDream Profiler
CDF
layer id
CDF Profiles of Layer Compute TImes & Output Sizes
# of Machines
PipeDream Optimizer
PipeDream's distributed runtime executes generated plan
CDF
layer id

Fig. 10. ***PipeDreams automated mechanism.***

instead of specific to the base task. The transition involves a process from generality to specificity.

The approach of transfer learning seems to be promising for learning on edge devices since it has greatly reduced resource demand, but a thorough investigation on its effectiveness is lacking. To bridge this gap, Sharma *et al.* [62] and Chen *et al.* [44] provide extensive studies on the performance (in both accuracy and convergence speed) of transfer learning, considering different student network architectures and different techniques for transferring knowledge from teacher to student. The result varies with architectures and transfer techniques. A good performance improvement is obtained by transferring knowledge from both the intermediate layers and last layer of the teacher to a shallower student while other architectures and transfer techniques do not fare so well and some of them even lead to negative performance impact.

Transfer learning technique regards the shallow layers of a pretrained DNN on one data set as a generic feature extractor that can be applied to other target tasks or data sets. With this feature, transfer learning is employed in many pieces of research and inspires the design of some frameworks. Osia *et al.* [60], which we have mentioned in Section IVC4, use transfer learning to determine the degree of generality and particularity of a private feature. Arden, proposed in [59], partitions a DNN across the mobile device and the cloud data center, where the raw data are transformed by the shallow portions of the DNN on the mobile device side. As [59] referred, the design of DNN splitting in Arden is inspired by transfer learning.

6) Gossip Training: Aiming at shortening the training latency, gossip training is a new decentralized training method, which is built on randomized gossip algorithms. The early work on random gossip algorithms is gossip averaging [63], which can fast converge toward a consensus among nodes by exchanging information peer to peer. The gossip distributed algorithms enjoy the advantage of full asynchronization and total decentralization as they have no requirement on centralized nodes or variables. Inspired by this, Gossip SGD (GoSGD) [64] is proposed to train DNN models in an asynchronous and decentralized way. GoSGD manages a group of independent nodes, where each of them hosts a DNN model and iteratively proceeds two steps: gradient update and mixing update. Specifically, each node updates its hosted DNN model locally in gradient update step and then shares its information with another randomly selected node in mixing update step, as shown in Fig. 11. The steps repeat until all the DNN converge on a consensus.

The aim of GoSGD is to address the issue of speeding up the training of convolutional networks. Instead, another gossip-based algorithm, gossiping SGD [65], is designed to retain the positive features of both synchronous and asynchronous SGD methods. Gossiping SGD replaces the all-reduce collective operation of synchronous training with a gossip aggregation algorithm, achieving an asynchronous manner.

Both Blot *et al.* [64] and Jin *et al.* [65] apply gossip algorithms on the updates of SGD, but neither of them has performance convergence degradation at large scale. By deployment on large-scale systems, Daily *et al.* [66] show that the trivial gossip-based algorithms at scale lead to a communication imbalance, poor convergence, and heavy communication overhead. To mitigate these issues, Daily *et al.* [66] introduce GossipGraD, a gossip communication protocol-based SGD algorithm that is practical for scaling deep learning algorithms on large-scale systems. GossipGrad reduces the overall communication complexity from $\Theta(\log(p))$ to $O(1)$ and considers diffusion such that computing nodes exchange their updates (gradients) indirectly after every $\log(p)$ steps. It also considers the rotation of communication partners for facilitating direct diffusion of gradients and asynchronous distributed sample shuffling during the feedforward phase in SGD to prevent overfitting.

D. Summary of Existing Systems and Frameworks

In this section, we summary the systems and framework for distributed EI model training on the edge. An overview of the above-mentioned existing systems and frameworks is given in Table 2, including the architecture, EI level, objectives, employed technologies, and effectiveness.

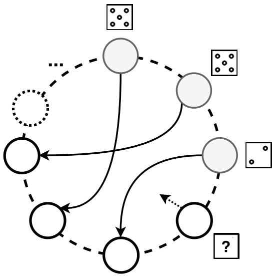

Fig. 11. ***Communication with randomly selected partner in gossip manner.***

Table 2 Overview of Systems and Frameworks on EI Model Training

System or Framework	Architecture	EI Level	Objectives	Employed Technology	Effectiveness
FedAvg [45]	Hybrid	Level-4	• Robustness to non-IID and unbalanced optimization • Low communication cost • Privacy preservation	• Federated Learning • Iterative model averaging	• Reduce communication rounds by 10-100 × as compared to synchronized stochastic gradient descent
SSGD [46]	Hybrid	Level-4	• Jointly training an DNN model among clients • Privacy preservation	• Federated Learning • Selective SGD	• Clients' privacy is preserved while the model accuracy beyond training solely
Zoo [67]	Hybrid	Level-4	• Reducing communication cost • Privacy preservation	• Federated Learning • Composable services	• Processes each image within constant time despite the size difference of images
BlockFL [49]	Decentralized	Level-6	• Federated Learning in decentralized manner • Low latency • Privacy preservation	• Federated Learning • Blockchain	• Latency increase up to 1.5% to achieve the optimal block generation than the simulated minimum latency
Gaia [50]	Centralized	Cloud Intelligence	• Geo-distributed scalability • Intelligent communication mechanism over WANs • Generic and flexible for most machine learning algorithms	• Aggregation frequency control • ASP model	• Speedup 1.8-53.5× over distributed machine learning systems • Within 0.94-1.40× of the speed of running the same machine learning algorithm on machines on a local area network (LAN).
DGC [53]	N/A	N/A	• Reducing the communication bandwidth • High compression rate without losing model accuracy • Fast Convergence	• Gradient Compression • Momentum correction • Local gradient clipping • Momentum factor Masking • Warm-up training	• Achieve a gradient compression ratio from 270× to 600× without losing accuracy • Cut the gradient size of ResNet-50 from 97MB to 0.35MB and for DeepSpeech from 488MB to 0.74MB.
eSGD [54]	Hybrid	Level-4	• Scaling up edge training of CNN • Reducing communication cost	• Selective transmit important gradient coordinates • Momentum residual accumulation	• Reach 91.2%, 86.7%, 81.5% accuracy on MNIST data set with gradient drop ratio 50%, 75%, 87.5% respectively
INCEPTIONN [68]	Hybrid	Level-5	• Maximizing the opportunities for Compression • Avoiding the bottleneck at aggregators	• Lossy gradient compression NIC-integrated compression accelerator • Gradient-centric aggregator-free training	• Reduce the communication time by 70.9%-80.7% • Offer 2.2-3.1× speedup over the conventional training system while achieving the same level of accuracy.
Arden [59]	Centralized	Cloud Intelligence	• Maximize utilization of computing resources • Low latency • Fast convergence	• DNN splitting • Arbitrary data nullification • Random noise addition	• The average reductions compared with the other four DNNs in terms of time, memory, and energy are 60.10%, 92.07%, and 77.05%, respectively
PipeDream [61]	Hybrid	Level-5	• Maximizing utilization of computing resources • Low latency • Fast convergence	• DNN splitting • Pipeline parallelism	• Using 4 machines to train the > 100 million parameter VGG16 on the ImageNet1K dataset, PipeDream converges 2.5× faster than using a single machine and 3× faster than data parallel training
GoSGD [64]	Decentralied	Level-6	• Speeding up DNN training • Fast convergence	• Gossip Training	• Do a better use of the exchanges comparing to EASGD • Converge a lot faster comparing to EASGD
Gossiping SGD [65]	Decentralied	Level-6	• Speeding up DNN training • Scaling up DNN training • Asynchronous training	• Gossip Training • Model partition	• One iteration of gossiping SGD is faster than one iteration of all-reduce SGD • Work quickly at the initial step size.
GossipGraD [66]	Decentralied	Level-6	• Reducing communication complexity • Fast convergence • Privacy preservation	• Gossip Training • Model partition	• Achieve about 100% compute efficiency for ResNet50 using 128 NVIDIA Pascal P100 GPUs while matching the top-1 classification accuracy published in literature.

