Fog-enabled Edge Learning for Cognitive Content-Centric Networking in 5G

Gaolei Li, Jianhua Li, and Jun Wu

Abstract—By caching content at network edges close to the users, the content-centric networking (CCN) has been considered to enforce efficient content retrieval and distribution in the fifth generation (5G) networks. Due to the volume, velocity, and variety of data generated by various 5G users, an urgent and strategic issue is how to elevate the cognitive ability of the CCN to realize context-awareness, timely response, and traffic offloading for 5G applications. In this article, we envision that the fundamental work of designing a cognitive CCN (C-CCN) for the upcoming 5G is exploiting the fog computing to associatively learn and control the states of edge devices (such as phones, vehicles, and base stations) and in-network resources (computing, networking, and caching). Moreover, we propose a fog-enabled edge learning (FEL) framework for C-CCN in 5G, which can aggregate the idle computing resources of the neighboring edge devices into virtual fogs to afford the heavy delay-sensitive learning tasks. By leveraging artificial intelligence (AI) to jointly processing sensed environmental data, dealing with the massive content statistics, and enforcing the mobility control at network edges, the FEL makes it possible for mobile users to cognitively share their data over the C-CCN in 5G. To validate the feasibility of proposed framework, we design two FEL-advanced cognitive services for C-CCN in 5G: 1) personalized network acceleration, 2) enhanced mobility management. Simultaneously, we present the simulations to show the FEL’s efficiency on serving for the mobile users’ delay-sensitive content retrieval and distribution in 5G.

Keywords—Content-centric networking (CCN); 5G networks; cognitive ability; fog-enabled edge learning (FEL); artificial intelligence (AI)

I. INTRODUCTION

For the past decades, the great success of mobile Internet has brought many innovations on the modernization of cities and industries. Nowadays, to meet the various communication requirements in the “Internet of Everything” era, many attempts are underway to design the green fifth generation (5G) mobile communication services that will be equipped with strong cognitive ability. Among these research attempts, content-centric networking (CCN), as a novel networking paradigm for data transmission, can provide guarantee for efficient content retrieval and distribution among a large amount of 5G users. The key functionalities of CCN contain content naming and in-network caching [1]. In CCN, the data are delivered based on the data names instead of the conventional addressing packets. Meanwhile, the popular data can be cached close to requesters intelligently. Moreover, since the CCN makes it possible for content providers to directly percept which content is the users most interested in and neglect who is the most frequent connector, it can be envisioned that the CCN have great capacity for utilization by the upcoming 5G [2, 3]. In addition, international telecommunication union (ITU) also gives a lot of attention on CCN in 5G and contributes a significant recommendation standard for 5G named “data aware networking (information centric networking)-requirements and capabilities” [4].

However, there are many novel challenges in deploying the current CCN in 5G. Firstly, due to the volume, velocity, and variety of data generated by various 5G users, an urgent and strategic issue is how to elevate the cognitive ability of the CCN to realize context-awareness, timely response, and traffic offloading for 5G applications. In the 5G area, the cognitive ability means that a network element can associate the application context with the states of in-network resources (e.g., storage, networking, and computing) to cognitively produce an optimized transmission decision for the requested data. Secondly, as each mobile user acting as a CCN node in 5G can exploit their smart terminals to generate, process, and share the data (e.g., electricity, picture, and video), integrating the cognitive ability into such a decentralized architecture will bring some additional computing tasks such as jointly processing the sensed data, dealing with the massive content statistics, and enforcing mobility control for terminals [5, 6]. But, these resource-limited and mobile terminals may not have sufficient computing resources to provide guarantees for handling these heavy additional computing tasks [7].

To address these issues, this article explores the unified orchestration of the edge network resources (computing, networking, and caching) to achieve the cognitive content-centric networking (C-CCN) in 5G. Specifically, we propose a fog-enabled edge learning framework, which contains the following three features: 1) The idle computing resources of edge network elements are aggregated into virtual fogs and scheduled to cognitively handle the local delay-sensitive learning tasks; 2) These learning tasks are dynamically placed on different virtual fogs according to the context limitations (such as computing price, caching cost and communication delay); and 3) The context limitations are perceived by using artificial intelligence (AI) to analyze the massive statistics such as public scenario description, real-time observations, and users feedback in the whole CCN. Fig. 1 shows the basic framework of fog-enabled edge learning (FEL) for C-CCN in 5G. Each 5G entity will be equipped with CCN, AI, and fogs. The FEL exploit the AI to process the cached content of CCN at the local fogs. The FEL makes each 5G entity acting as a CCN node can cognitively cache and offload network traffic.

