



# Applications of edge analytics: a systematic review

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**Abstract.** With the development and expansion of the Internet of Things, computing at the edge is becoming increasingly important, especially for applications where real-time response is important. In this paper, we made a systematic review of the literature on analytics at the edge. We extracted data from 40 selected primary relevant studies from the complete set of 419 papers retrieved from scientific databases. In our analysis of the full text of every primary study we investigated: temporal distribution of primary studies, publication types, domain and application areas of the primary papers, used machine learning and deep learning methods. We also elaborated on the main themes of the primary studies and recommended some possible interesting future research possibilities.

## 1 Introduction

With the expansion of the Internet of Things, the number of smart devices equipped with various sensors that generate a large amount of data is also increasing. The most common use case is that all this data is then sent to a centralized server or cloud. Due to the large amount of data, there can be problems with applications that need to work in real time. In addition, the costs of sending and storing data on the cloud are not negligible. This

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is why computing at the edge is becoming more and more popular, which processes all or part of the IoT data processing closer to the smart devices themselves, without sending all the data to the cloud. Edge computing is more efficient because latency is greatly reduced. At its most basic, edge computing brings data processing and storage closer to the devices that collect the data, rather than relying on a central location that may be physically thousands of kilometers away. Also a lot of AI/Machine Learning/Deep Learning algorithms can be implemented more efficiently closer to the source of the data.

There are some existing reviews on the edge analytics (e.g. most comprehensive are [32] and [34]), but non have focus on applications and domains of edge analytics and do not include the newest papers from 2022 and 2023. Application and domains are very important information in edge analytics, from which practitioners and researchers can conclude which applications are the most prevalent and suitable for the use of edge analytics, and which still need further research. That part is elaborated in detail in our paper and is its main contribution. In addition, we have listed at the end possible future research questions that may be useful to readers and researchers from this and related scientific fields. Analytics at the edge is increasingly important today, as it enables real-time processing and avoids the latency that is inevitable if data is immediately sent to the cloud, and can include diagnostics, descriptive or predictive analytics.

This work is organized as follows: Section 2 describes in detail the steps of the performed systematic literature review procedure. The section 3 explains the results of the systematic review on applications of edge analytics. Last section in this paper lists the conclusions and possible future research possibilities.

## 2 Research methodology

We have performed our review by using the systematic literature review (SLR) methodology described by Kitchenham and Charters [23] that is developed to be suitable for software engineering research reviews. According to the mentioned SLR methodology there are three main review implementation phases: planning, conducting, and reporting. These main steps of the SLR protocol are listed and elaborated in the next subsections.

### 2.1 Planning

Planning step of the chosen SLR methodology deals with the explanation of the necessity of conducting a certain systematic literature review with a concrete

theme. In the Introduction section of this work, we have defined the specific need to do a systematic review on applications and domains of edge analytics.

Next, the following main research questions were defined:

RQ1: How has research on edge analytics evolved over time?

RQ2: How is edge analytics research reported and what is the maturity level of this research field?

RQ3: What are main applications and domains of the edge analytics?

RQ4: What types of data are processed mostly in the edge analytics?

RQ5: Which machine learning and deep learning methods are mostly used in edge analytics?

When defining our review protocol, we have decided to include the following scientific databases: IEEE Xplore, Science Direct, and Web of Science Core Collection. The search strings/keywords were simply defined as "edge analytics". We have defined the following inclusion criteria (IC): the main objective of the paper must discuss or investigate an issue related to the applications of edge analytics; the paper must be a research (scientific) work written in English; it should be published as a conference or a journal paper.

We excluded the following papers(EC): studies that are not related to the our defined research questions; papers reported only by abstracts or slides; duplicate studies; papers that do not show any applications/proof-of-concept /domains where edge analytics is used.