In general, a key challenge for distributed EI model training is the data privacy issue. It is because the distributed data sources may originate from individual persons and different organizations. For users, they may be sensitive to their own private data, not allowing any private information to be shared. For companies, they have to consider the privacy policy to avoid legal subpoenas and extrajudicial surveillance. Therefore, the design of distributed training systems needs to carefully consider privacy preservation. Systems considering privacy issue in Table 2 include FedAvg, BlockFL, GossipGraD, and so on. The decentralized architecture is naturally friendly to user's privacy, for which the systems that are based on the decentralized architecture such as BlockFL and GossipGraD typically preserve privacy better. By contrast, the centralized architecture involves a centralized data collection operation, and the hybrid architecture requires a data transmission operation. For this reason, the systems based on these two architectures would implement more extra efforts in data privacy protection.

Compared with the DNN training under the cloud-based framework, the DNN training under edge-based framework pays more attention to protecting users' privacy and training an available deep learning model faster. Under cloud-based training, a large amount of raw data generated at the client side is directly transmitted to the cloud data center through the long WAN, which not only causes hidden dangers of user privacy leakage but also consumes huge bandwidth resources. Moreover, in some scenarios such as military and disaster applications when access to the cloud center is impossible, the edge-based training will be highly desirable. On the other hand, the cloud data center can collect a larger amount of data and train an AI model with more powerful resources, and hence, the advantage of cloud intelligence is that it can train a much larger-scale and more accurate model.

V. EDGE INTELLIGENCE MODEL INFERENCE

After the distributed training of deep learning model, the efficient implementation of model inference at the edge will be critical for enabling high-quality EI service deployment. In this section, we discuss the DNN model inference at the edge, including the architectures, key performance indicators, enabling techniques, and existing systems and frameworks.

A. Architectures

Besides the common cloud-based and device-cloud inference architectures, we further define several major edge-centric inference architectures and classify them into

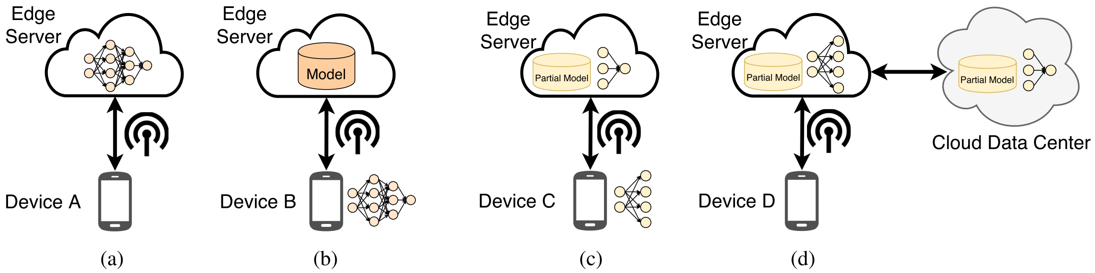

Fig. 12. *Major edge-centric inference modes. (a) Edge-based mode. (b) Device-based mode. (c) Edge-device mode. (d) Edge-cloud mode.*

four DNN model inference modes, namely, edge-based, device-based, edge-device, and edge-cloud modes, which are illustrated in Fig. 12(a)–(d), respectively. We describe the main workflow of each mode as follows.

1) Edge-Based Mode: In Fig. 12(a), device A is in the edge-based mode, which means that the device receives the input data then send them to the edge server. When the DNN model inference is done at the edge server, the prediction results will be returned to the device. In this inference mode, since the DNN model is on the edge server, it is easy to implement the application on different mobile platforms. However, the main disadvantage is that the inference performance depends on network bandwidth between the device and the edge server.

2) Device-Based Mode: In Fig. 12(b), device B is in the device-based mode. The mobile device obtains the DNN model from the edge server and performs the model inference locally. During the inference process, the mobile device does not communicate with the edge server. Therefore, the inference is reliable, but it requires a large amount of resources such as CPU, GPU, and RAM on the mobile device. The performance depends on the local device itself.

3) Edge-Device Mode: In Fig. 12(c), device C is in the edge-device mode. In the edge-device mode, the device first partitions the DNN model into multiple parts according to the current system environmental factors such as network bandwidth, device resource, and edge server workload. Then, the device will execute the DNN model up to a specific layer and send the intermediate data to the edge server. The edge server will execute the remaining layers and sends the prediction results to the device. Compared to the edge-based and device-based modes, the edge-device mode is more reliable and flexible. It may also require huge resource on the mobile device because the convolution layers at the front position of a DNN model are computational-intensive generally.

4) Edge-Cloud Mode: In Fig. 12(d), device D is in the edge-cloud mode. It is similar to the edge-device mode and is suitable for the case that the device is highly resource constrained. In this mode, the device is responsible for input data collection, and the DNN model is executed through edge-cloud synergy. The performance of this model heavily depends on the network connection quality.

