International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Effective Taxonomy of Advanced Mobile Edge Computing of Long-Term Evolution for 5G

Dr. S. Brindha

Assistant Professor
Department of Computer Applications, Vellalar College for Women, Thindal, Erode, Tamilnadu, India
brindha.balajiee[at]gmail.com

Abstract: ***With the development of Internet of Things (IoT), the quantity of mobile terminal devices is increasing rapidly. We aspire to reduce the energy consumption of all the UE;s by optimizing the UAV's trajectories, utilize associations and resource allocations. To tackle the multi-UAV's trajectories problem, a convex optimization-based CAT has been proposed. A DRL based AMECT including a matching algorithm has also been proposed. Simulation results explain that AMECT performance. Our analysis on the process of deploying Deep Learning models to mobile devices. This paper explain about the high transmission delay as well as limited bandwidth that can be considered the flying Advanced Mobile Edge Computing Taxonomy architecture, by taking advantage of the UAV's helps to serve as the moving platform. Any drawbacks related to this process are within our scope. The system can still sustain very good presentation with the rapid expansion of the number of utilizers or the amount of data.***

Keywords: Mobile Edge Computing, Taxonomy architecture, CAT Algorithm, 5G Mobile, Deep Learning

1.Introduction

AI technology has large history is actively and constantly changing and growing. It mainly focuses on intelligent agents that perceives environment and depends on which takes actions in order to maximize goal success chances. The modern AI basics and various representative application of AI. Most of the Artificial intelligence system has the ability to learn helps to allows people to improve their performance over time. AI tools, including machine learning, deep learning and predictive analysis intended toward increasing the planning, learning, reasoning, and action taking ability. The state-of-the-art AI of today is capable of doing, why it still cannot reach taking ability. The state of art AI of today is capable of doing, still cannot reach human level intelligence and the open challenges existing in front of AI to reach and outperform human level of intelligence.

The deployment of 4g/LTE (long Term Evolution) data network has helps to solve the major challenge of high capacities of data. To deeply and accurately learn the operating environment and users behaviors and their data requirements. It is also important to forecast their evolution to build a pro-actively and efficiently updatable data analysis. 5G is the next generation cellular that aspires to achieve significant enhancement on excellence of service like as developed quantity as well as lower latency. Taxonomy Mobile Edge Computing is an emerging technology that enables the evolution to 5G by bringing cloud capabilities to the end users in order to overcome the intrinsic problems of the traditional data cloud high latency and the lack of security. Taxonomy of Advanced Mobile Edge computing in 5G, gives of an existing of the art solutions of Mobile edge computing in 5G on the basis of objectives, computational platforms, attributes, 5G functions, performance measures and roles. The key requirements for its successful deployment in 5G and the applications of edge computing for 5G. The salient features of different Taxonomy Mobile Edge Computing paradigms for 5G.

2.Literature Review

In human activity recognition can be broadly categorized based on different devices, sensor model and data used for detection of activity details. Video based sensors are used to capture images video or surveillance camera features to recognize daily activity. The introduction of mobile phones and other wearable sensors, inertial sensor data (Bhattacharya & Lane, 2016; Bulling, Blanke, & Schiele, 2014b) are collected using mobile or wearable embedded sensors placed at different body positions in order to infer human activities details and transportation modes. The use of social data processing methods (Y. Jia et al.2016) that exploit appropriate utilizers information from multiple social data processing sources to understand user behaviour and interest have also been proposed recently. In addition, wireless signal created human activity recognition (Savazzi Rampa, Vicentini & Giussani, 2016) takes advantages of signal propagated by the wireless devices to categorise human activity.

Social data processing sources to understand utilizer behaviour and interest have also been proposed recently. In addition, wireless signal based human activity recognition. The research landscape in human motion analysis activity monitoring as well as discovery outstanding to their obvious advantages over other sensor sense modality (Cornacchia, Ozcan, Zheng, & Velipasalar, 2017). Usually, mobile phones and wearable founded sensors for human activity documentation are driven by their ubiquity.

Chang et al. [8] consider the problem of training a Deep Learning neural network with billions of parameters using tens of thousands of CPU cores, in the context of speech recognition and computer vision. A software framework, Disbelief, is developed that can utilize computing clusters with thousands of machines to train large-scale models. The framework supports model parallelism both within a machine via multithreading and across machines via message passing, with the details of parallelism, synchronization, and communication managed by Disbelief.

