ISSN No:-2456-2165

Machine Learning Driven Edge Analytics for Healthcare: Problems, Difficulties, Future Directions, and Applications-A Review

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Abstract:- With the use of edge technology, cloud resources (particularly computing, storage, and network) will be made available in close proximity to edge devices, or smart gadgets where data is generated and consumed. Edge computing and edge analytics are two new ideas in edge technology that have emerged as a result of computer and application integration in edge devices. To examine the information produced through edge gadgets, edge analytics employs a number of methods or algorithms. The development of edge analytics has made the edge gadgets a whole set. Edge analytics is currently unable to fully accomodate the analytic methodologies. Due to several limitations like a low power supply, a tiny memory, a lack of resources, etc., the edge gadgets cannot conduct complex and refined analytic algorithms. The purpose of this paper is to give a thorough explanation of edge analytics. The following are the paper's main contributions: a detailed description of the differences among the three edge technology ideas of edge gadgets, edge computing, and edge analytics, as well as their problems. The article also examines how edge analytics are being used in numerous industries, including retail, agriculture, industry, and healthcare, to solve a variety of issues. Additionally, the research papers based on cutting-edge analytics are thoroughly examined in this article to analyse the current problems, new difficulties, research prospects, as well as utilizations.

Keywords:- *Edge Analytics, Edge Gadgets, Big Data, Sensor, Edge Computing, AI, ML, Health-Care.*

I. INTRODUCTION

The technology is given a sense of infinite by cloud computing, which offers vast storage, powerful computing power, enormous infrastructure, and other benefits [3]. Thus, everyone is interested in the features of cloud computing. Due to the pay-as-you-go mechanism, clients can always increase their system capacity as needed for a small additional fee. With modern smart technology, every gadget is capable of using cloud computing to reach intelligent decisions. Smart collaboration is now simpler than ever thanks to the cloud [1].

But the proliferation of smart gadgets brings up the problem of big data [2]. Cisco predicted that there would be 500 billion smart devices by the year 2025 [6]. Data silos will be produced by billions of smart gadgets, most of which will be unnecessary, and these large data will be sent to the cloud for processing. Transmission of these superfluous data, which the cloud will eventually disregard or erase, consumes bandwidth and network resources. Furthermore, sending superfluous data consumes network resources and creates extra network traffic. As personal data is transmitted across great distances by cloud computing, privacy also becomes a significant issue. High latency is another problem; it takes a while for data to be transmitted, computed, and then returned to smart devices. Due to all of these problems, computing tasks must be done close to smart devices. As a result, edge technology, another technology, evolved. Edge computing is a new technology that can scale up to keep up with the expanding network resources and satisfy user demand. Given that cloud servers are located a great distance from end user with its gadgets hence, Satyanarayanan et al.[4] , suggested method of bringing the cloud (cloudlet)close to smart devices. Edge computing so develops and will be the foundation of all intelligent gadgets, such as Aerial Unmanned Vehicle, in future (UAV).Intelligent gadgets, such as smart-watches, intelligent-phones, modems, controllers/switch, portable access gadgets, and also, IoT gateways, all are known as edge gadgets in Edge technology[5]. The Edge gadget is designed to be adequate to gathering, cleaning, with evaluating the end-user information as well as providing a timely feedback. Edge computing and edge analytics refer to the computation and analysis that are carried out by edge devices, respectively. In the middle of Edge gadgets with technology of cloud, that is located closer towards these edge gadgets, are edge nodes. As a result, they can considerably improve edge device computation. They can also significantly decrease bandwidth and latency on the network.

The goal of Edge applied science is towards giving edge devices access to cloud computing functions. The cloud, on the other hand, has everything and is conceptually virtually infinite, including storage, processing power, infrastructure, etc. However, everything near to every Edge is finite, along constrained resources, fixed power, confined storage, with little-powered CPUs [8].The programme that uses a lot of computing power needs a lot of resources, strong processors, a lot of memory, and high power. Small devices that people carry or wear, such smartphones and smart watches, are known as edge devices. Without the assistance of edge nodes, embedding compute-intensive

ISSN No:-2456-2165

apps would be impossible.. Though many problems have been resolved and cloud computing has moved closer to the edge thanks to edge technologies. Besides the aid of Cloud computing and Edge Nodes, Edge analytics run some apps over Edge Gadgets to evaluate information, which gives them ability to reply to tiny too many demands mere rapidly. Considering instance, all equipment within one production have sensors that can monitor certain properties. In some circumstances, the products or machinery may be harmed if each of these metrics exceeds a certain threshold. Therefore, it is crucial to continuously monitor these factors. However, humans are unable to examine these criteria effectively, and in some circumstances, doing so could be hazardous.

Edge devices can monitor these metrics with the assistance of edge nodes in such circumstances and take a predetermined action before the issue spirals out of hand. The review papers on edge analytics are included in Table 1 below. These publications, however, examined edge analytics in a particular field. The article's main contributions from us are its exploration of the important problems, opportunities, and other aspects of edge analytics. As a result, we provide a thorough discussion of edge analytics in our essay. This study explores the broader area of cutting-edge edge analytics, revealing concerns and difficulties among Edge Analysis. Broad perception within applications for Edge Analysis is also presented. Firm on the classification of information used, Edge Analysis applications are categorised. Also covered is the rationale behind investigating ML and AI technologies as Edge Analytics.

Table-1 Examination of Articles on Edge Analysis and A Comparison with the Paper we've Proposed

Author of Paper	Published Year	Name of Paper	Area
Sai sabitha .et. al. [7]	20-18,ieee	A Review: Edge Analytics for Automation Building Systems	Automation, Smart Building Systems
Djamaluddin .et.al. [9]	20-19,SOPE	A Survey Literature Review of Real-Time Data Acquisition Towards Real-Time edge analytics-	Real-Time, Industry analysis
H.Zhong .et. al.[10]	20-19,ieee	A Review Edge video Analytics for Public -Safety:	Video edge analytics, Public Safety, security
Andrea Pazienza. et.al.[11]	20-20, CEUR-WS	Artificial Intelligence on Edge Computing: a Healthcare Scenario in Ambient Assisted Living	Healthcare, smart environment
Rushit Dave et. al[12]	20-21, SciEP	The Benefits of Edge Computing in Healthcare, Smart Cities, and IoT	Healthcare, smart cities

- The methodologies used in edge analytics are examined in order to show how edge analytics addresses problems in many industries and deployments, including healthcare and business. In addition, there are many uses for edge analytics beyond the ones listed in Table 1, such as in the field of medicine. The applications and issues of all cutting-edge research domains are shown in edge analytics. The approach for the literature review is described in the following subsection. According to the clustering method employed by previous studies, this subsection illustrates our study's clustering approach.

II. LITERATURE REVIEW

The segmentation of Edge Analytics papers and the motivation behind doing so are both thoroughly discussed in this subsection. In Sections 2, 3, 4, and 5, the overview of the Edge Analytics articles are discussed. Prominent journals and conferences publish the articles that were chosen for publication. In this article, four ideas related to:

A. *Categorization of Edge Analytics Depending on Dataset Type,*
B. *The Use of Machine Learning in Edge Analytics,*
C. *Edge Analytics Applications, and*
D. *The Use of Smart Technology in Edge Analysis are Examined.*

Originated from the kind of dataset, Edge Analytics are categorised: This taxonomy of edge analytics is presented in Section 2.5 based on the types of datasets: Imagatasets. As a result, Figure4 does not mention it. His section is home to all of the papers that were reviewed in this article. To improve clarity on certain issues, some recalls of articles were, however, moved against that area moreover placed to alternative sections.

ISSN No:-2456-2165

- Function of ML in Edge Analytics: This function of ML in Edge Analysis is covered in Section 2.8. Many studies on edge analytics have described machine learning algorithm implementations, but very few have gone into detail about the algorithms used by edge analytics. These publications were chosen for this section's discussion of ML algos.