We should emphasize that the above-mentioned four edge-centric inference modes can be adopted in a system simultaneously to carry out complex AI model inference tasks (e.g., cloud–edge-device hierarchy), by efficiently pooing heterogeneous resources across a multitude of end devices, edge nodes, and clouds.

B. Key Performance Indicators

To describe the service quality of the EI model inference, we introduce the following five metrics.

1) Latency: Latency refers to the time spent in the whole inference process, including preprocessing, model inference, data transmission, and postprocessing. For some real-time intelligent mobile applications (e.g., AR/VR mobile gaming and intelligent robots), they usually have stringent deadline requirement such as 100-ms latency. Latency indicator is affected by many factors, including the resources on edge devices, the way of data transmission, and the way to execute the DNN model.

2) Accuracy: Accuracy refers to the ratio of the number of the input samples that get the correct predictions from inference to the total number of input samples, reflecting the performance of the DNN models. For some mobile applications requiring a high level of reliability, such as self-driving car and face authentication, they demand the ultrahigh accuracy on the DNN model inference. Besides the DNN model's own inference capability, the inference accuracy depends on the speed of feeding the input data to the DNN model. For a video analytics application, under a fast feeding rate, some input samples may be skipped due to the edge device's constraint resources, causing a drop in accuracy.

3) Energy: To execute a DNN model, compared with the edge server and the cloud data center, the end devices are usually battery-limited. The computation and communication overheads of DNN model inference bring a large amount of energy consumption. For an EI application, energy efficiency is of great importance and is affected by the size of the DNN model and the resources on edge devices.

Table 3 Technologies for Distributed DNN inference at the Edge

Technology	Highlights	Related Work
Model Compression	• Weight pruning and quantization to reduce storage and computation	[70]–[77]
Model Partition	• Computation offloading to the edge server or mobile devices • Latency- and energy-oriented optimization	[10], [78]–[86]
Model Early-Exit	• Partial DNNs model inference • Accuracy-aware	[10], [15], [78], [87]–[91]
Edge Caching	• Fast response towards reusing the previous results of the same task	[92]–[96]
Input Filtering	• Detecting difference between inputs, avoiding abundant computation	[97]–[101]
Model Selection	• Inputs-oriented optimization • Accuracy-aware	[102]–[106]
Support for Multi-Tenancy	• Scheduling multiple DNN-based task • Resource-efficient	[38], [104], [107]–[111]
Application-specific Optimization	• Optimizations for the specific DNN-based application • Resource-efficient	[104], [112]

4) Privacy: IoT and mobile devices generate a huge amount of data, which could be privacy sensitive. Thus, it is also important to protect privacy and data security near the data source for an EI application during the model inference stage. Privacy protection depends on the way of processing the original data.

5) Communication Overhead: Except for the device-based mode, the communication overhead affects the inference performance of the other modes greatly. It is necessary to minimize the overhead during the DNN model inference in an EI application, particularly the expensive WAN bandwidth usage for the cloud. Communication overhead here mainly depends on the mode of DNN inference and the available bandwidth.

6) Memory Footprint: Optimizing the memory footprint of performing DNN model inference on mobile devices is very necessary. On the one hand, typically, a high-precision DNN model is accompanied by millions of parameters, which is very hungry for the hardware resources of mobile devices. On the other hand, unlike high-performance discrete GPUs on the cloud data center, there is no dedicated high-bandwidth memory for mobile GPUs on mobile devices [69]. Moreover, mobile CPUs and GPUs typically compete for shared and scarce memory bandwidths. For the optimization of the DNN inference at the edge side, the memory footprint is a nonnegligible indicator. Memory footprint is mainly affected by the size of the original DNN model and the way of loading the tremendous DNN parameters.

C. Enabling Technologies

In this section, we review the enabling technologies for improving one or more of the aforementioned key performance indicators for EI model inference. Table 3 summarizes the highlights of each enabling technology.

1) Model Compression: To alleviate the tension between resource-hungry DNNs and resource-poor end devices, DNN compression has been commonly adopted to reduce the model complexity and resource requirement, enabling local, on-device inference that, in turn, reduces the response latency and has fewer privacy concerns. That is, the model compression method optimizes the above four indicators; latency, energy, privacy, and memory footprint. Various DNN compression techniques have been proposed, including weight pruning, data quantization, and compact architecture design.

Weight pruning represents the most widely adopted technique of model compression. This technique removes redundant weights (i.e., connections between neurons) from a trained DNN. Specifically, it first ranks the neurons in the DNN according to how much the neuron contributes and then removes the low-ranking neurons to reduce the model size. Since removing neurons damages the accuracy of the DNN, then how to reduce the network size meanwhile preserving the accuracy is the key challenge. For modern large-scale DNNs, a pilot research in [70] tackled this challenge by applying a magnitude-based weight pruning method. The basic idea of this method is as follows: first, remove small weights whose magnitudes are below a threshold (e.g., 0.001) and then fine-tune the model to restore the accuracy. For AlexNet and VGG-16, this method can reduce the number of weights by 9× and 13× with no loss of accuracy on ImageNet. The follow-up work deep compression [71], which blends the advantages of pruning, weight sharing, and Huffman coding to compress DNNs, further pushes the compression ratio to 35–49×.

However, for energy-constrained end devices, the above magnitude-based weight pruning method may not be directly applicable since empirical measurements show that the reduction in the number of weights does not necessarily translate into significant energy saving [72]. This is because for DNNs as exemplified by AlexNet, the energy of the convolutional layers dominates the total energy cost, while the number in the fully connected layers contributes most of the total number of weights in the DNN. This suggests that the number of weights may not be a good indicator for energy, and the weight pruning should be directly energy-aware for end devices. As the first step toward this end, an online DNN energy estimation tool (https://energyestimation.mit.edu/) has been developed by MIT to enable fast and easy DNN energy estimation. This fine-grained tool profiles the energy for the data movement from different levels of the memory hierarchy, the number of MACs, and the data sparsity at the granularity of the DNN layer. Based on this energy estimation tool, an energy-aware pruning method called EAP [73] is proposed.