Qiao et al. [7] demonstrate that Deep Learning is able to discover intermediate data representations in a hierarchical learning manner, and that these representations are meaningful to, and can be shared among, different domains. In their work, a stacked denoising auto encoder is initially used to learn features and patterns from unlabelled data obtained from different source domains.

Kruczkowski et al. [16] collected faults in TF programs from SO and GitHub. They are categorized the symptoms and root causes of these faults through manual analysis. Gupta et al [18], and Amin al [17] extended their scope to the faults in programs written based on five popular DL frameworks to present more comprehensive results. A popular way is to deploy them on mobile devices. In addition, researchers have built number of DL based applications on mobile devices Shen [11], Chen [4], Gumaei [5]. To bridge the knowledge gap between gap between research and practice, Zhang et al [22] conducted an empirical study on large scale Android apps collected from Google play store and demonstrated the increasing popularity of Deep Learning in real world mobile apps. Despite such popularity and the related techniques for deploying deep learning models to mobile devices are still not very mature. Recently, Shinohara al. [23] investigated the performance gap when the trained deep learning models are migrated from PC to mobile devices with the help of TF life and Core ML.

3.Methodology

Taxonomy Advanced Mobile Edge Computing of Long-Term Evolution for 5G

Taxonomy Advanced Mobile Edge Computing in 5G offloads a massive amount of data from edge clouds. While edge servers offer distributed local storage for a significant amount of data. The Taxonomy Mobile Edge server provides different types of storage strategies to support different kinds of data. Local computation of Taxonomy Mobile Edge computing offloads and process from less complex UEs to edge clouds. The TAMEC-LTE traditional cache and access technologies provide simple computation; the edge cloud is an intelligent computing system that provides local computation and data processing capabilities in an independent and autonomous manner. The advantage is that TAMEC-LTE perform small tasks and provide real time responses locally, helps to reduce the cost and delay incurred to send the required data to the cloud. TAMEC-LTE local data analysis helps to processes and performs critical and real time data analysis on a massive amount of data gathered from different applications in close proximity to generate valuable information. The capability to make data analysis locally reduces the latency required to send data to and to wait for responses from the cloud. TAMEC-LTE enables remote control and monitoring particularly critical devices including those under unsafe environment from a distance are more comfortable or safer place [16]. TAMEC-LTE is a local security enhancement it serves as an additional layer between the cloud and connected devices in order to improve security. TAMEC-LTE can serve as secured distributed platforms that provide security credentials management, malware detection, software patches distribution and trustworthy communications to detect, validate and counter measure attacks. The close proximity to TAMEC-LTE malicious entities can be quickly detected and isolated and real time responses can be initiated to the effects of the attacks. This helps to minimize service distributions.

Data Acquisition and Pre-processing methods operate generally with complex, disparate sets of data with useful information residing in multiple systems such as Operation and Management Systems (OMS), Customer Relationship Management (CRM) systems. To gain the challenge for achieving high performing future mobile network are forced to adopt efficient big data tools to bring together all necessary and profitable datasets, and effective data management has to include all the necessary functions of collecting data, cleaning data filtering data correlating data from multiple sources and finding the relevant data.

Challenge's taxonomy of applying DL at the Edge in 5G data collections, which categorizes the research articles that focus primarily on applications of deep learning techniques utilized in data collection operations. Mobile edge computing (MEC) has the advantage of proximity to utilizers, which can meet the low latency (URLLC), high bandwidth (eMBB), and high availability (mMTC) goals of 5G. Data Collection by leveraging the breakthroughs discussed in the previous section. 5G Data Collection present interesting challenges best addressed at the mobile edge to reduce latency and incorporate locally significant information. Mobile edge computing can leverage proximity to utilizer to address a variety of challenges in 5G Data Collection in particular which often require automated management utilizing DL for increasingly complex series of tasks. Solutions combining DL for 5G promise better efficiency when conducted near the end utilizer in mobile edge computing rather than in the core data collection. For instance, mixing mobile edge computing with 5G data collection seamlessly connects existing cloud computing with edge computing to enable novel applications.

3.1 System Specification

For the execution of pattern classification and the computation of the text classification analysis the JAVA software. It is a realistic different library packages which the patterned the text document as an interactive programming environment.