- Edge Analysis and applications: Section 3 shows how edge analytics are being used in a variety of industries, including retail, agriculture, transportation, and healthcare. These articles were chosen because they included suggested solutions to the issues that exist in these domains.

- The function of Edge Analytics inside supporting Smart/intelligent Technology is elaborated on in Section 3.3. The papers considering the use of Edge Analysis to assist a part of Intelligent/Smart Technology, for example a intelligent watch and a intelligent power meter for a exceptional home, are chosen for this section. The analysis of these publications shows how edge analytics are used to analyse data more quickly and effectively, which is the goal of Intelligent/Smart Technology.

In conclusion, all survey articles fall under Types of Edge Analytics . Analysis of few articles, however, were left out from that area also placed in another sections since they help readers understand how to apply the relevant edge analytics themes.

The article is structured as follows: An introduction to edge analytics is provided in Section 2.1. Section 2.5 classifies Edge Analytics according to the kind of data. Section 2.6,2.6 examines cutting-edge edge analytics. Analysis of edge analytics and ML/AI are included in Section 2.8. In Section 3.3, the strengths and applications of edge technology are further discussed.. The relevant issues and difficulties with edge analytics are highlighted in Section 4. The promise and future of edge analytics are discussed in Section 5. A brief overview of edge analytics problems and a few other topics is included in Section 6. The article are concluded at Section 7

III. EDGE TECHNOLOGY OVERVIEW

IoT helped make cloud-based processing popular, but since the number of edge devices has increased dramatically, there are now numerous problems and difficulties. After user data is uploaded to the cloud, processing takes place, but people are concerned about their privacy because of this. Additionally, a lot of requests require extremely quick responses, which cloud processing cannot provide owing to the great distance. Thus, edge technology developed in order to address these problems and difficulties [13]. Table 2 makes distinctions between cloud and edge based on a number of factors.

A. The Following Causes are Briefly Explored as the Driving Forces Behind the Creation of Edge Technology:

- Huge information management: Due to the transmission of the data to the cloud, this enormous amounts of information produced by smart devices are managed, using up communication and bandwidth resources. However, edge technology may gather, process, and analyse tiny data on-site, significantly lowering the volume of information transmitted to the cloud and enhancing service. Therefore, it is advantageous for applications that deal with time-sensitive data and heavy traffic loads [14].

- Decreased Transmission capacity usage: While an end-user submits the tiny call, the Edge gadget can operate the call ,also provide an end- user the conclusion as soon as it has been produced. Due to the close proximity of edge devices to users, bandwidth consumption is low. However, because of the greater distance between the edge device and the cloud, sending big amounts of data demands a lot of bandwidth. Only critical data is transmitted to the cloud using edge devices' data filtering capabilities [15]. As a result, edge devices drastically cut down on the amount of bandwidth needed to send data from edge devices to the cloud.

- Reliability: Users may receive a limited amount of service from edge devices. The edge device continues to provide service to the user if connectivity with the cloud is lost. Requests are handled by edge nodes, which then respond to users. If an Edge node fails, the Edge gadget will also join to another Edge node. The Edge nodes cannot conduct the complex operation and the request must be put on hold until contact with the cloud [16] is made.

- Low latency: Users are close to edge devices. As a result, end-user information is initially gathered , kept on Edge gadgets. These gadgets were capable to process as well as analyse end-user information in case of little information. The output is rapidly sent to the users after that. Consequently, edge technology reduces latency [15]

- lower the cost of communicating: The bandwidth required to send information to servers or the cloud is lessened via data filtering and processing on Edge gadgets, as well as latency for request processing.. Thus, the cost of transmission is decreased by the decrease in latency and bandwidth utilisation.

- Scalability: The replacement or upgrade of edge nodes as well as the deployment of new edge computing frameworks are all quick and highly automated processes. As a result, it allows the scaling of edge technologies [16].

- Privacy: is maintained by gathering and processing user data on edge devices. The private information is not required to transit quite far to get to the cloud for processing [16].

- Operating Expenses: Reduced internet traffic, frequency use, and other network communication costs are made possible by Edge Technologies Additionally, it decreases the amount of data sent to the cloud, processed there, and stored there, which lowers the cost of the cloud service. [18]

- Adaptability: Using edge nodes makes it easier to handle networking's dynamic nature. The edge nodes can still offer consumers the most fundamental services if there is a communication breakdown with the cloud. In the case that one Edge node fails, the Edge gadgets also connect to additional edge nodes. Furthermore, setting up new edge nodes is easy, quick, and controlled [16].

- Ecological Restrictions: This Edge Technology can be used in applications where there are ecological restrictions, such as fraud detecting in financial venues (ATMs) and aircraft. The restrictions can be of a material or monetary character. On an airplane, minute flaws require some rapid evaluation and processing in order to prevent severe system breakdowns.

- Additionally, the aircraft generates a huge volume of data which cannot be handled at the central node. Therefore, a lot of judgments must be made inside the airplane itself [17].

Table-2 Compares Cloud Computing Technology Versus Edge Technology Based on A Number of Different Criteria.

Criterion	**C-Technology(cloud)**	**E-Technology (Edge)**
Need	—	C-Technology
Framework	Enormous	Finite
Setup Expenses	High	Low
Range	long	Immediate
Processing Assets	Enormous	Finite
Tele-communicating future (Analysis i.e5G, 6G ...)	Need min. Big data analysis	Partial/Fully dependent Edge Analysis
Chosen Algos for Com-putation	Not- particular	Frequently AI/ML, Img/Vid Algos
Lag/delay	high	Low
Repository	enormous	finite
Gross Expenses	High	Low
Experimenter core	minimizing	maximizing
Futurity range	Enormous	intensive algos computation with reduced resources and energy

IV. EDGE ANALYTICS OVERVIEW

Edge analytics, which combines AI and IoT [22], analyses data gathered by edge devices [19, 20, 21]. After gathering this information, edge analytics runs a few systematic algos equally machine learning algorithms / video analytics techniques, and then launches some predetermined actions, including alerting the appropriate parties or issuing a security alert. Edge computing is the term used to describe calculations carried out by edge devices. A component of Edge analytics is computing. As a result, Edge computing encompasses both edge analytics and Edge gadgets. The conventional Edge computing model is depicted in Figure 1.

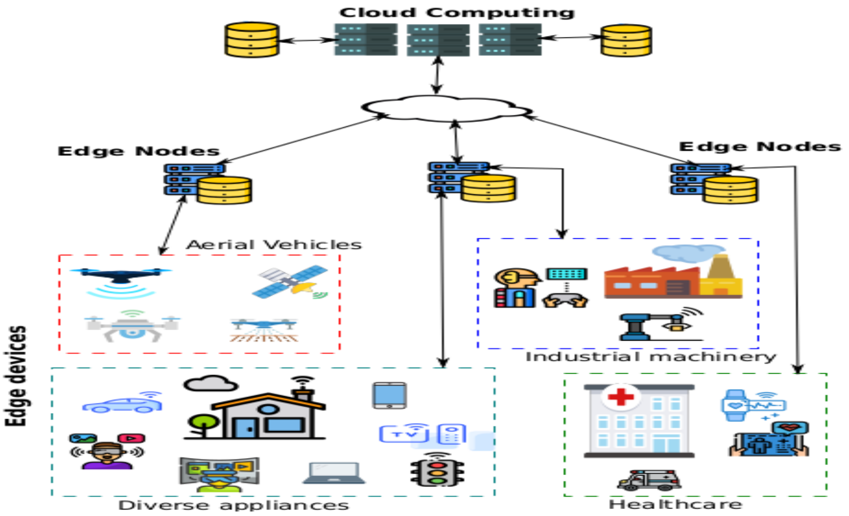

Fig 1 Edge technology infrastructure that shows how cloud infrastructures, Edge nodes, and Edge gadgets are connected.