The remainder of this article is structured as follows. We

Gaolei Li, Jianhua Li, and Jun Wu were with the School of Information Security Engineering, Shanghai Jiao Tong University, Shanghai Key Laboratory of Integrated Administration Technologies for Information Security, Shanghai, China. Corresponding author: Jun Wu (junwuhn@sjtu.edu.cn)
comprehensively review the recent advances in integration of fog computing, content-centric networking, and artificial intelligence in 5G. We describe the proposed framework of fog-enabled edge learning (FEL) for C-CCN in 5G. Based on the FEL framework, the C-CCN in 5G will enable personalized network acceleration, enhanced mobility control and energy saving. And also, the simulation results are given and discussed to show the FEL's efficiency. Finally, we conclude this article.

II. INTEGRATION OF FOG COMPUTING, ARTIFICIAL INTELLIGENCE, AND CONTENT-CENTRIC NETWORKING IN 5G

The FEL framework for C-CCN in 5G is motivated by the integration of fog computing, content-centric networking, and artificial intelligence in 5G. The system of FEL is illustrated as shown in Fig. 2. It gives a unified orchestration of edge resources in 5G by leveraging fog computing, content-centric networking, and artificial intelligence. In this section, we firstly review the recent advances in integration of fog computing, content-centric networking, and artificial intelligence in 5G, by introducing the following three different trends: 1) fog computing-enabled CCMN, 2) AI-based fog services in 5G, and 3) edge-award learning tasks replacement on 5G entities.

A. Fog Computing-enabled Content-Centric 5G Networks

Recently, fog-enabled mobile network (FMN) and content-centric mobile network (CCMN) have been considered to improve the network service quality and network resources utilization, respectively. A physical entity in the mobile network can be virtualized into multiple virtual nodes and monitored by the hierarchical fogs. And also, some lightweight processing tasks can be done in the local fogs. By such network virtualization and hierarchical fogs, both the service quality and resource utilization of the mobile network can be improved significantly. With the guidance of content centrality, naming the data and caching popular content at network edges (e.g., access points, sink nodes, base stations) also can efficiently
reduce duplicate content transmission in the mobile network, speed up the incident response and improve the utilization of network resources.

It is beneficial to extend the fog computing principles (e.g., geographically distributed, delay-sensitive, and context-aware) to manage the caching resources [8]. Fog computing-enabled content-centric 5G networks inherit the advantages of fog computing and content centricity. For example, the fog computing can be exploited to optimize the content sharing between mobile vehicles in content-centric vehicular networks, electricity usage and prices querying in content-centric smart grids, and drug transfusion monitoring in content-centric healthcare networks, by intelligently adjusting the caching strategy of edge entities in the content-centric 5G networks.

B. Artificial Intelligence for Cognitive Content Sharing in 5G

As an extension of the human need for daily communicating and experience sharing, various smart portable devices (such as mobile phones, tablets, and smart bands) replacing the personal computers are capable of creating, processing and sharing their own content easily and fast, and are changing the lifestyle, business and more of today’s society. Therefore, content sharing among these smart portable devices is one of the most important applications in 5G. Different from the centralized content aggregation and delivery in traditional networks, a smart portable device in 5G are required to cognitively select the most efficient communication mode to enforce content sharing with others to gain high quality of experience (QoE). Embedding some deep learning platforms into the smart portable devices is beneficial for achieving the cognitive content sharing in 5G [9].

For instance, deploying TensorFlow on the camera application of each smart phone to pre-process the local pictures can reduce the network traffic and the operation cost of picture uploading and downloading. Moreover, the AI technology can be exploited to provide personalized network acceleration services for users with different service levels, by predicting the users preference, tracing the users location, and estimating the content popularity in content-centric 5G networks. In addition, with the in-network distributed learning, the future 5G will be capable of supporting mobility control and energy energy saving in Internet of things (IoT) [10].