## 2.2 Conducting

The second step of the chosen SLR procedure is conducting. We have performed the search operation on the mentioned three electronic sources using search string "*edge analytics*" on 7th July 2023. We have used a reference management software *Zotero* to ease our SLR. We have organized the retrieved papers in Zotero collection together with their bibliographic information and full texts. Our first search resulted in 202 extracted papers. First search resulted in 419 paper: IEEE Xplore - 128 papers, Science Direct - 114 papers, and Web of Science Core Collection (177). First, we have removed the duplicate papers, because some papers were in more than one scientific databases. After additionally performing all the inclusion/exclusion criteria defined in the previous subsection on titles and abstracts, 129 papers remained. After excluding the unrelated works that are not focused or do not have any applications or domains for edge analytics defined, 78 papers remained. The final selection

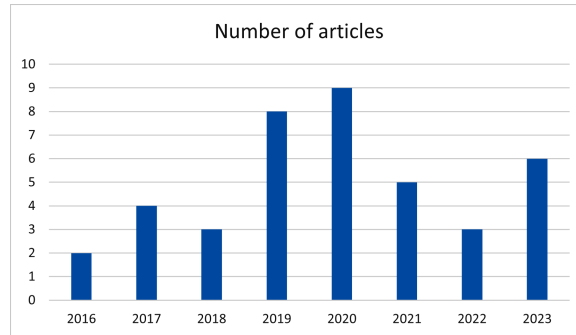


Figure 1: Distribution of the primary studies per year

was done by reading the whole text of the papers, and after this phase, we have selected 40 primary studies for our SLR (Table 1 and Table 2).

### 2.3 Reporting

Reporting phase includes specifying dissemination mechanisms and formatting the main report. We have extracted data from the 40 selected primary studies and did a synthesis taking into consideration the defined research questions. The results of our systematic literature review on applications of edge analytics are shown in the next sections, and this paper is main dissemination mechanisms of our performed SLR.

## 3 Results and discussion

### 3.1 Temporal overview of studies

The earliest found works on applications of edge analytics were published in 2016 (see Fig.1). The peak of number of papers was in 2019 and 2020. But this year (2023) is also very promising, and we expect that this research theme will be also very popular in the near future. We must take into consideration the date of our SLR search (7th July 2023), so our data for 2023 is actually only for the first half of the year.

### 3.2 Types of publications

The publication types of primary studies in SLR is demonstrated in Fig. 2. Of the primary studies, 22 were conference papers and 18 were journal papers.

ID	Title of the paper
P1	A Cloud Analytics-Based Electrical Energy Management Architecture Empowered by Edge Analytics Arduino with Push Notifications for Demand-Side Management [26]
P2	Adaptive Edge Analytics for creating memorable customer experience and venue brand engagement, a scented case for Smart Cities [16]
P3	Adaptive Edge Analytics for Distributed Networked Control of Water Systems [19]
P4	Adaptive Recovery of Incomplete Datasets for Edge Analytics [28]
P5	An Efficient Edge Analytical Model on Docker Containers for Automated Monitoring of Public Restrooms in India [13]
P6	Asset Monitoring using Smart Sensing and Advanced Analytics for the Distribution Network [24]
P7	Camera-Based Edge Analytics for Drilling Optimization [12]
P8	Cyber-Physical Analytics: Environmental Sound Classification at the Edge [8]
P9	Deep Learning for Reliable Mobile Edge Analytics in Intelligent Transportation Systems: An Overview [10]
P10	Edge Based Decision Making In Disaster Response Systems [43]
P11	Edge Computing for Having an Edge on Cancer Treatment: A Mobile App for Breast Image Analysis [5]
P12	Enabling Far-Edge Analytics: Performance Profiling of Frequent Pattern Mining Algorithms [1]
P13	GLEAN: Generalized-Deduplication-Enabled Approximate Edge Analytics [15]
P14	Heuristic Algorithms for Co-scheduling of Edge Analytics and Routes for UAV Fleet Missions [21]
P15	Implementation of Intrusion Detection Methods for Distributed Photovoltaic Inverters at the Grid-Edge [17]
P16	Improved Algorithms for Co-Scheduling of Edge Analytics and Routes for UAV Fleet Missions [22]
P17	Intelligent edge analytics for load identification in smart meters [40]
P18	IoT based Ocean Acidification monitoring system with ML based Edge Analytics [18]
P19	Leveraging edge analysis for Internet of Things based healthcare solutions [29]
P20	LiHEA: Migrating EEG Analytics to Ultra-Edge IoT Devices With Logic-in-Headbands [41]

Table 1: Selected primary studies of SLR on edge analytics (part1)