Another mainstream technique for model compression is data quantization. Instead of adopting the 32-bit floating point format, this technique uses a more compact format to represent layer inputs, weights, or both. Since representing a number with fewer bits reduces memory footprint and accelerates computation, data quantization improves the overall computation and energy efficiency. Most of the prior proposals for quantization tune the bit-width only for a fixed number type in an *ad hoc* manner, which may lead to a suboptimal result. To address this issue, the recent work [76] investigated the problem of optimal number representations at the layer granularity, in terms of finding the optimal bit-width for the canonical format based on the IEEE 754 Standard. This problem is challenging due to the combinatorial explosion of feasible number formats. In response, the authors developed a portable API called number abstract data type (ADT). It enables users to declare the data to be quantized in a layer (e.g., inputs, weights, or both) as number type. By doing so, ADT encapsulates the internal representation of a number, thus separating the concern for developing an effective DNN from the concern of optimizing the number representation at a bit level.

While most existing efforts use a single compression technique, they may not suffice to meet the diverse requirements and constraints on accuracy, latency, storage, and energy imposed by some IoT devices. Emerging studies have shown how different compression techniques can be coordinated to maximally compress DNN models. For example, both deep compression [71] and Minerva [74] combine weight pruning and data quantization to enable fast, low-power, and highly accurate DNN inference. More recently, researchers argue that for a given DNN, the combination of compression techniques should be selected on demand, i.e., adapting to the application-driven system performance (e.g., accuracy, latency, and energy) and the varying resource availability across platforms (e.g., storage and processing capability). To this end, the proposed automatic optimization framework AdaDeep [75] systematically formulates the goals and constraints on accuracy, latency, storage, and energy into a unified optimization problem and leverages DRL to effectively find a good combination of compression techniques.

2) Model Partition: To alleviate the pressure of the EI application execution on end devices, as shown in Fig. 13, one intuitive idea is the model partition, offloading the computational-intensive part to the edge server or the nearby mobile devices, obtaining a better model inference performance. Model partition mainly cares about the issues of latency, energy, and privacy.

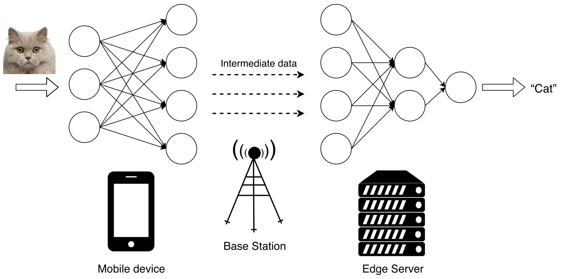

Fig. 13. ***Illustration for model partition between devices and edge server.***

The model partition can be divided into two types: partition between server and device and partition between devices. For the model partition between the server and the device, Neurosurgeon [79] represents an iconic effort. In Neurosurgeon, the DNN model is partitioned between the device and the server, and the key challenge is to figure out one suitable partition point to get the optimal model inference performance. Considering latency aspect and energy efficiency aspect, respectively, the authors propose a regression-based method to estimate the latency of each layer in the DNN model and return an optimal partition point that makes the model inference meet latency requirement or energy requirement.

Hereafter, Ko *et al.* [83] propose an edge-host partitioning method, which combines model partition with lossy feature encoding. That is, the intermediate data after model partition will be compressed using lossy feature encoding before transmission. Also, jointly leveraging model partition and lossy feature encoding, the JALAD [81] framework formulates the model partition as an integer linear programming (ILP) problem to minimize the model inference latency under a guaranteed accuracy constraint. For DNNs those are characterized by a directed acyclic graph (DAG) rather than a chain, optimizing the model partition to minimize the latency is proven to be NP-hard in general. In response, Hu *et al.* [80] propose an approximation algorithm that provides the worst case performance guarantee, based on the graph min-cut method. The above-mentioned frameworks all have an assumption that the server has the DNN model of the EI application. IONN [82] propose an incremental offloading technique for EI application. IONN partitions the DNN layers and incrementally uploads them to allow collaborative DNN model inference by mobile devices and the edge server. Compared to the approach that uploads the entire model, IONN significantly improves query performance and energy consumption during DNN model uploading.

Another type of model partition is the partition between devices. As the pioneering effort of model partition between devices, MoDNN [85] introduces a WiFi direct technique to build a microscale computing cluster in WLAN with multiple authorized WiFi-enabled mobile devices for partitioned DNN model inference. The mobile device that carries the DNN task will be the group owner and the others act as the worker nodes. Two partition schemes are proposed in MoDNN to accelerate DNN layer execution. The experiment shows that with two to four worker nodes, MoDNN accelerates the DNN model inference by 2.17–4.28×. In the follow-up work MeDNN [84], greedy 2-D partition is proposed to adaptively partition the DNN model into multiple mobile devices and utilize a structured sparsity pruning technique to compress the DNN model. MeDNN improves the DNN model inference by 1.86–2.44× with two to four worker nodes and saves 26.5% of additional computing time and 14.2% of extra communication time. Note that DNN layers are partitioned horizontally in MoDNN and MeDNN, whereas DeepThings [86] employs a fused tile partitioning method that partitions the DNN layers vertically to reduce the memory footprint.

DeepX [77] also tries to partition DNN models but it only partitions the DNN model into several submodels and distributes them on local processors. DeepX proposes two schemes: runtime layer compression (RLC) and deep architecture decomposition (DAD). The layer after compression will be executed by specific local processors (CPU, GPU, and DSP). An additional note is that when we have multiple tasks of model partition, we need to make optimization for the scheduler. LEO [113] is a novel sensing algorithm scheduler that maximizes the performance for multiple continuous mobile sensor applications by partitioning the sensing algorithm execution and distributing tasks on CPU, coprocessor, GPU and the cloud.

3) Model Early Exit: A DNN model with a high accuracy usually has a deep structure. It consumes a large number of resources to execute such a DNN model on the end device. To accelerate model inference, the model early-exit method leverages output data of early layer to get the classification result, which means that the inference process is finished by using the partial DNN model. Latency is the optimization target of model early exit.

BranchyNet [87] is a programming framework that implements the model early-exit mechanism. With BranchyNet, the standard DNN model structure is modified by adding exit branches at certain layer locations. Each exit branch is an exit point and shares part of DNN layers with the standard DNN model. Fig. 14 shows a CNN model with three five points. The input data can be classified at these diverse early-exit points.

Based on BranchyNet, a framework named DDNNs [88] for distributed DNNs across the cloud, edge, and devices is proposed. DDNNs have a three-layer structure framework, including device layer, edge server layer, and cloud layer. Each layer represents an exit point of BranchyNet. Three aggregation methods, including max pooling (MP), average pooling (AP), and concatenation (CC), are proposed. The aggregation methods work when multiple mobile devices send intermediate to an edge server or when multiple edge servers send intermediate data to the cloud data center. MP aggregates the data vectors by taking the maximum of each component. AP aggregates the data vectors by taking the average of each component. CC just simply concatenates the data vectors as one vector. Also, built on top of BranchyNet, Edgent [10] is proposed to navigate the accuracy-latency tradeoff when jointly applying model early-exit and model partition. The basic idea of Edgent is to maximize the accuracy under a given latency requirement via the regression-based layer latency prediction model.