C. Edge-award Learning Tasks Replacement on Virtual Fogs

In the past decades, cloud computing has evolved to be applied in many scenarios, where data are required to be aggregated into the data center for storing and processing. In the traditional cloud paradigm, the learning tasks are often distributed into one or multiple virtual machines in the data center. While the data center has almost inexhaustible computing resources that can provide guarantees to large-scale learning tasks, the long distance between users and data center makes it infeasible to support the low-latency 5G applications. The key idea of fog computing and mobile edge computing is to deploy more computing resources closer to end users. This novel computing paradigm has gained increasing academic attention and rapidly accepted by industries in recent years. The state of the art study exploits the crowd as a dynamic extension of mobile edge computing [11]. It is a fashion to exploit edge computing resources to handle the local and delay-sensitive learning tasks in recent two years [12]. Typical examples are DeepCham [13], DSVRG [14], and DLFRS [15].

To orchestrate the edge resources of 5G network dynamically, the FEL allocates the learning tasks on the virtual fogs rather than 5G entities. The available approaches to enforce distributed learning contain the model parallelism and the data parallelism. In the data center, model parallelism claims more frequent interactions between slaves than data parallelism so
that data parallelism presents fewer operation costs. However, different from the simplex task distributing among virtual machines in the data center, it is a challenging issue on how to place the learning tasks on virtual fogs because it is uneconomical to slice the data into multiple geographically distributed fogs. In this article, the FEL will hierarchically configure different processing models on different fog domains and place the learning tasks through model parallelism. Meanwhile, in the same fog domain, all fog entities (e.g., end devices, access points, and base stations) cooperatively complete the placed learning tasks by data parallelism.

III. FOG-ENABLED EDGE LEARNING FOR

Cognitive CCN in 5G

The learning objectives of the FEL for C-CCN in 5G are to gain the 1) content preference, and 2) network usage preference. In this section, we introduce the implementation architecture of proposed FEL framework for C-CCN in 5G as shown in Fig. 3. Each 5G entity is equipped with content-centricity, artificial intelligence, and fog computing. To gain the content retrieval preference and network usage preference, we design the user learning interface (ULI) and network learning interface (NLI) to manage the local users' retrieval records and network logs. In addition, to show the advantages of FEL framework, we present the unified orchestration of edge network resources in 5G, where we can exploit the predicted content retrieval preference and network usage preference to
enhance the cognitive ability of the CCN in 5G.

A. Content Retrieval Preference

To achieve more efficient network monitoring and control, predicting the content retrieval preference of users in 5G is a trend. A typical paradigm is software-defined networking, which realizes the decoupling of the data plane and the control plane, and provides a programmable northbound interface for users directly. However, the SDNs northbound interface only focuses on making it easy for users to retrieve and control the network states but not learns the users content retrieval preference.

To gain content retrieval preference, we design the ULI to manage the local users’ retrieval records. With the specified ULI, edge CCNs can securely aggregate the local users retrieval records and then selectively exploit fog computing to optimize the service quality, caching hit rate and learning cost. As the external reinforcement signals in FEL, the desensitized retrieval records of local users that are opened to the CCN ecosystems can be utilized to enforce personalized network acceleration services during the progress of end-to-end content retrieval and transmission.

B. Network Usage Preference

Similar to the concept of the southbound interface (e.g., OpenFlow protocol) of SDN, the network learning interface (NLI) is deployed at the gap between virtual fogs and CCN entities. However, different from the stateless OpenFlow protocol, the NLI is deployed on each 5G entity as a gatekeeper in a distributed way. The CCN nodes that have a large of idle computing resources can gain one ticket to join the fog layer. As shown in Fig. 2, the computing resources of edge CCNs are connected and aggregated into virtual fogs. Therefore, the caching decision strategy is generated by the virtual fogs but not by each CCN node. This separation between content caching and caching control logic will facilitate the edge CCNs to be virtualized, hierarchical, and cognitive.