ID	Title of the paper
P21	ML-assisted IC Test Binning with Real-Time Prediction at the Edge [14]
P22	On Delay-Sensitive Healthcare Data Analytics at the Network Edge Based on Deep Learning [9]
P23	Real-Time Monitoring of Agricultural Land with Crop Prediction and Animal Intrusion Prevention using Internet of Things and Machine Learning at Edge [35]
P24	Realising Edge Analytics for Early Prediction of Readmission: A Case Study [33]
P25	Towards Resource-Efficient Wireless Edge Analytics for Mobile Augmented Reality Applications [6]
P26	Using Edge Analytics to Improve Data Collection in Precision Dairy Farming [4]
P27	Using Siamese Networks to Detect Shading on the Edge of Solar Farms [38]
P28	An energy efficient IoT data compression approach for edge machine learning [2]
P29	An OCF-IoTivity enabled smart-home optimal indoor environment control system for energy and comfort optimization [20]
P30	Application of MES/MOM for Industry 4.0 supply chains: A cross-case analysis [31]
P31	Edge computing for Internet of Things: A survey, e-healthcare case study and future direction [37]
P32	Federated Learning for improved prediction of failures in Autonomous Guided Vehicles [39]
P33	Genetically optimized Fuzzy C-means data clustering of IoMT-based biomarkers for fast affective state recognition in intelligent edge analytics [25]
P34	A Deep Learning Approach for Voice Disorder Detection for Smart Connected Living Environments [42]
P35	A Novel Edge Analytics Assisted Motor Movement Recognition Framework Using Multi-Stage Convo-GRU Model [30]
P36	Design and Implementation of Cloud Analytics-Assisted Smart Power Meters Considering Advanced Artificial Intelligence as Edge Analytics in Demand-Side Management for Smart Homes [7]
P37	Edge analytics for anomaly detection in water networks by an Arduino101-LoRa based WSN [3]
P38	Liver Disease Detection: Evaluation of Machine Learning Algorithms Performances With Optimal Thresholds [36]
P39	Novel smart home system architecture facilitated with distributed and embedded flexible edge analytics in demand-side management [27]
P40	Smart surveillance system for real-time multi-person multi-camera tracking at the edge [11]

Table 2: Selected primary studies of SLR on edge analytics (part2)

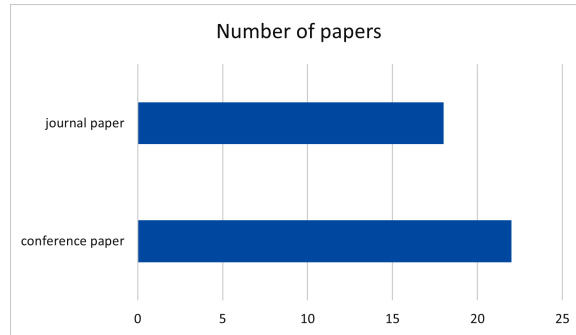


Figure 2: Publication types of primary studies in SLR

We did not find any relevant scientific book chapter. The number of papers in scientific journals and conferences is actually quite similar, which suggests that this research topic is already quite mature.

### 3.3 Data types used in edge analytics

Most of the primary studies have used the following data types in edge analytics: numeric sensor data (32 papers), video data (6 papers), and voice/sound data (2 papers). This distribution is shown in Fig. 3. Another view of the data type sphere can be according to the domain from which the data comes. In this sense, we can single out the following types of data that are most common in the set of primary studies obtained by performed SLR methodology: health data (10 papers), environment data (temperature, humidity etc. - 9 papers), industrial sensor data (5 papers), and security and disaster management data (4 papers). Graphical depiction of the mentioned distribution can be found at Fig. 4.