Hardware Requirements

The minimum Hardware requirements for a PC:

1. Operating System as Windows-7 or 8 having 2 or 4 GB RAM.
2. Hard Disk capacity of 40 G.B or higher.

Software Necessities

1. The language used to code the system is Java JDK 1.7.0 & JRE 6.
2. Eclipse or Net Beans 8.0 Version as programming is totally Java based.
3. For system designing the Software's required would-be Star UML.

3.2 Advanced Mobile Edge Computing Taxonomy

Advanced Mobile Edge Computing has the three main functional requirements of the 5G data collection are introduced to show that its full deployment requires computing, storage, and data collection infrastructure close to the utilizer and the infrastructure, whether fixed or mobile, of the end user. The second part introduces an Advanced Mobile Edge Computing Taxonomy, clarifying the functionalities and the geographic areas that edge computing covers to demonstrate the essentiality of Advanced Mobile Edge Computing Taxonomy in 5G deployments. Addressing the rapidly changing Internet demand requires rethinking data collection and information delivery designs. A combination of newly developed 5G data collections and advanced mobile edge computing Taxonomy (AMECT) will enable Internet service providers (ISPs) to meet consumer difficulties. AMECT for 5G several models of computing operate in the data collection environment, including mobile computing, cloud computing, fog computing, and edge computing. Taxonomy of the data collection computing paradigm. AMECT Advanced Mobile Computing creates an isolated, non-centralized, data collection edge, or off data collection environment made up of elements that share data collection, computing, and storage properties.

3.3 Data Collection

Mining SO: As one of the most popular community driven Q&A websites, SO's utilizers range from novices to experts, increasing the diversity of our collected faults. In addition, developers often post questions on SO for the faults that they cannot find solutions quickly, leading to more nontrivial faults in our dataset. Assemble the applicable on SO.

Knowledge Discovery is the learning stage to learn and understand the traffic pattern and congestion, user behaviour, resource usage, QoS, future location, problem elements/areas and their impacts on database efficiency. Knowledge Exploitation will make use of the extracted knowledge to make decisions about the actions to be applied to the elements/configurations. Some system improves the performance to be adapted to current upcoming situations and scenarios in the operating environment. Corporate investment in 5G has risen rapidly because the new cases opened by the next generation technology will reduce the expenditures and maintain flat rates for users. The build of large scale 5G networks, researchers are focusing on the application spaces could benefit from the low latency, proximity, high bandwidth, location awareness and real time insight provided by Taxonomy of Mobile Edge Computing.

The fundamental motivation for the use of edge computing over cloud computing ensures low latency to support delay sensitive applications and services in order to improve QoS. A dissimilar variety of services, counting decision making as well as data analysis, can be providing by edge servers in a real time manner. Local processing is feasible data and user requests can be processed by edge servers rather than the cloud. The bandwidth of the connection can be increased to prevent bottleneck and the traffic amount in the core network is reduced. High data is necessary to transmit the massive amount of data generated by a different range of applications to edge clouds [20]. The use of mm wave frequency bands in a small cell provides a high data rate transmission. High availability ensures the availability of the cloud services at the edge as well as the availability of the edge clouds is significant. Neural networks have been gaining increasing popularity in NLP community in recent years and various DNN models have been adopted in different NLP tasks. Apart from the feed forward neural networks and Convolutional Neural Networks (CNN), Recurrent/Recursive Neural Networks (RNN) as well as their variants are the most common neural networks used in NLP, because of their natural capability of management arrangements.