C. Unified Dynamic Orchestration of Edge Networks Resources

On the basis of the mentioned two interfaces, fog computing can provide some basic services (e.g., topology discovery, network state monitoring, privacy protection, and security authentication) and important functions (such as user preference prediction, traffic offloading, caching decision making, and learning task replacement).

Specially, the FEL for C-CCN in 5G enables unified dynamic orchestration of edge network resources, which can balance the service quality optimization, content caching, and learning task replacement. Such orchestration over the underlying heterogeneous infrastructures mainly needs to update the following aspects. More updates need a long time to discover and complete.

- The first one is the aspect of network function virtualization. As there are many different types of entities (including terminals, routers, access points, and base stations) in 5G that can act as CCN nodes and different types of entities in 5G have different network functions, the network functions of these entities in 5G should be abstracted as virtual resource slices additionally.
- The second one is the aspect of stakeholders. This unified dynamic orchestration makes the 5G entities can turn into contributors of the CCN ecosystem. On one hand, the virtualized network functions of each 5G entity can be reused by different types of tenants through a programmable application interface flexibly. One the other hand, the decentralized content sharing between the 5G entities can save the network bandwidth of the communication links to data center.
- The third one is the aspect of CCN nodes. The reconsideration of network function virtualization require the CCN nodes to support the user learning interface and network learning interface as mentioned in previous.
- The forth one is the selection of learning technology. To solve the problem that the aggregated sample data was not very enough, we envision that the multi-view learning technology should be provides.
- In addition, since the computing resources in virtual fogs are limited and intermittent, we suggest that the lightweight learning tasks should be deployed on the fogs close to users.

We aggregate the idle computing resources of edge CCNs into virtual fogs and then appropriately assign some learning tasks on the virtual fogs to enhance the cognitive ability of CCN in 5G. The objects of these learning tasks mainly contain users, entities, topology and so on.

IV. FEL-ADVANCED COGNITIVE CCN IN 5G

In 5G, it is a meaningful imagine to aggregate the idle computing resources of edge CCNs into virtual fogs and assign learning tasks on virtual fog according to the fog’s location. The FEL brings many disruptive promotions on the cognitive CCN in 5G. Here, we give two typical use cases. The first one is to enable personalized CCN acceleration, and the second one is to provide enhanced CCN mobility management.

A. FEL-based Personalized CCN Acceleration

Although the CCN enables the acceleration service of content transmission by caching the top-k content at network edges, personalized network acceleration is still one of the weakest functionalities of current CCN due to its nature of content centrality, conceivably. In the current CCN architecture, the top-k content caching is independent of the content requesters and content providers. However, the personalized CCN acceleration requires to bind the user identifiers with content names. In the IP network, the available binding approaches contain the following two different types. The first one is adding a special segment into IP header and the second one is configuring some explains on the packet payload.

The existing approaches in the IP network cannot be directly utilized to enable the personalized CCN acceleration. Firstly, adding a special segment into content name may incur the heavy name resolution and a series of additional processing
costs. Secondly, configuring the explains on data packet of the CCN is invalid because the content transmission closely relies on the interest packet.

In this section, we introduce the principle of personalized CCN acceleration in 5G. As shown in Fig. 4, it is common to see that there are $n$ types of end users (denoted as $\{U_1, U_2, ..., U_j, U_n\}$) that want to obtain content from the Internet over the CCN. Usually, end users need to enter their keywords to retrieve the target content. To improve the service quality (e.g., hit rate of targeted content), a translating function should be provided to precisely associate these entered keywords and translate them into the content names that requesters want to request.

The FEL-based personalized CCN acceleration extends the ranking function of top-k caching strategy by saving the table update records and putting these records into learning agents in the virtual fogs. To explain the principle of personalized network acceleration, we specify a content requester $U_x : Bob$ with a special identifier that needs to be provided personalized CCN acceleration. On the basis of the proposed FEL framework, the principle of personalized CCN acceleration consists of the following working steps.