### 3.4 Applications and domains of edge analytics

Table 3. lists the most important applications and domains of edge analytics in primary studies of our SLR. Some of the papers can have more than one application/domain, and for some papers it is impossible to determine the used domain. The most often domain is healthcare. More concretely in our set of SLR's primary studies we have papers using edge analytics to help cancer treatment (P11 [5]), patient monitoring (P19 [29], P24 [33], P35 [30]), EEG analytics (P20 [41]), e-healthcare (P31 [37]), voice disorder (P35 [30]), liver disease detection (P38 [36]). The labels in parentheses are the codes of the

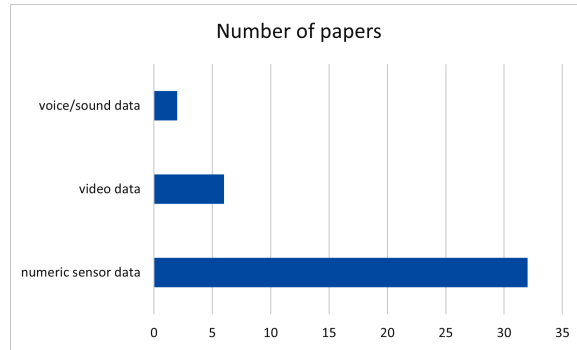


Figure 3: Data types used in edge analytics

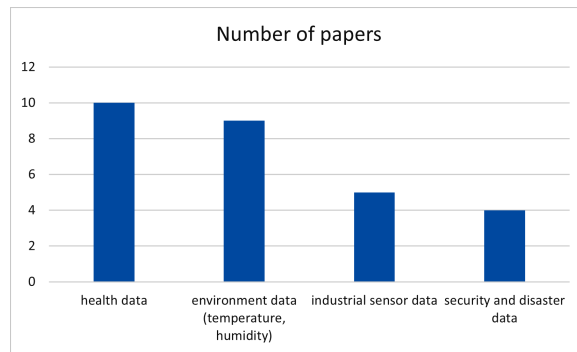


Figure 4: Types of data by domain

primary studies listed in Table 1 and Table 2 of this work (selected primary studies list of SLR on edge analytics part 1 and part 2).

The next domains with more papers are smart home, energy management, and transportation. In the smart home domains, most investigated themes are: smart power meters (P1 [26], P3 [19], P36 [7]), smart buildings (P4 [28]), smart sanitization system (P5 [13]). Papers focused on energy management deal with the following issues: smart energy management (P1 [26]), water leak management (P3 [19]), electric distribution network monitoring (P6 [24]), smart electric network (P17 [40]), and energy savings (P29 [20]). Regarding transportation domain in edge analytics, we have found the following themes in primary studies: intelligent transportation system (P9 [10]), Unmanned Aerial Vehicles or drones (P14 [21], P16 [22]), and driving behavior monitoring (P28 [2]).



Agriculture domains includes the paper on a smart irrigation (P23 [35]) and one work on a precision dairy farming (P26 [4]). Using edge analytics for disaster management is described in the paper P10 [43] and for security (more specifically intrusion detection) in the paper P16 [22]. Marketing domain has two papers, one on electronic scent diffusers (P2 [16]), and another one on market basket analysis (P12 [1]). Regarding industry domain, we have found one paper on drilling automation in oil and gas industry (P7 [12]) and one paper on IC test in semiconductor manufacturing (P21 [14]).

Domain of the application	Number of papers
Healthcare	9
Agriculture	2
Smart home	5
Energy management	5
Transportation	5
Disaster management	1
Security	1
Marketing	2
Industry	2

Table 3: Applications and domains of edge analytics

### 3.5 Used machine and deep learning methods

Table 4 lists the most used machine learning and deep learning methods in edge analytics according to primary studies set of our performed SLR. The most used methods are convolutional neural networks (7 papers), other types of artificial networks (4 papers), Kalman filter, k-nearest neighbours, recurrent neural network, and YOLO (all 5 mentioned in 3 papers). It turns out that the most commonly used methods are different forms of neural networks that are implemented on the edge, regardless of the limitations of edge devices in terms of processing capabilities as well as data storage capacity. The type of artificial neural network often depends on the type and characteristics of data processed at the edge. For anomaly detection, Kalman filter method is often used.