This Edge Technology is shown through the Venn diagram in Figure 2. Edge devices, edge computing, and Edge-analysis where three components of edge technology at that moment. Hardware and software are the two parts that make up an edge device. Figure 2 only takes the edge device's software into account. Edge computing in software refers to computation done on Edge gadgets, including Internet of Things (IoT) devices. [23].Edge analytics may use a single application or a number of them to analyze data. These apps engage in edge computing, which is computation. Edge computing refers to all computation done by Edge gadgets and Edge analysis. Edge computing therefore includes Edge gadgets with Edge analysis. This analysis is a feature of the Edge gadgets, not a separate entity that exists outside of them. Therefore, all of the computation done for edge analytics is likewise done for edge devices. Edge devices are therefore included in edge analytics. Along with performing edge analytics, edge devices also worked on tasks like data transformation, output data formatting, etc. The Edge gadgets also handle Edge analysis outputs that needs to be modified, filtered, or compressed to reduce file size for cloud repository. Edge analytics is thus a subset of Edge endpoints.

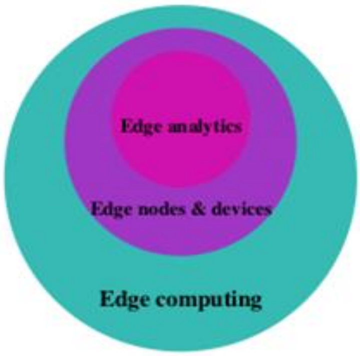

Fig 2 A venn diagram showing the relationship between E-computing, E- analytics, and E-devices

Some fields, like healthcare or certain businesses, constantly monitor certain metrics because if they go below or above a certain threshold, the results could be fatal. For instance, pressure, temperature, and other factors may be monitored or observed in many businesses. Sometimes, these characteristics may exceed a threshold value, which could have an impact on the product's quality, damage the product or equipment, result in accidents (like a fire or explosion), put the workers or the nearby community in risk, etc (e.g., radiation). These could result in severe losses or perhaps the industry's collapse. Only keeping an eye on these indicators is insufficient; prompt response is also necessary. In situations when human review may not always be possible, edge analytics is the best option. Edge devices in this article refers to both Edge peripherals with edge gadgets Figure1,Edge gadgets or edge nodes can both be used for edge analytics. In this article, we therefore employ edge devices analogously. The parameter readings are continuously collected by edge devices like sensors. The edge devices keep track of the higher or lower bounds. The Edge analysis in Edge gadgets run a few analysis algorithms based on those threshold values onto regulate whether or not the attributes have surpassed the limit value(threshold).If these attributes exceed this limit value(threshold), a suitable action is being used, like lowering or else halting this cause/source which generates these attributes(for example, turning off the fire-quantity to lower burden) or alerting an individual to assess this situation. Edge analytics has several predefined activities. Edge analytics then transfers clean information to the C(cloud) considering upcoming or subsequent study. Those various machinery used in the industries have various specifications. It is quite practical to observe all machines utilising edge devices. However, the cloud's function cannot be completely abolished. Due to their limited capacity, edge devices send data to the cloud for archival purposes. Additionally, some analyses need advanced computational techniques, such AI algorithms, to be run. In these situations, data-based training is carried out in the cloud. The generated inferences are then sent to the Edge(peripheral) gadgets by cloud. These Edge analytsis test this information based on these inferences. By doing this, it is possible to enable the use of sophisticated algos in edge gadgets. At the moment, academics are investigating how to run sophisticated algorithms on edge devices. This will aid in reducing Edge gadgets' reliance running on the cloud, particularly while computing with performing analytics.Table02 compares C –Technology and E-technology based on a no. of different factors.

V. BIG DATA ANALYSIS WITH EDGE ANALYSIS

As numerous Edge gadgets/devices are joined to the Edge gate-way are shown in Figure03, which also shows information Analysis from Edge analytics orelse Big data Analytics. Cloud-based analysis(big data) are available. Big data analytics is appropriate when massive amounts of information are gathered with this information possess ambiguous meaning, irregular visualizations, or unknowable results. Analytics of big data needs a lot of repository, framework, servers, and allocated devices to function. Additionally, sophisticated technology that handle big data and advanced analytics are needed to calculate the data. Analytics of big data is available in the C(cloud) as it can supply the enormous resources that are needed by big data analytics.

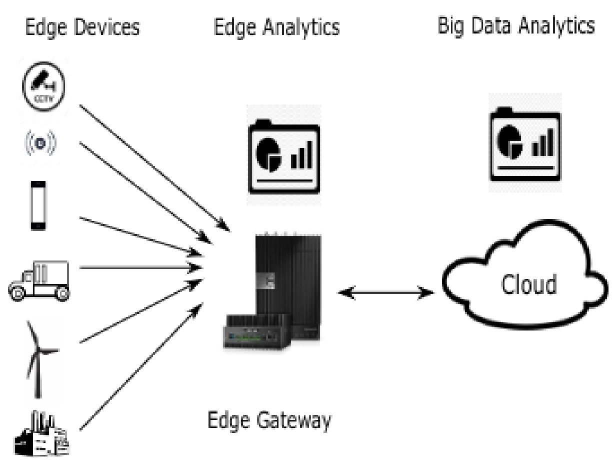

Fig 3 Edge analysis with big data analysis relationship

The goal of edge technology is to integrate analytics(data) into Edge gadgets. As in this situation, that data origin itself may carry out analytics. Edge analytics, meanwhile, are still in their planning stages. With the use of edge technology, a large computing system can fit into a tiny space (i.e., router). In addition to other advantages, it will lower transmission costs and bandwidth usage. The applications of Edge Analytics, however, is static not refined or highly developed. The source of power needed into enable like progressive functions is now a problem. Edge analysis is therefore reliant into the C-Technology(cloud) in the event of a call requiring more computation. This distinction in the middle of Edge analytics and Big data analysis is shown in Table03. The hierarchy of Edge analytics and Big-data analysis implementation is shown in Figure03.

Table-3 The following is A Comparative of Big data Analysis and Edge Analysis Based on A Number of Different Criteria.

Parameter	**E(edge) Analysis**	**(Big data)Analysis**
Development	Developing	Matured
Size of data	Small	Big data
Deployed	E(edge)gadgets (sensors, switches, modems)	Cloud
QoS dependence	Cloud	None
Storage	Small memory of edge device	Distributed System

VI. CONSTRUCTION AND DISPOSAL NEEDS

Images, videos, and information gathered from Edge gadgets like CC-TV, portable devices, with sensors are subjected to edge analytics. Reading license plates, keeping an eye on crowd size, or measuring river levels are a few examples of the applications. The edge nodes must execute analysis with constrained resources. In order to produce good results, several design and deployment considerations are necessary. edge analytics results[24].

- Data analytics: A precise parameter description is necessary for some edge analytics applications. These particular metrics support monitoring. When using machine learning methods, it is necessary to specify the contour in the drawing or audio outlook in order to set the system.
- Data quality: There should be enough data to determine the environment. Because sometimes supporting information is majorly important then primary item. For instance, looking for the car with a particular no.in CC-TV footage from the side of the road.
- Edge device configuration: Fixed edge devices, like CCTV cameras, can sometimes enhance processing. The results are more accurate because of the fixed position's assistance with established reference points.
- Data formats: There are many different types of data. Data from edge analytics must be transformed into the proper form; example, the video might need be divided within the certain no, of Frames. Thus, in order to execute edge analytics across a variety of data sets, an open data format is necessary. In some cases, the dataset is not of high quality. It suffers from issues of null values, duplicate entries, outliers, and so on. In other cases, you may have obtained data from multiple sources (or different ways) and then you have merged it, so explain the process followed.

VII. TYPES OF EDGE ANALYTICS

The classification of Edge Analysis depends onto whether the Edge gadgets were collecting textual, picture, or video data. Edge analytics can be categorized into two kinds based upon the picture or video: image analytics and video analytics. Similar to this, edge analytics is divided into two categories based on textual data: regression/predictive Analysis and descriptive Analysis. On the basis of audio information, Edge Analytics can be divided into different categories. Edge analytics have not yet been offered, hence we have left them off the taxonomy. However, there is a chance for Edge Analytics, which are covered in Section 5].