- **Step 1:** $U_x : Bob$ sends a message to learning agent and gives it the permission to access table update records of $U_x : Bob$.
- **Step 2:** The learning agent aggregates the network states. And then it will comprehensively analyze the last reward (including the initial reward), network states and $U_x : Bob$’s records to make a new caching strategy.
- **Step 3:** Repeat step 2 up to service termination, relying on a periodic learning plan or an event-driven learning plan.

**B. FEL-enhanced CCN Mobility Control**

Due to the receiver-driven nature of CCN, the mobility management of content users is required to be handled well.

If a content user moves to a new place and access content through a new access point (AP), the new AP needs to calculate and analyze the user preference newly for refreshing the caching strategy. However, this refreshing process may pose additional overhead such as computation consuming, service quality jitter, and so on. Moreover, as the rapid advancement of device-to-device communication in mobile wireless networks, the content transmission between these mobile devices has gained increasing popularity. The location change of a mobile device acting as a middle hop in the routing path of device-to-device communication will greatly impact the user’s QoE. In addition, the mobility of content sources will incur many invalid interest packets, heavy content discovery and massive redirections.

Thus, we exploit the FEL to enhance the mobility management in CCN environments that can provide low network refreshing time, low service interruption, and low content discovery overhead. Fig. 5 shows the FEL-enhanced CCN
Fig. 6: Performance evaluation of fog-enabled edge learning for cognitive content-centric networking in 5G: a) average response delay of users requests under cloud and fog paradigm; b) influence of proposed FEL on average latency for different types of contents; c) performance improvements of proposed FEL framework on average latency between requesters and providers under mobile circumstances.

mobility management in 5G. For convenience, we use $U_R$ to denote the mobile content requester and $-U_R$ to denote all content requesters in an access domain excluding $U_R$. Correspondingly, if $U_R$ moves into a new access domain, its label will be updated as $U_R'$ and the currently connected content requesters in the new domain are denoted with $-U_R'$. Different from the traditional redirection technology that needs global connectivity additional interaction, the FEL-enhanced CCN mobility management in 5G enables the requested content can be sent from the upstream CCN entities directly. For example, we can cache the requested content on the base station, when $U_R$ move into a new access domain and update its label as $U_R'$, $U_R'$ can gain the content from the base station but not the AP2. Moreover, the local virtual fog will learn the user preference, network states, and service quality.

V. PERFORMANCE EVALUATION

In this section, we discuss the simulation results to show the feasibility of our proposed architecture of fog-enabled edge learning for cognitive CCN in 5G. The fog enabled edge learning can decrease the content transmission delay significantly. In the simulation, we consider the average latency of content retrieval under three different application scenarios as follows.

For the first simulation, we consider a 5G system with five communities. Each community contains two different kinds of content requesters, one is configured with the period request model and the other is configured with the Zipf request model. Meanwhile, both cloud and fog are deployed in each 5G community. There are one access point, one base station, one gateway and the public Internet between a content requester and the cloud data center, while the fog node provides content directly through the base station. Fig. 6 a) shows the average response delay of users requests under cloud paradigm and fog paradigm. As placing learning tasks on the local fogs reduces the hop count between content requesters and providers, it can be observed that the average latency of both FEL-Zipf and FEL-Period are less than Cloud-Zipf and Cloud-Period.

Different from the first simulation, all of the base stations in the 5G system are enforced to join the fog networks when the second simulation works. Specially, the content requesters are divided into two different types according to the content names that they are requesting. The learning applications deployed on fog nodes will aggregate the content statistics and then adaptively provide personalized network acceleration service for each content requester in 5G. We also configure the content different requesters with the period request model and the Zipf request model, respectively. Influences of the proposed FEL on average latency of content retrieval with different content requesters are shown as illustrated in Fig. 6 b). The average latency of content retrieval is reduced significantly by using the proposed FEL framework. With this feature, the FEL can be exploited by network operators of 5G to enforce more customized networks services to embrace the upcoming Internet of everything.

The third simulation focuses on the issue of enhanced mobility management in 5G. Twenty content requesters are configured in this simulation. Each content requester has two different kinds of communication links: 1) radio access network (RAN), 2), device-to-device (D2D). We exploit the FEL to achieve smart communication link selection in mobile circumstances. As an example for illustration, we record the average content retrieval latency of each content requester in mobile circumstances. The performance improvement of proposed FEL framework on mobility management is shown in Fig. 6 c), it can be observed that the FEL framework performs better on mobility management.