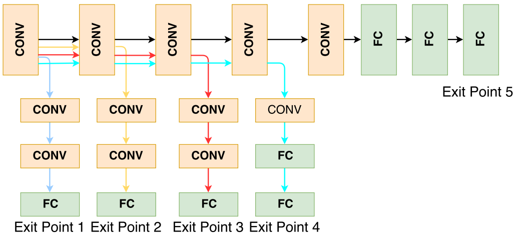

Fig. 14. ***CNN model with five exit points.***

In addition to BranchyNet, there are different methods to implement model early exit. For example, the cascading network [91] simply adds the MP layer and fully connected layer to the standard DNN model and achieves a speedup of 20%. DeepIns [15] proposes a manufacture inspection system for the smart industry using DNN model early exit. In DeepIns, edge devices are responsible for data collection, the edge server acts as the first exit point, and the cloud data center acts as the second exit point. Then, Lo *et al.* [90] propose adding an authentic operation (AO) unit to the basic BranchyNet model. The AO unit determines whether an input has to be transferred to the edge server or cloud data center for further execution by setting different threshold criteria of a confidence level for different DNN model output classes. Bolukbasi *et al.* [89] train a policy that determines whether the current samples should proceed to the next layer by adding regularization to the evaluation latency of the DNN model.

4) Edge Caching: Edge caching is a new kind of method used to accelerate DNN model inference, i.e., optimizing the latency issue by caching the DNN inference results. The core idea of edge caching is to cache and reuse the task results such as the prediction of image classification at the network edge, reducing the querying latency of EI application. Fig. 15 shows the basic process of the semantic cache technique; if the request from mobile devices hits the cached results stored in the edge server, the edge server will return the result, otherwise, the request will be transferred to the cloud data center for inference with the model of full precision.

Glimpse [92] is a pioneering effort to introduce cache technique to DNN inference task. For an object detection application, Glimpse proposes to reuse the stale detection result to detect the object on current frames. The results

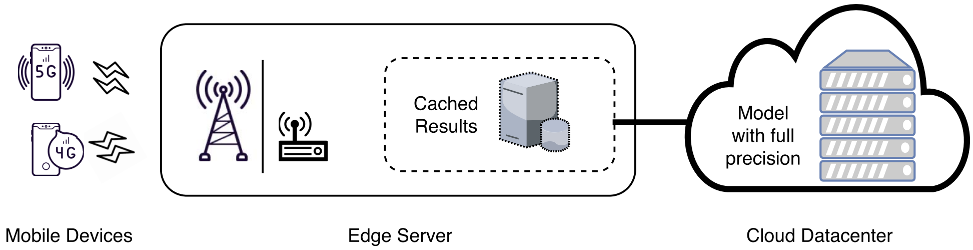

Fig. 15. ***Process of the semantic cache technique.***

of the detected object of the stale frames are cached on the mobile devices, and then, Glimpse extracts a subset of these cached results and computes the optical flow of features between the processed frames and the current frame. The computing results of optical flow will guide us to move the bounding box to the right location in the current frame. Glimpse achieves an acceleration of 1.6–5.5×.

However, caching results locally do not scale beyond tens of images, then Cachier [93] is proposed to achieve recognition of thousands of objects. In Cachier, results of EI application are cached in the edge server, storing the features of input (e.g., image) and the corresponding task results. Then, Cachier uses the least frequently used (LFS) as the cache replacement strategy. If the input cannot hit the cache, the edge server will transfer the input to the cloud data center. Cachier can increase responsiveness by 3× or more. Precog [94] is the extension of Cachier. In Precog, the cached data are not only stored in the edge server but also in the mobile device. Precog uses predictions of Markov chains to prefetch data onto the mobile device and reach a speedup of 5×. In addition, Precog also proposes to dynamically adjust the cached feature extraction model on the mobile device according to the environment information. Shadow Puppets is another improved version of Cachier. Cachier extracts features from the input using the standard feature extraction like locality-sensitive hashing (LSH), but these features may not reflect the similarity as precise as the human dose. Then, in Shadow Puppets [96], it uses a small-footprint DNN to generate hash codes to represent the input data and get a remarkable latency improvement of 5–10×.

Considering the application scenario that the same application runs on multiple devices in close proximity and the DNN model often processes similar input data, FoggyCache [95] is proposed to minimize these redundant computations. There are two challenges in FoggyCache: one is that the input data distribution is unknown so the problem is how to index the input data with a constant lookup quality and the other is how to represent the similarity of the input data. To address these two challenges, FoggyCache proposes adaptive LSH (A-LSH) and homogenized kNN (H-kNN) schemes, respectively. FoggyCache reduces computation latency and energy consumption by a factor of 3× to 10×.

5) Input Filtering: Input filtering is an efficient method to accelerate DNN model inference, especially for the video analytics. As shown in Fig. 16, the key idea of input filtering is to remove the nontarget-object frames of input data, avoiding redundant computation of the DNN model inference, thus improving inference accuracy, shortening inference latency, and reducing energy cost.

NoScope [97] is proposed to accelerate video analysis by skipping the frames that have little change. To this end, NoScope implements a difference detector that highlights temporal differences across frames, for example, the detector monitors the frames to check whether cars appear in the frames and the frame with cars will be processed in the DNN model inference. The difference is detected by using lightweight binary classifiers. In a scenario of continuous video transmission from a swarm of drones, Wang *et al.* [98] optimize for the first hop wireless bandwidth of DNN inference. In particular, four strategies are proposed to reduce total transmission: EarlyDiscard, Just-in-Time-Learning (JITL), Reachback, and Context-Aware.

FFS-VA [100] is a pipelined system for multistage video analytics. There are three stages to build the filtering system of FFS-VA. The first is a stream-specialized different detector (SDD) that is used to remove the frames only containing a background. The second is a stream-specialized network model (SNM) to identify target-object frames. The third is a Tiny-YOLO-Voc (T-YOLO) model to remove the frames whose target objects are fewer than a threshold. Canel *et al.* [101] propose a two-stage filtering system for video analytics. It first extracts the semantic content of the frames by outputting the intermediate data of DNN, and then, these output features are accumulated in a frame buffer. The buffer is viewed as a DAG, and the filtering system uses the Euclidean distance as the similarity metric to figure out top-k interesting frames.