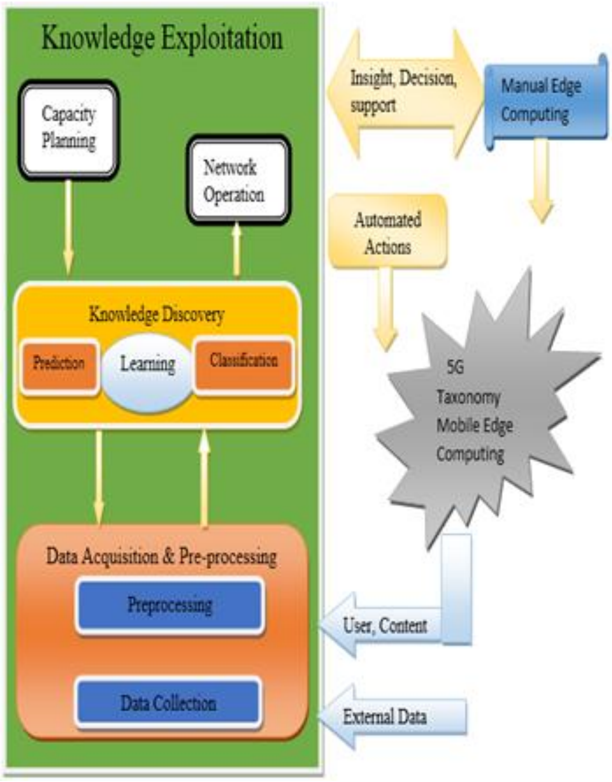

Figure 3.1: Integrating AI/ML in the planning process of Taxonomy of Advanced Mobile Edge Computing of Long-Term Evolution for 5G

The growth of TAMEC-LTE will interrupt the current cloud computing paradigm to localized computing near the user. TAMEC-LTE may have the richer and more complex characteristics of other systems. The artificial intelligence has been generally used in the documentation of black-box systems. Among them, the regional economy has concerned much consideration. Its exclusive edge computing competences have fetched vitality to the modeling of nonlinear systems.

3.4 Edge-ward Mobile Edge Computing Algorithm

Edge-ward Mobile Edge Computing is based on a first come first served (FCFS) strategy and the results in placing data as close as possible to the edge of the network on fog nodes. Specific Fog node cannot serve the requirements of an application; Edge-ward mobile edge computing selects additional Fog devices. The algorithm generates tuples of devices representing the paths application modules are executed. The fog device selected to run an application does not have available computational capacity then the algorithm searches for a Fog device with capacity at the top layer of the data analysis situs hierarchy. Application requests are answered based on the order in which they arrive and it presents better performance when planning resources of fog devices in a hierarchical way. If a fog device is unable to meet the requirements of an application module, then it can be scheduled in the cloud. Edge-ward Mobile Edge Computing Algorithm provides the pseudo code for Edge ward where p: path d: device w: modules: selected module.

Proposed Algorithm – Advanced Mobile Edige Computing of Long Term Evolution for 5G.

1. while p € paths do
2. place modules:={}
3. while fog device d € p do {}
4. Module sto place := {}
5. while module w € app do
for placement on device d
6. if all pre dec. of w are in placed modules then if all predecessors are placed add w to modules to place
7. end if
8. end while
9. while module 0 € modules to place do
10. if d has instance of 0 as 0' then
11. if cpu 0>=cpu d then
have cpu capacity to host 0
12. 0' := merge(0,0')
13. f :=parent(d)
14. while cpu 0>=cpu f do north of d for hosting 0
15. f :=parent (f)
16. end while
17. add 0 to placed modules
18. else if
19. place 0 on device d
20. add 0 to placed modules the
21. end if
22. else if no device of d has an instance 0 then
23. if cpu 0<= cpu d then handled by subsequent iterations
24. place 0 on device d
25. add 0 to placed modules
26. end if
27. end if
28. end while
29. end while
30. end while

Through analysis, it can be realized that compared with other basic algorithms, edge computing runs faster and has greater advantages in precision and recall. Compared with weak classifiers decision tree, it integrates learning. Edge computing has more regularization of the self-model than other models, making this type of model has stronger generalization ability. Outstanding to differences in hardware conformation, different computer execution results may have nonconformities, but the proportional changes between the running times of dissimilar algorithms should be similar.

4.Experimental Results

Compare to various dataset like Edward related dataset; deploy dataset and Reuters-21578 the Edward related dataset helps to improve the Taxonomy Advanced Mobile Edge Computing Long Term based Evolution using 5G dataset.

Datasets / Methods	Edward related dataset	Deploy dataset	Reuters-21578
MEC	0.192	0.120	0.138
MCC	0.101	0.142	0.182
TAMEC-LTE	0.199	0.150	0.140

4.1 Mean Average Precision

Mean Average Precision which is a measure of precision at relevant documents combines precision, recall with ranking. Break Even Point tells the value of precision or recall at which the precision recall intersects the precision=recall. Estimate average precision (AP) for each query calculate precision at each "seen" relevant document.