VI. CONCLUSION

In this article, we reviewed the recent advances in integration of fog computing, content-centric networking, and artificial intelligence in 5G. We proposed a fog-enabled edge learning
(FEL) framework for cognitive CCN (C-CCN) in 5G. The FEL-advanced cognitive CCN in 5G provides unified orchestration of edge network resources, which can be utilized to enforce service quality optimizing, content caching, learning task placement flexibly. We presented the implementation diagram of the FEL framework. Both content retrieval preference and network usage preference are considered when we a CCN node exchanged its data with others. To validate the feasibility of proposed framework, we envisioned two promising use cases: 1) FEL-based personalized CCN acceleration and FEL-enhanced CCN mobility control. Meanwhile, we exploited the ndnSim platform to compare the average latency between content requesters and providers under tree different scenarios.

ACKNOWLEDGEMENTS

This work is supported by National Natural Science Foundation of China (Grant No.61431008) and National Key Research and Development Plan of China (Grant No.2016QY01W0104).

REFERENCES

[1] C. Wang, Y. He, F. R. Yu, Q. Chen, L. Tang, “Integration of Networking, Caching and Computing in Wireless Systems: A Survey, Some Research Issues and Challenges,” IEEE Communications Surveys & Tutorials, vol. PP, no. 99, pp. 1-1, 2017.

[2] C. Xu, M. Wang, X. Chen, L. Zhong, A. L. Grieco, “Optimal Information Centric Caching in 5G Device-to-Device Communications,” IEEE Transactions on Mobile Computing, vol. PP, no. 99, pp. 1-1, 2018.

[3] R. Ravindran, A. Chakraborti, S. O. Amin, A. Azig, G. Wang, “5G-ICN: Delivering ICN Services over 5G Using Network Slicing,” IEEE Communications Magazine, vol. 55, no. 5, pp. 101-107, 2017.

[4] International Telecommunication Union/ITU Teleseconctor, “Data aware networking (information centric networking) - Requirements and capabilities,” pp. 1-18, 2017.

[5] Y. He, F. R. Yu, N. Zhao, V. C. M. Leung, H. Yin, “Software-Defined Networks with Mobile Edge Computing and Caching for Smart Cities: A Big Data Deep Reinforcement Learning Approach,” IEEE Communications Magazine, vol. 55, no. 12, pp. 31-37, 2017.

[6] R. Huo, F. R. Yu, T. Huang, R. Xie, J. Liu, V. C. M. Leung, Y. Liu, “Software Defined Networking, Caching, and Computing for Green Wireless Networks,” IEEE Communications Magazine, vol. 54, no. 11, pp. 185-193, 2016.

[7] G. T. Singh, F. M. Al-Turjman, “Learning Data Delivery Paths in QoI-Aware Information-Centric Sensor Networks,” IEEE Internet of Things Journal, vol. 3, no. 4, pp. 3-16, 2016.

[8] M. Wang, J. Wu, G. Li, J. Li, Q. Li, “Fog Computing based Content-aware Taxonomy for Caching Optimization in Information-Centric Networks,” IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pp. 474-475, 2017.

[9] R. Li, Z. Zhao, X. Zhou, G. Ding, Y. Chen, Z. Wang, Z. Zhang, “IEEE Wireless Communications,” IEEE Wireless Communications, vol. 24, no. 5, pp. 175-183, 2017.

[10] B. Tang, Z. Chen, G. Hefferman, S. Pei, T. Wei, H. He, Q. Yang, “Incorporating Intelligence in Fog Computing for Big Data Analysis in Smart Cities,” IEEE Transactions on Industrial Informatics, vol. 13, no. 5, pp. 2140-2150, 2017.

[11] P. Bellavista, S. Chessa, L. Foschini, L. Gioia, M. Girolami, “Human-Enabled Edge Computing: Exploiting the Crowd as a Dynamic Extension of Mobile Edge Computing,” IEEE Communications Magazine, vol. 56, no. 1, pp. 145-153, 2018.