VIII. IMAGE/VIDEO BASED EDGE ANALYTICS

The Edge Analysis is divided into1) image Edge Analytics ,2) video Edge Analytics based on that image/video dataset. Video is the data source for picture edge analytics. A set of frames that make up a video are also images. Thus, a frame is provided as information to picture Edge Analytics. A video is input for video edge analytics. A movie is partite in to groups of vid Frames rather than being processed as a whole because there is less computing power and resource available [26, 27]. The remaining part of this section provides the brief overview of the several Edge Analysis methods. The current modernized effort on video Edge Analytics is depicted in Table04 along with its advantages and disadvantages. Similarly, the drawbacks of the current work.

The decentralised hybrid cloud architecture known as Giga Sight [19] is a VM-based cloud that supports video edge analytics. The edge nodes in architecture are referred to as cloudlets, which carry out video analytics, modify video streams to preserve privacy, and retain films for brief periods of time in accordance with billing regulations. Each movie is altered in a unique virtual machine in the Denaturation is automatically lowered dependent on cloudlet. based on the user's chosen video stream's fidelity This VM only has access to the original video to protect user privacy.

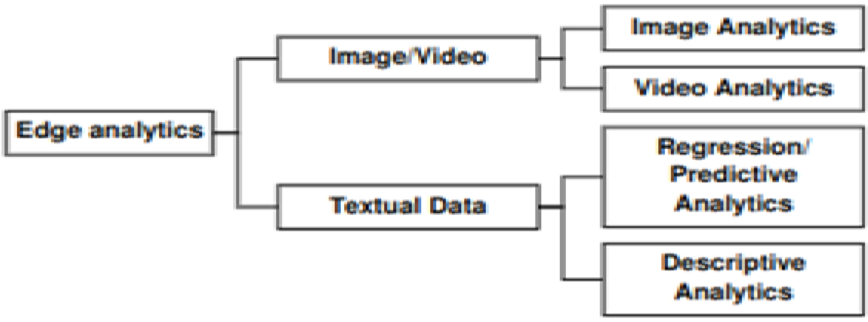

Fig 4 Different types of Edge Analytics are categorised according to the type of dataset.

Table- 4 Advantages and Disadvantages of Several Edge Analytics Methods that Leverage Video Datasets are Presented.

Methods	Advantages	Disadvantages
Framework of Giga-Sight [19]	1)The alteration of the video stream protects privacy. 2)Thumbnail video facilitates sorting and search procedures 3)Filtering on the basis of information has a lower computational complexity.	The Denaturing procedure needs too much computing power • Searching requires a lot of computing power. • According to cost guidelines, video is occasionally erased. • Sorting operations are quite time-consuming.
Video encoder system based on ROI[26]	1)Low complexity of the tracker process; 2)Frame transfer to the aggregator node has less bandwidth overhead. 3) Object detection algorithm execution is limited to the aggregator node, reducing the computational load on other edge nodes.	1)The amount of inexplicable macro blocks rises as successive frame intervals increase. 2) Restricting the use of contributed system characteristics by only running the object detection algorithm in the aggregator node.
D. Zhang..et al. [27]	• Crowd counting makes use of metadata. • Offers higher data privacy protection than a picture. • The time complexity of the object recognition method is average.	• High computation is needed for the crowd counting algorithm. • In high-quality footage, the crowd counting algorithm provides imprecise results. • The accuracy and precision are reduced as the number of videos increases.

IX. TEXTUAL DATA BASED EDGE ANALYTICS

Predictive Edge Analytics calculates ML with AI algos to develop a model that predicts the outcome of future data. In some cases, only results are sent to the Edge gadget once the model has been constructed in the cloud. The information is then analysed using Edge Analytics, which reduces the level of processing necessary on the edge device but increases the device's reliance on the cloud. Descriptive edge analytics is used to describe the dataset.

Table- 5 Textual Data Based Edge Analytics

Techniques	Features	limitations
Cao .et .al[20]	1)At every level of the network, the highly dynamic data and resource utilisation are optimally balanced. • Modular • Minimal latency • Reducing compute overhead on edge nodes by the division of data processing into several descriptive analytical processes	• Complexity exists in descriptive analytics. • Uses a lot of power.
Nikolaou et al. [21]	• Reduces data usage. • Removes undesirable info. • Lessens the burden of communicating.	• Training regression models with large windows requires more time. • Results for training regressive models are less accurate when using small windows.

X. EDGE ANALYTICS WITH MACHINE LEARNING

Researchers are constantly looking for ways to make ML algos low demanding on computing. By incorporating artificial Intelligence with ML algos into Edge gadgets, Edge endpoints can learn starting with their experience, with the data they have access to, producing responses on occurrences that do not require scripting. This is made possible by Edge Technology. Interpretation uses fewer computing assets into run also produce results considering fresh information. hence, when performed at edge nodes, inference aids in providing a low-latency response to the user's request. In order towards couple ML with Edge-Technology, Microsoft offered Azure IoT edge [28]. ML inference was carried out nearby in Edge gadgets in AWS Greengrass [29] utilising cloud-based models. Due to machine learning methods, the edge nodes experience a variety of problems. The following list of problems is taken from [30]:

A. Data Subset: an Edge Node Receives Data in A Subset. as A Result, These ML Algos Learning On These Edge Gadgets Prevail Subpar.

- Real-time information are dynamic in nature. As a result, training carried out through this ML algo. eventually turn out outdated.
- Requires a lot of computing power: This applies to all machine learning techniques. Therefore, edge nodes with low levels of all characteristics, such as power, computing, resources, etc., cannot support such algorithms.

The efficiency of information gathering as well as processing is enhanced by the(ECNN) Edge-Deployed Convolution Neural Network , the distributed information analytics architecture for intelligent- grid [31].

The Edge entryway design with the predicting analysis component that employs DL techniques was proposed by Sarrabi-Jacome et al. [32]. This construction are interoperable, safe, with support of confidentiality.

Table- 6 Techniques that Combines Machine Learning and Edge Analytics

Techniques	Features	Limitations
I. Lacalle.et al. [32]	The constrained resources are managed through container-based virtualization. • The virtualization method based on containers uses the resources uniformly. • Compatible It's safe. • Preserves privacy.	• DL models are resource-intensive. • DL model training is carried out in the cloud. • D- neural network inference generation requires more time. • The generating time for inferences grows as connected edge devices proliferate.
ECNN [31]	• Improves data aggregation and analytics performance. • Smaller features or local inferences have lower transmission costs.	• Cloud-based inferences produce more information conclusions. • Edge end-points are unable to support all CNN layers.

XI. APPLICATIONS

Edge analytics is used in a variety of industries, including energy, logistics, manufacturing, and retail. Retail consumer behavior analysis, manufacturing and logistics equipment monitoring, remote monitoring and maintenance of energy operations, healthcare and fraud detection at financial facilities (ATMs) are some examples of applications for edge analytics [33]. This section talks about using edge analytics to solve issues that arise in some of the aforementioned fields.

Table- 7 Edge Analytics Techniques Along with their Features and Limitations for use Cases in Agriculture, Transportation and Retail

Techniques	Features	Limitations
T. Song.et al. [35]	• Through smart contracts secure data sharing as well as storage is achieved • Decentralized control with low complexity	Poor convergence performance results from low learning rates. • The average reward and average transaction size are inversely correlated.
Soni et a[34]	• Simple configuration and Management • Recent transactions govern the computation • Management of data is relatively cheaper	• Linkage of social media and enterprise entity correctly is difficult. • Finding similar entity using social media accounts is difficult

XII. EDGE ANALYTICS IN PRACTICALITY

Some edge analytics are covered in this section, which businesses develop for use in actual applications

Developed by the Oracle business, Oracle Edge Analytics (OEA)[36] is a form of edge analytics based on real-time intelligence extended to embedded devices for achieving filtration, correlation and processing of event in real-time. To occupy lesser amount of RAM, OEA leverages the use of Oracle Real-time streaming analytics technology. The reason being it offers localized storage and analysis, along with high-speed data gathering and processing, filtering, correlation, and pattern matching, OEA is suitable

ISSN No:-2456-2165

for industrial automation. OEA keeps an eye out for situations that could result in downtime for the management of appliances.