- Not incorporated
- For respectively applicable doc not refunded, precision = 0
- Calculate the mean of the APs for all the queries Mean Average Precision

4.2 Average Precision (AP)

1. Not relevant 6 Not relevant
2. Relevant 1/2 = 0.5 7 Not relevant
3. Not relevant 8 Relevant 3/8=0.375
4. Not relevant 9 Not relevant
5. Relevant 2/5 = 0.4 10 Relevant 4/10=0.4

Not found 0
AP (0.5 + 0.4 + 0.375 + 0.4 + 0 + 0 + 0 + 0 + 0) / 9 = 0.1861

4.3 Mean average precision (MAP)

- Calculate average precision for the top N documents
- Precision@10, precision@20, etc.
- Easy to calculate, interpretation is intuitive
- Doesn't average well – fails to account for different recall levels (diff queries have different number relevant docs)
- R-precision
- R is entire quantity of applicable docs
- Calculate precision @R for each query as well as average
- Compute the normal for the precisions for each applicable doc where R = number of relevant docs for that query and ranking the particular relevant document.

$$\mathbf{AP} = \left(\sum_{i=1}^{R} \sum^{R} \frac{i}{rank}\right)/R$$

In the average precision for that query and i/ranki= 0 if document I was not retrieved. Also called, average precision at seen relevant documents. Precision at each point and a new related document gets recovered Use P=0 for each relevant document that was not retrieved. Average over queries

$$\mathbf{MAP} = \frac{1}{N}\sum_{j=1}^{n}\frac{1}{Q_j}\sum_{i=1}^{Q_j} P(doc_i)$$

Qj- number of relevant documents for query j

N- number of queries
P(doci)- precision at i[th] relevant document.

A document is not recovered at all, the accuracy value in the above calculation is taken to be 0. For a single information essential, the normal exactness approaches the area under the incorporated precision-recall curve, and so the MAP is unevenly the average area under the precision-recall curve for a set of queries. Using MAP, fixed recall levels are not chosen, as well as there is no interpolation. The MAP value for a test collection is the arithmetic mean of average precision values for individual information needs. Many documents are relevant to some queries whereas very few are relevant to other queries.

Mean Average Precision gains generally diverge extensively across information requirements when slow within a single system, for instance, between 0.1 and 0.7. Indeed, there is generally more arrangement in MAP for an individual information essential across systems than for MAP scores for different information needs for the same system. This means that a set of test information needs must be large and diverse enough to be representative of system effectiveness across different queries.

4.4 Frequency

Combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score:

$$F=2 \cdot \frac{Precision*recall}{Precision+recall}$$

The average of the two when they are close, and is more commonly the harmonic mean, which, for the case of two numbers, coincides with the square of the geometric mean divided by the arithmetic mean. There are several reasons that the F-score can be criticized in particular circumstances due to its bias as an evaluation metric. There are other parameters and strategies for performance metric of information retrieval system, such as the area under the precision-recall curve (AUC). For web document retrieval, if the user's objectives are not clear, the precision and recall can't be optimized. Weighted harmonic means of P and R

$$F_{\alpha} = \frac{PR}{(1-\infty)P+\infty R}$$

High α: Precision is more important
Low α: Recall is more important

Most commonly used with α=0.5

$$F_{0.5} = \frac{2PR}{P+R}$$

Maximum value of F0:5-measure (or F-measure for short) is a good indication of best P/R compromise. F-measure is an approximation of cross-over point of precision and recall.

4.5 Solution of Computation Delay in Edge Computing Layer

The target function of computation delay is

$$f(x) = \min \sum_{i=1}^{m} \frac{1}{V_{z_i}} a_i x_i^2,$$

$$h_i(x) = \begin{cases} 0 < x_i < x_i^{\max} \\ \sum_{i=1}^{m} x_i = X. \end{cases}$$

4.5 Data Processing Delay Optimization in Advanced Mobile Edge Computing Taxonomy

Based on the collected MEC, a service server uses AMECT analytics to discover hidden patterns and information. The importance of AMECT analytics stems from its roles in building complex mobile systems that could not be assembled and configured on small datasets. AMECT analytics is more versatile than conventional big data problems as data sources are portable and data traffic is crowd sourced. AMECT analytics deals with massive amount of portable and data traffic is crowd sources. AMECT analytics deals with massive amount of data which is collected by millions of mobile devices. The main characteristics of AMECT which complicate data analytics and learning on AMECT compared to small datasets.

The computation delay of cloud servers, do not consider the data loss rate. The principle of conservation of $\Sigma i \in M \lambda ij = yj$ shows that the amount of data that needs to be processed by cloud server. To achieve useful traffic prediction, it is necessary to predict utilizer mobility and, the demand for data collection resources, as well as be able to classify traffic origin in real time to assign to the correct slice.