[12] O. B. Sezer, E. Dogdu, A. M. Ozbayoglu, “Context Aware Computing, Learning and Big Data in Internet of Things: A Survey,” IEEE Internet of Things Journal, vol. PP, no. 99, pp. 1-1, 2017.

[13] D. Li, T. Salonidis, N. V. Desai, M. C. Chuah, “DeepCham: Collaborative Edge-Mediated Adaptive Deep Learning for Mobile Object Recognition,” IEEE/ACM Symposium on Edge Computing (SEC), pp. 64-76, 2016.

[14] K. Portelli, C. Anagnostopoulos, “Leveraging Edge Computing through Collaborative Machine Learning Kurt Portelli; Christos Anagnostou- lonos,” 5th International Conference on Future Internet of Things and Cloud Workshops (FiCloudW), pp. 164-169, 2017.

[15] C. Liu, Y. Cao, C. Luo, G. Chen, V. Vokkarane, Y. Ma, S. Chen, P. Hou, “A New Deep Learning-based Food Recognition System for Dietary Assessment On An Edge Computing Service Infrastructure,” IEEE Transactions on Services Computing, vol. PP, no. 99, pp. 1-1, 2017.

Gaolei Li (S’15) received the B.S. degree in electronic information engineering from Sichuan University, Chengdu, China, in 2015 and he is pursuing the Ph.D. degree in School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai, China. He participates in many national projects, such as National Natural Science Foundation of China, National “973 Planning of the Ministry of Science and Technology, China, etc. He is a TPC member of international conference on Internet of Things (iThings2017) and IEEE SmartCity 2018. He is a member of IEEE CSIM Technical Committee. His research interests are focusing on information-centric networking (ICN), fog computing, Internet of thing (IoT), software-defined networking(SDN), etc.

Jianhua Li is a professor/Ph.D. supervisor and the dean of School of Information Security Engineering, Shanghai Jiao Tong University, Shanghai Key Laboratory of Integrated Administration Technologies for Information Security, Shanghai, China, Shanghai, China. He got his BS, MS and Ph.D. degrees from Shanghai Jiao Tong University, in 1986, 1991 and 1998, respectively. He was the chief expert in the information security committee experts of National High Technology Research and Development Program of China (863 Program) of China. He also is a committee expert of Information Technique Standardization Committee of Shanghai, China. He was the leader of more than 30 state/province projects of China, and published more than 300 papers. He authored over six books and holds about 30 patents. He made three standards and has five software copyrights. He is a member of the committee of information security area of the state 10th five-year plan of China. He got the First Prize of National Technology Progress Award of Shanghai in 2003 and 2004, and he got two First Prize of National Technology Progress Awards of Shanghai in 2004. He got the Second Prize of National Technology Progress Award of China in 2005. He was the Chief Expert in the Information Security Committee Experts of National High Technology Research and Development Program of China of China. His research interests include cyberspace security, data science, next-generation networks, smart grid, industrial Internet of things (IoT), etc.

Jun Wu (S’08-M’12) is an Associate Professor of School of Cyber Security, Shanghai Jiao Tong University, Shanghai Key Laboratory of Integrated Administration Technologies for Information Security, and Vice Director in National Engineering Laboratory for Information Content Security, Shanghai Jiao Tong University, Shanghai, China. He has been a postdoctoral researcher for the Research Institute for Secure Systems (RISEIC), National Institute of Advanced Industrial Science and Technology (AIST), Japan, from 2011 to 2012. He worked as a researcher for the Global Information and Telecommunication Institute (GITI), Waseda University, Japan, from 2011 to 2013. He has hosted and participated in several research projects for the National Natural Science Foundation of China, National 863 Plan and 973 Plan, Japan Society of the Promotion of Science (JSPS) projects, etc. He is the associate editor of IEEE Access. He has been a Guest Editor for the IEEE Sensors Journal and TPC Member of more than ten international conferences including EAI WINCON, IEEE ICC, IEEE GLOBECOM, etc. His research interests include the advanced computing and communications techniques, smart grids, Internet of Things, industrial security, etc.