In order to improve system scope, geography, and topology, Cisco [37] proposed an edge analytics fabric system. This fabric system is based on modular design. This allows for easy maintenance of components as well as addition and deletion of components, as and when required. In order to lower network costs, improve speed, and boost scalability, the edge component aggregates, filters, and compresses data.

XIII. HEALTHCARE APPLICATION

Health monitoring is made possible by capturing the patient data through biosensors which is are usually embedded in wear-able devices/sensors[38]. Edge analytics aids in deciding what needs to be done when a patient has an abnormal state. These biosensors acquire metrics related to skin temperature, body's blood pressure, current heart rate, oxygen saturation level to name few important parameters captured. For the propagation of this captured data to an edge node for performing edge analytics, these smart devices use little-range wireless radio technologies such as Blue-tooth, Zig-Bee, etc

The data are stored and the analysis is done at the edge node. Edge analytics continuously analyses the patient's physiological signals to look for any unusual symptoms. Any time aberrant symptoms are found, a predetermined response is taken, such as summoning an ambulance or alerting the appropriate doctor.

Table8 highlights the merits and demerits of three re-search papers on the utilization of Edge- Analytics related to health-care. A data-driven method for the utilization of edge analytics in healthcare is CHMS. Cardiac Health Management System (CHMS) [41] proposed to use edge analytics to increase clinical efficacy analytics. Edge devices gather physiological data such as phonocardiograms (PCG) signal. The edge analytics finds unusual or PCG cardiac signals that are abnormal when using a reliable machine algorithm for learning. The artificial intelligence algorithm employs enhancing method to prevent over fitting owing to underdeveloped learners. The boosting procedure Ad boost [42] is used by the edge analytics.

It is an iterative process, though, and calls for greater resources and energy. Any anomaly in the patient is predicted using the training data. The outcome is provided via the Edge gadget to alert the endd user if any exception is discovered. The edge device uses the application differential privacy to de-risk sensitive data. Since the boosting process uses more resources and energy than necessary, it should be replaced. This lowers the effectiveness of Edge Analysis.

A healthcare solution leveraging the use of edge analytics was put forth by Madukwe et al. [39]. It is a three-tier architecture with the device being the bottom layer, followed by the gateway for data communication and finally edge analytics being the last layer of the architecture. The Kaa IoT platform has the architecture in place [40]. The patient wears a bio-sensor that records their data and sends it to a mobile app. The platform's software development kit preprocesses the data. The information is then sent to the server for analysis. In edge analytics, certain data analysis is done to clean out the data's noise and preserve its security. Once the data analysis is performed, MQTT protocol delivers the response back to the smartphone. The MQTT protocol maintains low latency and tiny packet sizes while enabling stable communication in less robust networks. Additionally, it features a push notification function. Edge analytics is alone in charge of data filtering and is entirely dependent on the server for calculation. Implementing straightforward techniques to carry out computation in edge devices should be the primary goal.

The IoT Edge Analytics methodoly for healthcare utilizing deep learning was given by Fadlullah et al. [43]. In this approach, Edge Analytics utilizes the DL algorithm DCNN. Edge gadgets, are situated in each user's environment. This method is divided into three stages: data collection, t/processing training, followed by prognosis. During the information collection phase, users' information is gathered periodically by Smartphones. The data is entered into the DCNN model as a load matrix for storage. Training/processing stage uses DCNN for the extraction of stable weight matrices from the incoming input information. This weight matrix from that training phase are used to determine future data load in the prognosis phase. The access points utilize the future data load estimate to forecast the accuracy. Prediction inaccuracy is minimal. The batch size affects the execution time. With these benefits, the detection of unusual test scenarios is made possible at end-user's premises by the access points. Hence, offers analytics that are practically real time.

Table- 8 Healthcare Edge Analysis Comparison of Various Edge Analysis Techniques Related to Healthcare in Regard to Features and their Limitations

Techniques	Features	Limitations
CHMS[41]	• Highly accurate • Protection of privacy • Flexibility for frequent retraining • Reliability for edge analysis • Robustness • No over fitting even if boosted	• Increased energy and resource requirement when boosted • No reference to Machine Learning Algorithm used
O. N. Iloanusil[39]	• Noise reduction in data • Failure proof connectivity using Kaa	• Thres hold valuation of para meters are predefined but it changes for different

	• Stable communication even in weaker networks using MQTT	patients
K.Pathan,Fad-lulaa et al.[43]	• Low error rate in prediction stage • Loss rate reduction • D-C-N-N improvises the accuracy	• Batch size governs execution time • D-C-N-N did not encode the place and direction of the object into their prognosis. • Internal information related to pose and orientation is lost

XIV. EDGE ANALYTICS WITH SMART TECHNOLOGY

By incorporating computing into small intelligent devices like smartphones and sensors, smart technology has become intelligent or smart itself. In the coming future, Smart-cities, homes and issues related to waste management might be heavily impacted by the usage of Intelligent grid systems. Intelligent technologies will heavily rely on edge technologies to accomplish this. In order to automate device activities, smart technologies must gather all relevant data, analyze it, and determine the appropriate course of action. Surrounding us, are the edge devices positioned appropriately for ensuring continuous collection of data.

The quick manifestation, confidentiality maintenance, migration, and promotion of smart devices are all facilitated by connecting them to edge devices [47]. The edge gadget utilises edge analytics to analyse the data. Machine learning algorithms are being incorporated into Edge-Analysis to stay Intelligent Technology. However, there are several difficulties with this information produced by the Edge gadgets[7], which makes it challenging to embed these algos. These information produced via intelligent gadgets is unprocessed information. However, because the raw data diminishes accuracy, it would not be used as entry data (input)for the ML algo. These algorithms therefore need structured trained data, which has been labeled, classified, as well as arranged for accuracy and efficiency.

A unique smart house architecture enabled by Demand Side Management was proposed by Lin and Hsiu [45]. (DSM).The Household Gateway (HG), a second flexible edge sensing device included in the suggested architecture, enables remote monitoring and management of home appliances. When it comes to edge computing capabilities, the HG acts as the master. An sophisticated RISC machine processor-based system is used to implement HG. A number of Home Edge-Sensing (HES) devices are also included in the framework and are connected to one another via wireless communication [48].

The smart power meter architecture Chen et al[44].With the help of edge analytics for the smart home, the DSM is a feature of house architecture and is present in the smart grid.to reduce carbon emissions and create green smart homes and saving money on electricity. The framework is made up with Electrical Energy Management System, Electrical Energy push notifications, Smart AIoT (AI across IoT), and EMS DSM in smart homes is achieved via a fiction service. EMS use cloud analytics to optimise energy use by keeping an eye on and managing its utilization. A smart AIoT Edge analytics-processed smart meters with embedded Edge-performing Artificial Intelligence (AI) models with ardui no MCU-based analytics. This Radial Basis Function AI method is utilized Network Artificial Neural (RBF-ANN).

An intelligent method for load identification in intelligent meters using edge analytics was proposed by Sirojan et al. [46] . The proposed solution offers lowered costs, enhancement in scalability, promotes accuracy and enhancement in (NILM)Non-Intrusive load Monitoring of the unit placed in the main circuit.

By the use of high-frequency or ultra-high-frequency transient characteristics for the identification of load, edge analytics is able to offer improved accuracy and extensible. The Discrete Wavelet Transform (DWT) is used for the division of the transient data into manageable frequency ranges during the feature extraction process phase. Then load identification is performed using a neural network approach. Only the findings are supplied to service providers following the load identification process because the acquired raw data becomes dated.