5.Conclusion

Society has progressively arrived the era of “big data,” as with the initiation of cloud computing, the demand for big data processing and application functions is increasing. Edge-ward Mobile Edge Computing algorithm can outperform Mapping. This has been observed, for instance, in scenarios where selected Fog devices could not match the processing needs of specific applications. Taxonomy of Advanced Mobile Edge Computing of Long-Term Evolution for 5G the edge device detects that the human behavior has not changed for a long time, the transmission frequency can be slowed down. To improved decrease the energy ingesting of the equipment, storing document data, because the collected data is in the form of key value pairs, the more popular databases scan be used, which can progress the efficiency of transmission and storage.

References

[1] Amin, S.; Singhal, A.; Rai, J.K. Identification and classification of neuro-degenerative diseases using statistical features and support vector machine classifier. In Proceedings of the 2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Delhi, India, 3–5 July 2017; pp. 1–8.

[2] A. Gumaei, M. al-Rakhami, M. M. Hassan et al., “Deep learning and blockchain with edge computing for 5G-enabled drone identification and flight mode detection,” IEEE Network, vol. 35, no. 1, pp. 94–100, 2021.

[3] B Gupta et al, “Advances in security and privact of multimedia big data in mobile and cloud computing, Multiledia Tools Appl 77(7): 9203-9208,” 2018. [28] F. Jiang et al, “Deep learning based multi-channel intelligent attack detection for data security,” IEEE transactions on Susta.
[4] C. Zhang, Y. Zhang, W. Xu, Z. Ma, Y. Leng, and J. Guo, “Mining activation force defned dependency patterns for relation extraction,” Knowledge-Based Systems, vol. 86, pp. 278–287, 2015.
[5] E. Ahmed and M. H. Rehmani, “Mobile edge computing: Opportunities, solutions, and challenges,” Future Generation Computer Systems, vol. 70, pp. 59–63, May 2017.
[6] G. Liu, X. Chen, R. Zhou, S. Xu, Y. C. Chen, and G. Chen, “Social learning discrete particle swarm optimization based two-stage X-routing for IC design under intelligent edge computing architecture,” Applied Soft Computing, vol. 104, no. 6, p. 107215, 2021.
[7] H. Wang, M. Zeng, Z. Xiong, and F. Yang, “Finding main causes of elevator accidents via multi-dimensional association rule in edge computing environment,” China Communications (English Edition), vol. 14, no. 11, pp. 39–47, 2017.
[8] H. Haochen, L. Yutong, T. Wang, Q. Zhaoming, and C. Junwei, “A control strategy for energy Internet edge computing system based on mixed stochastic H_2/H_∞ method,” Proceedings of the Chinese Society of Electrical Engineering, vol. 656, no. 21, pp. 115–125, 2020.
[9] Kruczkowski, M.; Szynkiewicz, E.N. Support Vector Machine for Malware Analysis and Classification. In Proceedings of the 2014 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT), Warsaw, Poland, 11–14 August 2014; Volume 2, pp. 415–420. .
[10] K. Jain and S. Mohapatra, “Taxonomy of edge computing: Challenges, opportunities, and data reduction methods,” in Edge Computing. Springer International Publishing, Nov 2018, pp. 51–69.
[11] M. Elhoseny, “Multi-object detection and tracking (MODT) machine learning model for real-time video surveillance systems,” Circuits, Systems, and Signal Processing, First Online, vol. 39, pp. 611–630, 2019.
[12] M. Zhou, Y. Wang, Z. Tian, Y. Lian, Y. Wang, and B. Wang, “Calibrated data simplification for energy-efficient location sensing in internet of things,” IEEE Internet of Things Journal, vol. 6, no. 4, pp. 6125–6133, 2019.
[13] M. Zhou, Y. Wang, Z. Tian, Y. Lian, Y. Wang, and B. Wang, “Calibrated data simplification for energy-efficient location sensing in internet of things,” IEEE Internet of Things Journal, vol. 6, no. 4, pp. 6125–6133, 2019.
[14] R. Li, Q. Ma, J. Gong, Z. Zhou, and X. Chen, “Age of processing: age-driven status sampling and processing offloading for edge computing-enabled real-time IoT applications,” IEEE Internet of Things Journal, no. 99, pp. 1–7, 2021.