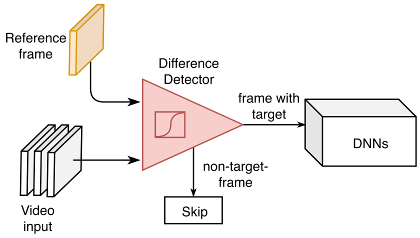

Fig. 16. ***Workflow of input filtering.***

The above-mentioned frameworks focus on filtering uninteresting frames of a video stream for a single camera. ReXCam [99] accelerates DNN model inference on cross-camera analytics. The ReXCam leverages a learned spatiotemporal model to filter video frames. ReXCam reduces computation workload by 4.6× and improves DNN model inference accuracy by 27%.

6) Model Selection: Model selection method is proposed to optimize the DNN inference issue of latency, accuracy, and energy. The main idea of model selection is that we can first train a set of DNN models for the same task with various model sizes offline and then adaptively select the model for inference online. Model selection is similar to the model early exit, and the exit point of the model early-exit mechanism can be viewed as a DNN model. However, the key difference is that the exit point shares part of DNN layers with the main branch model, and the models in the model selection mechanism are independent.

Park *et al.* [102] propose a big/little DNN model selection framework. That is, a little and fast model is used to try to classify the input data and the big model is only used when the confidence of the little model is less than a predefined threshold. Taylor *et al.* [103] point out that different DNN models (e.g., MobileNet, ResNet, and Inception) reach the lowest inference latency or highest accuracy on different evaluation metrics (top-1 or top-5) for different images. Then, they propose a framework for selecting the best DNN in terms of latency and accuracy. In this framework, a model selector is trained to select the best DNN for different input images. Similarly, IF-CNN [105] also trains a model selector called the recognition predictor (RP) to change the model used in the task. RP is a DNN model of multitask, meaning that RP has multiple outputs. The output of RP represents the probability of top-1 label of each candidate DNN model. The input of RP is the image and if the output of RP is over the predefined threshold, the corresponding DNN model will be selected.

Besides the optimization for DNN model inference latency, aiming at energy saving, Stamoulis *et al.* [106] cast the adaptive DNN model selection issue as a hyperparameter optimization problem by taking into account the accuracy and communication constraints imposed by the devices. Then, a Bayesian optimization (BO) is adopted to solve this problem, achieving an improvement by up to 6× in terms of minimum energy per image under accuracy constraints.

7) Support for Multitenancy: In practice, an end or edge device typically runs more than one DNN applications concurrently. For example, the advanced driver-assistance system (ADAS) for Internet vehicles simultaneously runs DNN programs for vehicle detection, pedestrian detection, traffic sign recognition, and lane line detection. In this case, multiple DNN applications would compete for limited resource. Without careful support for multitenancy, i.e., resource allocation and task scheduling for those concurrent applications, the global efficiency would be greatly deteriorated. The support for multitenancy focuses on the optimization of energy and memory footprint.

Taking the dynamics of runtime resources into consideration, NestDNN [107] is proposed to offering flexible resource–accuracy tradeoffs for each DNN model. NestDNN implements a new model pruning and recovery scheme, transforming the DNN model into a single compact multicapacity model that consists of a set of descendent models. Each descendent model offers a unique resource–accuracy tradeoff. For each concurrent descendent model, NestDNN encodes its accuracy and latency into a cost function and then builds a resource–accuracy runtime scheduler to make the optimal tradeoff for each concurrent descendent model. Also, addressing the challenge of enabling flexible tradeoffs, Mainstream [110] uses the popular transfer-learning DNN training method to train multiple DNN models with different degrees of accuracy and implements a greedy approach to find the optimal scheduler that fits the cost budget. For multiple DNN model executions on one single device, HiveMind [111] is proposed to improve the GPU utilization for these concurrent workloads. HiveMind consists of two key components: a compiler and a runtime module. The compiler optimizes the data transmission, data preprocessing, and computation across the workloads, and then, the runtime module transforms the optimized models into an execution DAG, which will be executed on the GPU while trying to extract as much concurrency as possible.

At a finer granularity, DeepEye [108] is proposed to optimize the inference of multitask on the mobile device by scheduling the executions of heterogeneous DNN layers. DeepEye first segregates DNN layers of all tasks into two pools: convolution layers and fully connected layers. For the convolution layers, a first-in(endash)first-out (FIFO) queue-based execution strategy is employed. For the fully connected layers, DeepEye adopts a greedy approach for caching the parameters of the fully connected layers to maximize memory utilization.

8) Application-Specific Optimization: While the above-mentioned optimizing techniques are generally applicable to EI applications, application-specific optimization can be exploited to further optimize the performance of EI applications, i.e., accuracy, latency, energy, and memory footprint. For example, for video-based applications, two knobs, i.e., frame rate and resolution, can be flexibly adjusted to reduce resource demand. However, since such resource-sensitive knobs also deteriorate the inference accuracy, they naturally incur a cost-accuracy tradeoff. This requires us to strike a good balance between the resource cost and inference accuracy when tuning the video frame rate and resolution.

Toward the above goal, Chameleon [104] adjusts the knobs for each video analytic task by sharing the best top-k configuration between each task. In Chameleon, the video tasks are grouped according to the spatial correlation, and then, the leader of the group will search for the best top-k configurations and share them with the followers. DeepDecision [112] formulates the knob-tunning problem as a multiple-choice multiple-constraint knapsack program and solves it with an improved brute-force search method.

It is also worth noting that, in the computer architecture community, hardware acceleration for efficient DNN inference has been a very hot topic and gathered extensive research efforts. Interested readers are encouraged to refer to the recent monograph [114] for more comprehensive discussions about recent advancements on hardware acceleration for DNN processing.

D. Summary of Existing Systems and Frameworks

To showcase the application of the above enabling techniques for EI model inference, the relevant systems and frameworks are summarized in Table 4, including the perspectives of target applications, architecture and EI level, optimization objectives and adopted techniques, as well as effectiveness.