Table-9 Edge Analytics and Smart Technology Advantages and Drawbacks of Different Edge Analytics Methods that Enable Smart Technology

Techniques	Features	Limitations
I. lin,[45]	• Minimal energy usage. • Cuts back on carbon emissions and electricity expenses. • Offers a facility for home health care. • Action responsiveness in real-time.	• All devices cannot be connected to a single system with current technology. • The implementation was not widespread.
H. Chunget al. [44]	• By monitoring and managing use, electrical energy consumption is optimised.	Considered AI model requires a lot of computing power. • Energy usage is rising as a result of edge analytics.

E. Ambikairajahet al. [46]	Enhances the NILM approach. • Offers increased precision. • Excellent scalability • Employs capable and affordable commodity embedded hardware.	• No raw data are uploaded to the cloud. • Neural networks require a lot of computation. • When near-real time data is involved, massive amounts of data are sent to the cloud. • A high sampled data set is necessary for near-real time analysis.

XV. CHALLENGES WITH ISSUES

A. The following are the Primary Concerns and Difficulties with Edge Analytics;

- Workload optimization: To determine how to optimize the workload, four characteristics are taken into account: energy consumption, latency, bandwidth, and construction and maintenance costs [49]. The resources, batteries, and other components of the edge devices are compact in size as a result. The four parameters are subject to extra limitations, which complicates the optimization process.
- Small memory: The small size of device also restricts the size of memory available for processing. Thus, processing of larger file in case of Edge Analytics, either as an input or generation of output is near to impossible. Since an edge gadget with limited memory cannot process large data sets, it has to confine on fewer data sets for training which results in model's or generator's lowered accuracy.
- Data storage: Edge devices highly rely on cloud storage for data storage. The reason for this limitation is limited memory, the raw data produced by sensors must be cleaned and delivered towards cloud repository. If there is delay in this process, it could lead to data being overridden in the memory of edge device leading to data loss.
- Data Processing: Edge devices accept raw data and process it. Processing the entire data is unnecessary. Therefore, edge analytics requires the use of certain effective data filtering methods. Additionally, some pre-processing of the data is necessary to turn the fresh information towards the shape that can be inputted to the algorithm for analysis.
- Battery: These edge analytic gadgets are limited size devices and mostly rely on battery to power them. The batteries should be compact, non-hazardous, long backup and importantly quickly rechargeable. There is a limitation on the size of batteries that can be used utilized for powering these devices. An energy harvesting system is composed of an energy harvester, power regulator and a storage capacitor. One significant drawback is that the power generated is erratic and poor. This leads to frequent power outages, and the execution is stopped as a result.
- Computing: Edge analytics is attempting to leverage computationally intensive tasks such as DL into application. The resources required to implement these potent computational applications cannot be expected from the edge devices [54]. Edge analysis also envisions to integrate a number of computationally demanding and complex algorithms into a single edge unit. As a result, it is challenging to schedule and allocate resources among various computationally intensive algorithms.
- Tasks Offloading: Designing an optimal decision engine is the most crucial challenge in the case of computational offloading [51]. The decision engine decides whether to run the computation in parallel or in a divided fashion and when a task has to be offloaded to a cloud or external server. Offloading is a cost since the decision is made after taking into account a number of factors, such as calculation time, latency, and offload time [52,53].
- Handling of Overhead: Due to limited computation power present in edge devices, it gets overloaded with multiple decision-making situations. These situations include but are not limited to load balancing, allocation of resources and offload location of device[55]. Since processing of these situations substantially delay user requirements and block the queue, these represent the associated overhead.
- 2.0(Big data) : The scale of data that will be generated in the future will be in the range of terabytes [56]. Such data cannot be processed on commodity hardware. The processing of the data will therefore necessitate the use of supercomputers. Edge analytics must therefore be prepared using sophisticated technology.
- Cloud Dependency : The edge analytics heavily depends onto cloud for two important resources namely computation and storage. The transfer of data from edge gadget to cloud is primarily because of limited memory on edge device. This information is then overridden at the edge device's end. ML and Artificial Intelligence, require a lot of computing resources. In these situations, edge analytics transfers the data-set via cloud, where the algorithm is then executed on this data.
- ·Security: Edge devices generate the data. And is hence susceptible to cyber-attacks. By attacking the edge layer entire system can be accessed. There are two main types of attacks concerning, DoS(Denial of Service) and eve-dropping which violates the privacy. The attacker uses battery usage, sleep deprivation, , and other methods in a D-o-S assault.

XVI. FUTURE SCOPE

Textual or image/video data are the main sources for edge analytics. Audio is a different type of data. This is a fantastic chance to improve national security without upsetting the peace. Voice or phone calls are a common way to contact stern individuals (such as stalkers) or terrorists. In many nations, the police need a formal warrant and supporting documentation before they can view someone's phone history. In order to conduct surveillance and stop terrorism and other unlawful actions, the government requests permission to examine the location and call history of individuals' mobile phones. The opinion of monitoring breaching the right to confidentiality is a thought of general public. Edge analytics will help with this issue.

Edge analytics is an upcoming technology which has the potential to open up a lot of new possibilities and business prospects [57]. It is the emerging technology that will soon rule the entire industry. The evolution of tiny hard-ware with most assets and computational capacity represents this biggest opportunity. From a software perspective, the algorithms and techniques must use fewer resources while still being extremely effective and precise.

Researchers are currently looking into Federated Learning (FL) as an edge technology. A machine learning technique called federated learning [58] trains an algorithm across numerous devices in a distributed fashion. For edge analytics, which operate in a limited context, federated learning is perfect. An FL server is a request for edge analytics used to train a machine learning system. The FL server chooses a few edge devices, which use their local dataset to train the model. The FL server receives periodic model updates (i.e., weight with another para-meters) from the edge devices for aggregation. This procedure is repeated until the desired precision is attained. Federated learning is a great way to apply machine learning algorithms for data analytics, but there are still a lot of problems that need to be solved.

Edge devices will be a crucial component supporting the sixth generation of communication networks in the future (6G). A latency of less than 1ms is a crucial need for 6G. The 6G is expected to heavily rely on edge gadgets for world-wide, high node density coverage offering security. Edge technology will be the key enabled in 6G revolution[59]. In order to deliver elevated velocity with unbroken Internet assistance, edge gadgets will enable 6G. Instantaneous data analysis will be performed. During disastrous situations or calamities, edge devices will perform the functions of primary network nodes such as in the form of drones or unmanned vehicles. Edge gadgets will be placed in strategic places and connected with wireless networking.

Because the network keeps users connected to the outside world, this will be very helpful. The provision of basic essential commodities and medical assistance cannot be availed in desperate times due to a lack of communication. Edge gadgets are expected to be key implementing catalysts in trending and advanced technologies like telesurgery, tactile/haptic internet, holographic communication, and augmented/virtual reality [60]. By controlling the environment, grid, home, traffic, and other factors, it will also help the intelligent city.

XVII. DISCUSSION

Table 10 will be composed of the comparison of all analytic techniques mentioned in this article, compared on the basis of type of edge analytics, service it primarily offers, the algorithms associated and their implementation to offer services, dependency on cloud for the purpose of storage and compute.

Edge analytics promises huge research opportunities for researchers. However, there are many problems with Edge Analytics, and these problems with edge computing and edge gadgets are having an impact on Edge analytics. The size of the edge gadgets is one of the primary problems with edge analytics. The size of edge gadgets hugely restricts the type and complexity of hardware that can be embedded into them. Large dimensions provide greater room for a large power supply battery or additional processing components.