Machine and deep learning methods	Number of papers
Convolutional Neural Network	7
Kalman filter	3
Random Forest	2
K-Nearest Neighbours	3
Support Vector Machine	2
Recurrent Neural Network (RNN)	3
Polynomial regression	1
Support Vector Clustering (SVC)	2
Other types of Artificial Neural Network	4
XGBoost	1
Genetic algorithms	1
Naïve Bayes	1
Logistic Regression	2
YOLO	3
Siamese neural network	2

Table 4: Used machine and deep learning methods

## 4 Conclusions

Recently, the number of different smart devices that facilitate various activities in industry, smart homes, healthcare and other domains has been increasing. Many applications that use smart devices and related solutions need to work in real time. Because of this, it is often impractical to send the large amounts of data generated by today's IoT devices to a remote cloud. In many cases, edge computing is being used, which enables data processing and storage to be done closer to the devices themselves, thus reducing latency. In this paper, we made a systematic review of the literature on the applications of analytics at the edge.

In this conclusion, we look back at the research questions we defined at the beginning of the SLR procedure and look at the results after a detailed reading of all 40 primary studies.

RQ1: How has research on edge analytics evolved over time?

Research on edge analytics started in 2016, and the most papers were published in 2019 and 2020. In the first half of the year 2023 we can see a repeated growth in the popularity of this research topic.

RQ2: How is edge analytics research reported and what is the maturity level of this research field?

The maturity of this research topic is quite high, because in the case of primary

studies, we have almost the same number of works performed at scientific conferences and in scientific journals.

RQ3: What are main applications and domains of the edge analytics?

The main application and domains of the edge analytics are healthcare, smart home, energy management, and transportation. More detailed analysis can be found in Section 3.4.

RQ4: What types of data are processed mostly in the edge analytics?

Numeric sensor data, video data, and voice/sound data are most common data types used in edge analytics.

RQ5: Which machine learning and deep learning methods are mostly used in edge analytics? Generally, the most used methods are different types of artificial neural networks. More detailed analysis on this topic can be found in Section 3.5 of this work.

Future research can include techniques, methods, and methodologies to enable and efficiently execute deep learning (various types of artificial neural networks) on the edge devices that are limited by processing power as well as the amount of data they can store. Interoperability of edge analytics data, different IoT devices and services, and edge devices and frameworks is also challenging future research theme. Edge analytics as a service can be another interesting possibility for future research.

## References

- [1] K. A. Alam, R. Ahmad, et al., Enabling far-edge analytics: performance profiling of frequent pattern mining algorithms, *IEEE Access* **5** (2017) 8236–8249. ⇒ [349](#), [353](#)
- [2] J. Azar, et al., An energy efficient IoT data compression approach for edge machine learning, *Future Generation Computer Systems* **96** (2019) 168–75. ⇒ [350](#), [352](#)
- [3] M. Babazadeh, Edge analytics for anomaly detection in water networks by an Arduino101-LoRa based WSN, *ISA Transactions*, **92** (2019) 273–85. ⇒ [350](#)
- [4] K. Bhargava, et al., Using edge analytics to improve data collection in precision dairy farming, *2016 IEEE 41st Conference on Local Computer Networks Workshops (LCN Workshops)*, Dubai, United Arab Emirates, 2016, pp. 137–44. ⇒ [350](#), [353](#)
- [5] E. Charteros, I. Koutsopoulos, Edge computing for having an edge on cancer treatment: a mobile app for breast image analysis, *2020 IEEE International Conference on Communications Workshops (ICC Workshops)*, virtual, 2020, pp. 1–6. ⇒ [349](#), [351](#)