[15] R. Olaniyan, O. Fadahunsi, M. Maheswaran, and M. F. Zhani, “Opportunistic edge computing: concepts, opportunities and research challenges,” Future Generation Computer Systems, vol. 89, no. DEC, pp. 633–645, 2018.
[16] Rute Sofia. A tool to estimate roaming behavior in wireless architectures. In International Conference on Wired/Wireless Internet Communication, pages 247–258. Springer, 2015.
[17] R. Li, Q. Ma, J. Gong, Z. Zhou, and X. Chen, “Age of processing: age-driven status sampling and processing offloading for edge computing-enabled real-time IoT applications,” IEEE Internet of Things Journal, no. 99, pp. 1–7, 2021.
[18] W. J. Chang, L. B. Chen, C. Y. Sie, and C. H. Yang, “An artificial intelligence edge computing-based assistive system for visually impaired pedestrian safety at zebra crossings,” IEEE Transactions on Consumer Electronics, vol. 67, no. 1, pp. 3–11, 2021.
[19] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, “Edge computing: vision and challenges,” Internet of Things Journal, IEEE, vol. 3, no. 5, pp. 637–646, 2016.
[20] W. J. Chang, L. B. Chen, C. Y. Sie, and C. H. Yang, “An artificial intelligence edge computing-based assistive system for visually impaired pedestrian safety at zebra crossings,” IEEE Transactions on Consumer Electronics, vol. 67, no. 1, pp. 3– 11, 2021.
[21] Xuan-Qui Pham, Tien-Dung Nguyen, Van Dung Nguyen, and Eui-Nam Huh. Joint node selection and resource allocation for task offloading in scalable vehicle assisted multi-access edge computing. Symmetry, 11(1):58, 2019.
[22] Y. Li, J. Zhang, and Z. Ma, “Clustering in wireless propagation channel with a statistics-based framework,” in Proceedings of the 2018 IEEE Wireless Communications and Networking Conference (WCNC), pp. 1–6, Barcelona, April 2018.
[23] Y. Shinohara, “Adversarial multi-task learning of deep neural networks for robust speech recognition,” INTERSPEECH, pp. 2369–2372, 2016.
[24] Y. Liu, C. Xu, Y. Zhan, Z. Liu, J. Guan, and H. Zhang, “Incentive mechanism for computation offloading using edge computing: a Stackelberg game approach,” Computer Networks, vol. 129, no. DEC.24, pp. 399–409, 2017.
[25] Y. Shen and L. Chang, “Visual analysis of enterprise electricity consumption behavior based on edge computing gateway,” Electrical Appliances and Energy Efficiency Management Technology, vol. 592, no. 7, pp. 89–94, 2020.
[26] Z. Lv, L. Qiao, D. Chen, R. Lou, J. Li, and Y. Li, “Machine learning for proactive defense for critical infrastructure systems,” IEEE Communications Magazine, 2020.
[27] Z. Lv, Y. Han, A. K. Singh, G. Manogaran, and H. Lv, “Trustworthiness in industrial IoT systems based on artificial intelligence,” IEEE Transactions on Industrial Informatics, vol. 17, no. 2, pp. 1496–1504, 2021.
[28] Z. Jianmin, F. Yang, Z. Wu, Z. Zhengkun, and W. Yuwei, “Multi-access edge computing (MEC) and key technologies,” Telecommunications Science, vol. 35, no. 3, pp. 160–160, 2019.
[29] Z. Lv, D. Chen, R. Lou, and Q. Wang, “Intelligent edge computing based on machine learning for smart city,” Future Generation Computer Systems, vol. 115, pp. 90–99, 2021.

[30] Zhilin Yang et al. Xlnet: Generalized autoregressive pretraining for language understanding. Advances in neural information processing systems, 2019

Author Profile

Dr. S. Brindha received B.Sc degree in Science from Bharathiyar University. She done her Master Degree in Information Science and Management in Periyar University and she awarded M.Phil Computer Science from the Bharathiyar University. She received the Ph.D degree in Computer Science from the Bharathiar University. She has 6 years of teaching experience and 6 years of Technical Experience in Hash Prompt Softwares Pvt. Ltd. At present she is working as Assistant Professor of Computer Applications in Vellalar College for Women, Erode, Tamilnadu, India. She published around 17 research papers in International Journals and Conferences, International Publisher, published E-learning Concepts and Development Tools on 2021. Her Research area includes Text Mining and Image Processing, Pattern Taxonomy Mining.