The maker of edge devices, on the other hand, also wants to boost mobility by producing small-sized edge devices. These devices need the computing load to be reduced because they lack high computing power. Caching is one way to minimize processing on edge devices. Edge caching [61] saves computed answers and prevents edge analytics from being executed repeatedly on the same input data. The caching mechanism to prevent duplicating the efforts for the same data known as edge caching is also of paramount importance that will maximize effectiveness of Edge gadgets. The limited power supply is the main problem with edge computing. Data collection requires a constant power source. Edge computation might take the place of cloud services, making data collection increasingly crucial. One example is the use of CCTV for security.

For effective and precise analysis, edge analytics incorporate AI or machine learning algorithms. Deep learning algorithms were also favoured by several strategies for edge analytics. Smart houses and intelligent transportation systems, for example, have an architecture made up of numerous different types of sensors [62]. These various sensors produce heterogeneous data with significant dimensions. Because it is particularly suitable to pick out with model complicated attributes in the dataset with vast measurements, DL algos are effective when calculating corresponding information. DCNN successfully detects the item and extracts features from images [63].

For the 6G mobile network, edge technology is a key first step [59]. Min delay, lower data speed, dependability, global connectedness,.. are among the benefits of 6G. Without the aid of edge devices, all of these promises will be ineffective. In order to deliver on the promises of 6G, Edge gadgets—the future Gen. of mobile network endpoints—will be installed thoroughly [64]. The Internet of Everything (IoE) is also becoming a reality thanks to the Internet of Things (IoT) [65]. Therefore, resolving the edge analytics problems is crucial for developing future technologies.

Table- 10 Edge Analytics Methods: Evaluation of Edge Analytics Methods Using Different Criteria.
No Specific Algorithm is Mentioned.

Approach	**Data set**	**Type of Analysis**	**Implemented Algos**	**Cloud computing Depency**	**Distributed structure**
Framework of Giga—sight [19]	Vid..	Vid. Analyses	CV Algos	NO	NO
Ballas et al.[27]	Vid..	Mass Counting	Deep learning	NO	NO
Vid en-coder Sys. based on ROI[26]	Vid..	Mass monitor	DL	NO	NO
Cao..et. al. [20]	Descriptive	Mobile edge nodes	Own algorithm	NO	NO
D. Pezaros [21]	Prediction	Data-Cleaning	Reg. models	YES	NO
I. Lacalle.et al. [32]	Prediction	Ed-ge gateway	Deep -NN	YES	NO
E-C-NN[31]	Prediction	Intelligent grid	SFS,CNN	YES	NO
T. Song.et al. [35]	Video	intelligent transportation system	Block chain, Deep reinforcement Learning, Deep Learning	NO	NO
Soni et al. [34]	Descriptive	Personalised and real time recommendation	Matching algorithm	NO	YES
CHMS [41]	Descriptive	Health-care (monitoring)	Machine learning	NO	NO
O. N. Iloanusi et al. [39]	Descriptive	Health-care	**	YES	NO
K.Pathan,Fad-lulaa et al.[43]	Descriptive	Related to health-care	Deep convolutional neural net- wor	NO	NO
I. lin,[45]	Descriptive	Intelligent-Homes	ML\AI	NO	NO
H. Chunget al. [44]	Prediction	Intelligent-power-meters	(ANN-RBF)	YES	NO
E. Ambikairajah et al. [46]	Descriptive	Identification of load on Intelligent-meters	NN	NO	YES

XVIII. CONCLUSION

The slowness of the cloud is revealed when we start to consider the exponential growth and data generation around the globe. Edge computing is already gaining traction as it brings resources closer to the users as is the case with edge computing and edge functions. This article demonstrates the use of edge gadgets in the information analysis. It also examines and compares various applications of edge devices, used in multiple fields of life. It observes the use of edge gadgets to reduce the cloud transmission, network choking and waste of resources at cloud. It also describes that how AI with ML can be leveraged to envision smart edge gadgets that can perform with-out human assistance.. This has strong use case in healthcare industry where the need of intelligent wearables is evident.

It would not be wrong to say that Edge analy-tics are immoblie in young stage and presently facing challenging problems which are still required to be solved. However, given its due attention has the power to change our everyday lives.

REFERENCES

[1]. A. u. R. Khan, M. Othman, S. A. Madani, S. U. Khan, A survey of mobile cloud computing application models, IEEE Communi- cations Surveys & Tutorials 16 (1) (2014) 393–413.
[2]. S. Xiong, B. Ye, Analysis on the development path of smart city in the era of big data, in: 2019 IEEE 4th International Conference on Big Data Analytics (ICBDA), 2019, pp. 177–181.
[3]. S. Sakr, A. Liu, D. M. Batista, M. Alomari, A survey of large scale data management approaches in cloud environments, IEEE Communications Surveys & Tutorials 13 (3) (2011) 311–336.
[4]. M. Satyanarayanan, P. Bahl, R. Caceres, N. Davies, The case for vm-based cloudlets in mobile computing, IEEE Pervasive Com-puting 8 (4) (2009) 14–23. doi:10.1109/MPRV.2009.82
[5]. S. Safavat, N. N. Sapavath, D. B. Rawat, Recent advances in mobile edge computing and content caching, Digital Commu-nications and Networks 6 (2) (2020) 189–194

[6]. J. Camhi, Former cisco ceo john chambers predicts 500 billion connected devices by 2025, Business Insider.

[7]. A. Sharma, A. Sai Sabitha, A. Bansal, Edge analytics for build-ing automation systems: A review, in: 2018 International Con-ference on Advances in Computing, Communication Control and Networking (ICACCCN), 2018, pp. 585–590

[8]. C. Pan, M. Xie, S. Han, Z.-H. Mao, J. Hu, Modeling and op- timization for self-powered non-volatile iot edge devices with ultra-low harvesting power, ACM Trans. Cyber-Phys. Syst. 3 (3) (2019) 32:1–32:26.

[9]. B. Djamaluddin, T. Jovin, B. Nugraha, et al., Towards real-time edge analytics-a survey literature review of real-time data acqui-sition evolution in the upstream oil and gas industry, in: Abu Dhabi International Petroleum Exhibition & Conference, Societyof Petroleum Engineers, 2019, p. D021S064R002.

[10]. Q. Zhang, H. Sun, X. Wu, H. Zhong, Edge video analytics for public safety: A review, Proceedings of the IEEE 107 (8) (2019)1675–1696

[11]. Pazienza, A., Mallardi, G., Fasciano, C., & Vitulano, F. (2019). Artificial Intelligence on Edge Computing: a Healthcare Scenario in Ambient Assisted Living. AI*AAL@AI*IA.

[12]. Dave, Rushit & Seliya, Naeem & Siddiqui, Nyle. (2021). The Benefits of Edge Computing in Healthcare, Smart Cities, and IoT.

[13]. L. Zhou, M. H. Samavatian, A. Bacha, S. Majumdar, R. Teodor-escu, Adaptive parallel execution of deep neural networks on het-erogeneous edge devices, in: Proceedings of the 4th ACM/IEEE Symposium on Edge Computing, SEC '19, ACM, New York, NY,USA, 2019, pp. 195–208.

[14]. O. Gómez-Carmona, D. Casado-Mansilla, D. López-de Ipiña,J. García-Zubia, Simplicity is best: Addressing the computational cost of machine learning classifiers in constrained edge devices,in: Proceedings of the 9th International Conference on the Inter-net of Things, IoT 2019, ACM, New York, NY, USA, 2019, pp.18:1–18:8

[15]. R. Cziva, D. P. Pezaros, Container network functions: Bringing nfv to the network edge, IEEE Communications Magazine 55 (6)(2017) 24–31

[16]. C. K. u. J. H. Maximilian Bischoff, Johannes M. Scheuermann,The edge is near: An introduction to edge computing!,

[17]. Ccenture, Edge analytics pushing advanced analytics to the edge, Accessed on 26th November 2019

[18]. T. E. C. Mitch Tseng (Huawei), L. C. S. SE), Introduction to edge computing in iiot, Accessed on 26th November 2019

[19]. M. Satyanarayanan, P. Simoens, Y. Xiao, P. Pillai, Z. Chen,K. Ha, W. Hu, B. Amos, Edge analytics in the internet of things,IEEE Pervasive Computing 14 (2) (2015) 24–31

[20]. H. Cao, M. Wachowicz, S. Cha, Developing an edge computing platform for real-time descriptive analytics, in: 2017 IEEE In-ternational Conference on Big Data (Big Data), 2017, pp. 4546–4554.