- 
- [6] L. E. Chatzieftheriou, et al., Towards resource-efficient wireless edge analytics for mobile augmented reality applications, *2018 15th International Symposium on Wireless Communication Systems (ISWCS)*, Lisbon, Portugal, 2018, pp. 1–5. ⇒ 350
- [7] Y.Y. Chen, et al., Design and implementation of cloud analytics-assisted smart power meters considering advanced artificial intelligence as edge analytics in demand-side management for smart homes, *Sensors*, **19**, 9 (2019), 2047. ⇒ 350, 352
- [8] D. Elliott, et al., Cyber-physical analytics: environmental sound classification at the edge, *2020 IEEE 6th World Forum on Internet of Things (WF-IoT)*, New Orleans, LA, USA, 2020, pp. 1–6. ⇒ 349
- [9] Z. M. Fadlullah, et al., On delay-sensitive healthcare data analytics at the network edge based on deep learning, *2018 14th International Wireless Communications Mobile Computing Conference (IWCMC)*, Limassol, Cyprus, 2018, pp. 388–93. ⇒ 350
- [10] A. Ferdowsi, et al., Deep learning for reliable mobile edge analytics in intelligent transportation systems: an overview, *IEEE Vehicular Technology Magazine*, **14**, 1 (2019) 62–70. ⇒ 349, 352
- [11] B. Gaikwad, A. Karmakar, Smart surveillance system for real-time multi-person multi-camera tracking at the edge, *Journal of real-time image processing*, **18**, 6 (2021) 1993–2007. ⇒ 350
- [12] C. P. Gooneratne, Camera-based edge analytics for drilling optimization, *2020 IEEE International Conference on Edge Computing (EDGE)*, virtual, 2020, pp. 111–15. ⇒ 349, 353
- [13] R. Gore, et al., An efficient edge analytical model on Docker containers for automated monitoring of public restrooms in India, *2020 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS)*, New Delhi, India, 2020, pp. 1–6. ⇒ 349, 352
- [14] T. Honda, et al., ML-assisted IC test binning with real-time prediction at the edge, *2023 7th IEEE Electron Devices Technology & Manufacturing Conference (EDTM)*, Seoul, Korea, 2023, pp. 1–4. ⇒ 350, 353
- [15] A. Hurst, et al., GLEAN: Generalized-deduplication-enabled approximate edge analytics, *IEEE Internet of Things Journal*, **10**, 5 (2023) 4006–4020. ⇒ 349
- [16] A. Ilapakurti, et al., Adaptive edge analytics for creating memorable customer experience and venue brand engagement, a Scented Case for Smart Cities, *2017 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computed, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCAL-COM/UIC/ATC/CBDCOM/IOP/SCI)*, San Francisco, CA, USA, 2017, pp. 1–8. ⇒ 349, 353
- [17] C. B. Jones, et al., Implementation of intrusion detection methods for distributed photovoltaic inverters at the grid-edge, *2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, Washington, DC, USA, 2020, pp. 1–5. ⇒ 349

- 
- [18] K. V. [Gopika](#), et al., IoT based ocean acidification monitoring system with ML based edge analytics, *2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, 2022, pp. 345–53. ⇒ [349](#)
- [19] S. [Kartakis](#), et al., Adaptive edge analytics for distributed networked control of water systems, *2016 IEEE First International Conference on Internet-of-Things Design and Implementation (IoTDI)*, Berlin, Germany, 2016, pp. 72–82. ⇒ [349](#), [352](#)
- [20] A. N. [Khan](#), et al., An OCF-IoTivity enabled smart-home optimal indoor environment control system for energy and comfort optimization, *Internet of Things*, **22** (2023) 100712. ⇒ [350](#), [352](#)
- [21] A. [Khochare](#), Y. Simmhan, et al., Heuristic algorithms for co-scheduling of edge analytics and routes for UAV fleet missions, *IEEE INFOCOM 2021 - IEEE Conference on Computer Communications*, Vancouver, British Columbia, Canada, 2021, pp. 1–10. ⇒ [349](#), [352](#)
- [22] A. [Khochare](#), F. B. Sorbelli, et al., Improved algorithms for co-scheduling of edge analytics and routes for UAV fleet missions, *IEEE/ACM Transactions on Networking*, **1** (2023) 1–17. ⇒ [349](#), [352](#), [353](#)
- [23] B. [Kitchenham](#), S. [Charters](#), [Guidelines for performing systematic literature reviews in software engineering](#)(2007). ⇒ [346](#)
- [24] S. [Kulkarni](#), et al., Asset monitoring using smart sensing and advanced analytics for the distribution network, *2019 North American Power Symposium (NAPS)*, Wichita, USA, 2019, pp. 1–6. ⇒ [349](#), [352](#)
- [25] A. [Kumar](#), et al., Genetically optimized fuzzy C-Means data clustering of IoMT-based biomarkers for fast affective state recognition in intelligent edge analytics, *Applied Soft Computing*, **109** (2021) 107525. ⇒ [350](#)
- [26] Y.H. [Lin](#), A cloud analytics-based electrical energy management architecture empowered by edge analytics Arduino with push notifications for demand-side management, *2019 IEEE 2nd International Conference on Power and Energy Applications (ICPEA)*, Signapore, 2019, pp. 1–6. ⇒ [349](#), [352](#)
- [27] Y.H. [Lin](#), Novel smart home system architecture facilitated with distributed and embedded flexible edge analytics in demand-side management, *International Transactions on Electrical Energy Systems*, vol. 29, no. 6, June 2019, p. 1214. ⇒ [350](#)
- [28] I. [Lujic](#), et al., Adaptive recovery of incomplete datasets for edge analytics, *2018 IEEE 2nd International Conference on Fog and Edge Computing (ICFEC)*, Washington DC, DC, USA, 2018, pp. 1–10. ⇒ [349](#), [352](#)
- [29] K. J. [Madukwe](#), et al., Leveraging edge analysis for Internet of things based healthcare solutions, *2017 IEEE 3rd International Conference on Electro-Technology for National Development (NIGERCON)*, Owerri, Nigeria, 2017, pp. 720–25. ⇒ [349](#), [351](#)
- [30] A. Manocha, R. Singh, A novel edge analytics assisted motor movement recognition framework using multi-stage Convo-GRU model, *Mobile Networks & Applications*, **27**, 2 (2022) 657–676. ⇒ [350](#), [351](#)