Clearly, the existing systems and frameworks have adopted different subsets of enabling techniques tailored to specific EI applications and requirements. To maximize the overall performance of a generic EI system, comprehensive enabling techniques and various optimization methods should work in a cooperative manner to provide rich design flexibility. Nevertheless, we would face a high-dimensional configuration problem that is required to determine a large number of performance-critical configuration parameters in real time. Taking video analytics, for example, the high-dimensional configuration parameters can include video frame rate, resolution, model selection, and model early exit. Due to the combinatorial nature, the high-dimensional configuration problem involves a huge search space of parameters and is very challenging to tackle.

VI. FUTURE RESEARCH DIRECTIONS

Based on the comprehensive discussions above on existing efforts, we now articulate the key open challenges and future research directions for EI.

A. Programming and Software Platforms

Currently, many companies around the world focus on the AI cloud computing service provisioning. Some leading companies are also starting to provide programming/software platforms to deliver edge computing services, such as Amazon's Greengrass, Microsoft's Azure IoT Edge, and Google's Cloud IoT Edge. Nevertheless, currently, most of these platforms mainly serve as relays for connecting to the powerful cloud data centers.

As more and more AI-driven computation-intensive mobile and IoT applications are emerging, EI as a service (EIaaS) can become a pervasive paradigm and EI platforms with powerful edge AI functionalities will be developed and deployed. This is substantially different from ML as a service (MLaaS) provided by public clouds. Essentially, MLaaS belongs to cloud intelligence and it focuses on selecting the proper server configuration and ML framework to train model in the cloud in a cost-efficient manner. While in a sharp contrast, EIaaS concerns more about how to perform model training and inference in resource-constrained and privacy-sensitive edge computing environments. To fully realize the potential of EI services, there are several key challenges to overcome. First, the EI platforms should be heterogeneity-compatible. In the future, there are many dispersive EI service providers/vendors, and the common open standard should be set such that users can enjoy seamless and smooth services across heterogeneous EI platforms anywhere and anytime. Second, there are many AI programming frameworks available (e.g., Tensorflow, Torch, and Caffe). In the future, the portability of the edge AI models trained by different programming frameworks across heterogeneously distributed edge nodes should be supported. Third, there are many programming frameworks designed specifically for edge devices (e.g., TensorFlow Lite, Caffe2, CoreML, and MXNet); however, empirical measurements [115] show that there is no single winner that can outperform other frameworks in all metrics. A framework that performs efficiently on more metrics can be expected in the future. Last but not least, lightweight virtualization and computing techniques such as container and function computing should be further explored to enable efficient EI service placement and migration over resource-constrained edge environments.

B. Resource-Friendly Edge AI Model Design

Many existing AI models such as CNN and LSTM were originally designed for applications such as computer vision and natural language processing. Most of the deep learning-based AI models are highly resource-intensive, which means that powerful computing capability supported by abundant hardware resources (e.g., GPU, field-programmable gate array (FPGA), and TPU) is important to boost the performance of these AI models. Therefore, as mentioned above, there are many studies to exploit model compression techniques (e.g., weight pruning) to resize the AI models, making them more resource-friendly for edge deployment.

Along with a different line, we can promote a resource-aware edge AI model design. Instead of utilizing the existing resource-intensive AI models, we can leverage the AutoML idea [116] and the neural architecture search (NAS) techniques [117] to devise resource-efficient edge AI models tailored to the hardware resource constraints of the underlying edge devices and servers. For example, methods such as RL, genetic algorithm, and BO can be adopted to efficiently search over the AI model design parameter space (i.e., AI model components and their connections) by taking into account the impact of hardware resource (e.g., CPU and memory) constraints on the performance metrics such as execution latency and energy overhead.

Table 4 Overview of Systems and Frameworks on EI Model Inference

System or Framework	Application	Architecture	EI Level	Objectives	Optimization Technology	Online/Offline	Effectiveness
VideoEdge [38]	Video Analytics	Cloud-Edge-Device	Level-1	● Accuracy ● Resource cost	● Frame rate adaptation ● Resolution adaptation ● Multi-tenancy ● Service placement	Online	● Accuracy improvement: 5.4-25.4×
Chameleon [104]	Video Analytics	Device-cloud	Level-1	● Accuracy ● Resource cost	● Frame rate adaptation ● Resolution adaptation ● Model selection	Online	● Resource reduction: 2-3×
DeepX [77]	Mobile Sensing Apps	On Device	Level-2	● Accuracy ● Energy	● Model compression ● Model partition	Online	● Energy reduction: 7.12-26.7×
Edgent [10]	N/A	Device-Edge	Level-2	● Accuracy ● Latency	● Early-exit ● Model partition	Offline	● Accuracy improvement
AdaDeep [75]	N/A	On Device	Level-3	● Accuracy ● Energy ● Storage	● Model compression	Online	● Latency reduction: 9.8× ● Energy reduction: 4.3× ● Storage reduction: 38×
DeepIns [15]	IIoT	Edge-Cloud	Level-1	● Accuracy ● Latency	● Early-exit	Offline	● Latency reduction: 0.98-1.21x
Neurosurgeon [79]	N/A	Device-Cloud	Level-1	● Latency ● Energy	● Model partition	N/A	● Latency reduction: 3.1-40.7× ● Energy reduction: 59.5%-94.7%
Minerva [74]	N/A	On Device	Level-3	● Energy	● Hardware Acceleration ● Model Compression	Offline	● Energy saving: 8×
FoggyCache [95]	IIoT	Device-Edge	Level-2	● Accuracy ● Latency	● Edge Caching	Online	● Latency reduction: 3-10×x ● Energy reduction: 3-10×
NoScope [97]	Video Analytics	Cloud	Cloud Intelligence	● Latency	● Input filtering	N/A	● Latency reduction: 265-15500×
JALAD [81]	N/A	Device-Cloud	Level-1	● Latency	● Model compression ● Model partition	Offline	● Latency reduction: 1-25.1×
DDNNs [88]	N/A	Cloud-Edge-Device	Level-1	● Latency ● Accuracy	● Model selection	N/A	● Latency reduction: over 20×
FFS-VA [100]	Video Analytics	On Device	Level-3	● Latency	● Input filtering ● Multi-tenancy	N/A	● Latency reduction: 3× ● Throughput improvement: more than 7×
Cachier [93]	N/A	Cloud-Edge	Level-1	● Throughput	● Edge Caching	N/A	● Throughput improvement: more than 3×
Taylor et al. [103]	N/A	On Device	Level-3	● Accuracy ● Latency	● Input filtering ● Model selection	N/A	● Accuracy improvement: 7.52% ● Latency reduction: 1.8×
DeepDecision [112]	Video Analytics	Cloud-Edge	Level-1	● Accuracy ● Latency ● Energy	● Application-level optimization ● Model selection	N/A	● Latency reduction: 2-10×

C. Computation-Aware Networking Techniques

For EI, computation-intensive AI-based applications are typically run on the distributed edge computing environment. As a result, advanced networking solutions with computation awareness are highly desirable, such that the computation results and data can be efficiently shared across different edge nodes.

For the future 5G networks, the ultrareliable low-latency communication (URLLC) has been defined for mission-critical application scenarios that demand low delay and high reliability. Therefore, it will be promising to integrate the 5G URLLC capability with edge computing to provide ultrareliable low-latency EI (URLL-EI) services. Also, advanced techniques such as software-defined network and network function virtualization will be adopted in 5G. These techniques will enable flexible control over the network resources for supporting on-demand interconnections across different edge nodes for computation-intensive AI applications.

On the other hand, autonomous networking mechanism design is important to achieve efficient EI service provisioning under dynamic heterogeneous network coexistence (e.g., LTE/5G/WiFi/LoRa), allowing newly added edge nodes and devices to self-configure in the plug and play manner. Also, the computation-aware communication techniques are starting to draw attention, such as gradient coding [118] to mitigate straggler effect in distributed learning and over-the-air computation for DSGD [119], which can be useful for edge AI model training acceleration.

D. Tradeoff Design With Various DNN Performance Metrics

For an EI application with a specific mission, there is usually a series of DNN model candidates that are capable of finishing the task. However, it is difficult for software developers to choose an appropriate DNN model for the EI application because the standard performance indicators such as top-k accuracy or mean average precision fail to reflect the runtime performance of DNN model inference on edge devices. For instance, during the EI application deployment phase, beside accuracy, inference speed and resource usage are also critical metrics. We need to explore the tradeoffs between these metrics and identify the factors that affect them.

For the object recognition application, Huang *et al.* [120] investigate the influence of the main factors, e.g., number of proposals, input image size, and the selection of feature extractor, on inference speed and accuracy. Based on their experiment results, a new combination of these factors is found to outperform the state-of-the-art method. Therefore, it is necessary to explore the tradeoffs between different metrics, helping in improving the efficiency of deploying EI application.

E. Smart Service and Resource Management

By the distributed nature of edge computing, edge devices and nodes that offer EI functionality are dispersive across diverse geolocations and regions. Different edge devices and nodes may run different AI models and deploy different specific AI tasks. Therefore, it is important to design efficient service discovery protocols such that users can identify and locate the relevant EI service providers to fulfill their need in a timely manner. Also, to fully exploit the dispersive resource across edge nodes and devices, the partition of complex edge AI models into small subtasks and efficiently offloading these tasks among the edge nodes and devices for collaborative executions are essential.

Since for many EI application scenarios (e.g., smart cities), the service environments are of high dynamics and it is hard to accurately predict future events. As a result, it would require the outstanding capability of online edge resource orchestration and provisioning to continuously accommodate massive EI tasks. Real-time joint optimization of heterogeneous computation, communication, and cache resource allocations and the high-dimensional system parameter configuration (e.g., choosing the proper model training and inference techniques) tailored to diverse task demands are critical. To tackle the algorithm design complexity, an emerging research direction is to leverage the AI techniques such as DRL to adapt efficient resource allocation policy in a data-driven self-learning way.

F. Security and Privacy Issues

The open nature of edge computing imposes that the decentralized trust is required such that the EI services provided by different entities are trustworthy [121]. Thus, lightweight and distributed security mechanism designs are critical to ensure user authentication and access control, model and data integrity, and mutual platform verification for EI. Also, it is important to study novel secure routing schemes and trust network topologies for EI service delivery when considering the coexistence of trusted edge nodes with malicious ones.

On the other hand, the end users and devices would generate a massive volume of data at the network edge, and these data can be privacy sensitive since they may contain user's location data, health or activities records, or manufacturing information, among many others. Subject to the privacy protection requirement, e.g., EU's General Data Protection Regulation (GDPR), directly sharing the original data sets among multiple edge nodes can have a high risk of privacy leakage. Thus, federated learning can be a feasible paradigm for privacy-friendly distributed data training such that the original data sets are kept in their generated devices/nodes and the edge AI model parameters are shared. To further enhance the data privacy, more and more research efforts are devoted to using the tools of differential privacy and homomorphic encryption and secure multiparty computation for designing privacy-preserving AI model parameter-sharing schemes [122].

G. Incentive and Business Models

EI ecosystem will be a grand open consortium that consists of EI service providers and users, which can include but not limited to: platform providers (e.g., Amazon), AI software providers (e.g., SenseTime), edge device providers (e.g., Hikvision), network operators (e.g., AT&T), data generators (e.g., IoT and mobile device owners), and service consumers (i.e., EI users). The high-efficiency operation of EI services may require close collaboration and integration across different service providers, e.g., for implementing expanded resource sharing and smooth service handover. Thus, proper incentive mechanism and business model are essential to stimulate effective and efficient cooperation among all members of the EI ecosystem. Also, for EI service, a user can be a service consumer and, meanwhile, a data generator as well. In this case, a novel smart pricing scheme is needed to factorize user's service consumption and the value of its data contribution.

As a means for decentralized collaboration, blockchain with a smart contract may be integrated into EI service by running on decentralized edge servers. It is worthwhile to do research on how to smartly charge the price and properly distribute the revenue among the members in the EI ecosystem according to their proof of work. Also, designing resource-friendly lightweight blockchain consensus protocol for EI is highly desirable.

VII. CONCLUSION

Driving by flourishing of both AI and IoT, there is a stringent need to pushing the AI frontier from the cloud to the network edge. To fulfill this trend, edge computing has been widely recognized as a promising solution to support computation-intensive AI applications in resource-constrained environments. The nexus between edge computing and AI gives birth to the novel paradigm of EI.

In this paper, we conducted a comprehensive survey of the recent research efforts on EI. Specifically, we first reviewed the background and motivation for AI running at the network edge. We then provided an overview of the overarching architectures, frameworks, and emerging key technologies for the deep learning model toward training and inference at the network edge. Finally, we discussed the open challenges and future research directions on EI. We hope this survey is able to elicit escalating attentions, stimulate fruitful discussions, and inspire further research ideas on EI. ■

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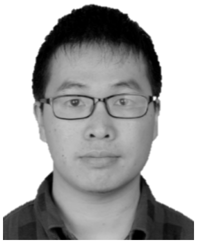

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