- 
- [31] S. [Mantravadi](#), et al., Application of MES/MOM for Industry 4.0 supply chains: a cross-case analysis, *Computers in Industry*, **148** (2023) 103907. ⇒ [350](#)
- [32] M.G.S. [Murshed](#), et al., Machine learning at the network edge: a survey, *ACM Computing Surveys*, **54**, 8 (2022) 1–37. ⇒ [346](#)
- [33] Y. [Nan](#), et al., Realising edge analytics for early prediction of readmission: a case study, *2020 IEEE International Conference on Cloud Engineering (IC2E)*, Sydney, Australia, 2020, pp. 95–104. ⇒ [350](#), [351](#)
- [34] S. [Nayak](#), et al., A review on edge analytics: issues, challenges, opportunities, promises, future directions, and applications, *Digital Communications and Networks*, (2022). ⇒ [346](#)
- [35] R. [Nikhil](#), et al., Real-time monitoring of agricultural land with crop prediction and animal intrusion prevention using internet of things and machine learning at edge, *2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT)*, Bangalore, India, 2020, pp. 1–6. ⇒ [350](#), [353](#)
- [36] A. [Pan](#), et al., Liver disease detection: evaluation of machine learning algorithms performances with optimal thresholds, *International journal of healthcare information systems and informatics*, **17**, 2 (2022). ⇒ [350](#), [351](#)
- [37] P. P. [Ray](#), et al., Edge computing for Internet of things: a Survey, e-healthcare case study and future Direction, *Journal of Network and Computer Applications*, **140** (2019) 1–22. ⇒ [350](#), [351](#)
- [38] S. [Shapsough](#), et al., Using Siamese networks to detect shading on the edge of solar farms, *2020 7th International Conference on Internet of Things: Systems, Management and Security (IOTSMS)*, Paris, France, 2020, pp. 1–8. ⇒ [350](#)
- [39] B. [Shubyn](#), et al., Federated learning for improved prediction of failures in autonomous guided vehicles, *Journal of Computational Science*, **68** (2023) 101956. ⇒ [350](#)
- [40] T. [Sirojan](#), et al., Intelligent edge analytics for load identification in smart meters, *2017 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)*, Auckland, New Zealand, 2017, pp. 1–5. ⇒ [349](#), [352](#)
- [41] T. [Tazrin](#), et al., LiHEA: migrating EEG analytics to ultra-edge IoT devices with logic-in-headbands, *IEEE Access*, **9** (2021) 138834–138848. ⇒ [349](#), [351](#)
- [42] L. [Verde](#), et al., A deep learning approach for voice disorder detection for smart connected living environments, *ACM Transactions on Internet technology*, **22**, 1 (2022) 8. ⇒ [350](#)
- [43] J. [Wagner](#), M. Roopaei, Edge based decision making in disaster response systems, *2020 10th Annual Computing and Communication Workshop and Conference (CCWC)*, Las Vegas, NV, USA, 2020, pp. 10469–73. ⇒ [349](#), [353](#)