[21]. S. Nikolaou, C. Anagnostopoulos, D. Pezaros, In-network predic-tive analytics in edge computing, in: 2019 Wireless Days (WD),2019, pp. 1–4.

[22]. H. Jin, L. Jia, Z. Zhou, Boosting edge intelligence with collabora-tive cross-edge analytics, IEEE Internet of Things Journal (2020)1–1

[23]. W. Z. Khan, E. Ahmed, S. Hakak, I. Yaqoob, A. Ahmed, Edge computing: A survey, Future Generation Computer Systems 97(2019) 219–235.

[24]. GSMA, Opportunities and use cases for edge comput-ing in the iot, Accessed on 16th January 2020

[25]. L. Prosperi, A. Costan, P. Silva, G. Antoniu, Planner: Cost-efficient execution plans placement for uniform stream analytics on edge and cloud, in: 2018 IEEE/ACM Workflows in Support of Large-Scale Science (WORKS), IEEE, 2018, pp. 42–51

[26]. S. B. Jagarlapudi, P. Gorur, B. Amrutur, A distributed object detector-tracker aided video encoder for smart camera networks, in: Proceedings of the 11th International Conference on Dis-tributed Smart Cameras, ICDSC 2017, Association for Com-puting Machinery, New York, NY, USA, 2017, p. 69â ˘A ¸S75

[27]. C. Bailas, C, D. Zhang, N. E. O'Connor, S. Little, Per-formance of video processing at the edge for crowd-monitoring applications, in: 2018 IEEE 4th World Forum on Internet of Things (WF-IoT), 2018, pp. 482–487

[28]. T. Technologies, Iot edge analytics & machine learning for real-time device control

[29]. D. Zimine, Aws greengrass â ˘AˇT the missing manual

[30]. A. Aral, I. Brandic, Consistency of the fittest: Towards dynamic staleness control for edge data analytics, in: European Confer-ence on Parallel Processing, Springer, 2018, pp. 40–52

[31]. C. Song, T. Li, X. Huang, Z. Wang, P. Zeng, Towards edge com-puting based distributed data analytics framework in smart grids,in: International Conference on Artificial Intelligence and Secu-rity, Springer, 2019, pp. 283–292.

[32]. D. Sarabia-Jacome, I. Lacalle, C. E. Palau, M. EstevÃl', Effi-cient deployment of predictive analytics in edge gateways: Fall detection scenario, in: 2019 IEEE 5th World Forum on Inter-net of Things (WF-IoT), 2019, pp. 41–46.

[33]. R. Dontha, Edge analytics â ˘A ¸S what, why, when, who, where,how?,

[34]. S. Soni, K. Narang, T. A. Faruquie, V. S. Batra, L. Subrama-niam, Edge analytics as serviceâ ˘AˇTa service oriented framework for real time and personalised recommendation analytics, in: Pro-ceedings of 2013 IEEE International Conference on Service Op-erations and Logistics, and Informatics, IEEE, 2013, pp. 494–499.

[35]. X. Jiang, F. R. Yu, T. Song, V. C. M. Leung, Intelligent re-source allocation for video analytics in blockchain-enabled in-ternet of autonomous vehicles with edge computing, IEEE In-ternet of Things Journal (2020) 1–1

[36]. ORACLE, Oracle edge analytics
[37]. Cisco, The cisco edge analytics fabric system
[38]. L. Deng, J. Gui, T. Wang, J. Tan, X. Li, An intelligent hy-brid mac protocol for a sensor-based personalized healthcare system, Digital Communications and Network
[39]. K. J. Madukwe, I. J. F. Ezika, O. N. Iloanusi, Leveraging edge analysis for internet of things based healthcare solutions, in:2017 IEEE 3rd International Conference on Electro-Technology for National Development (NIGERCON), 2017, pp. 720–725.
[40]. Kaa, Kaa iot platform,
[41]. A. Ukil, A. Jara, L. Marin, Data-driven automated cardiac health management with robust edge analytics and de-risking, Sensors (Switzerland) 19 (12),
[42]. Y. Freund, R. E. Schapire, A decision-theoretic generalization of on-line learning and an application to boosting, Journal of com-puter and system sciences 55 (1) (1997) 119–139
[43]. Z. M. Fadlullah, A.-S. K. Pathan, H. Gacanin, On delay-sensitive healthcare data analytics at the network edge based on deep learn-ing, in: 2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC), IEEE, 2018, pp. 388–393
[44]. Y.-Y. Chen, Y.-H. Lin, C.-C. Kung, M.-H. Chung, I. Yen, 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, Sensors19 (9) (2019) 2047
[45]. Y.-H. Lin, Novel smart home system architecture facilitated with distributed and embedded flexible edge analytics in demand-side management, International Transactions on Electrical En-ergy Systems (2019) e12014
[46]. T. Sirojan, T. Phung, E. Ambikairajah, Intelligent edge analytics for load identification in smart meters, in: 2017 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia), 2017, pp. 1–5.
[47]. P. Porambage, J. Okwuibe, M. Liyanage, M. Ylianttila, T. Taleb, Survey on multi-access edge computing for internet of things realization, IEEE Communications Surveys & Tutorials 20 (4)(2018) 2961–2991.
[48]. J. Chen, S. Chen, S. Luo, Q. Wang, B. Cao, X. Li, An intelligent task offloading algorithm (itoa) for uav edge computing network,Digital Communications and Networks 6 (4) (2020)433–443
[49]. M. Alrowaily, Z. Lu, Secure edge computing in iot systems: Re-view and case studies, in: 2018 IEEE/ACM Symposium on Edge Computing (SEC), 2018, pp. 440–444.
[50]. S. Xia, Z. Yao, Y. Li, S. Mao, Online distributed offload-ing and computing resource management with energy har-vesting for heterogeneous mec-enabled iot, IEEE Transactions on Wireless Communications (2021) 1–1
[51]. Y. Li, S. Xia, m. Zheng, B. Cao, Q. Liu, Lyapunov optimization based trade-off policy for mobile cloud offloading in heteroge-neous wireless networks, IEEE Transactions on Cloud Comput-ing (2019) 1–1
[52]. A. Samanta, Y. Li, Latency-oblivious incentive service offloading in mobile edge computing, in: 2018 IEEE/ACM Symposium on Edge Computing (SEC), 2018, pp. 351–353.
[53]. J. Guo, G. Huang, Q. Li, N. N. Xiong, S. Zhang, T. Wang, Stmto:A smart and trust multi-uav task offloading system, Information Sciences 573 (2021) 519–540.
[54]. Accenture, Find your edge bringing analytics to data at the edge of iot
[55]. M. MarjanoviÄ ˜G, A. AntoniÄ ˜G, I. P. Å¡arko, Edge computing architecture for mobile crowdsensing, IEEE Access 6 (2018) 10662–10674
[56]. S. Nayak, R. Patgiri, T. D. Singh, Big computing: Where are we heading?, EAI Endorsed Transactions on Scalable Information Systems 7 (27)
[57]. Gartner, Gartner identifies five emerging technology trends with transformational impact,
[58]. W. Y. B. Lim, N. C. Luong, D. T. Hoang, Y. Jiao, Y. C. Liang, Q. Yang, D. Niyato, C. Miao, Federated learning in mobile edge networks: A comprehensive survey, IEEE Communications Sur-veys & Tutorials 22 (3) (2020) 2031–2063
[59]. S. Nayak, R. Patgiri, 6g communication: Envisioning the key is-sues and challenges (2020).
[60]. S. Nayak, R. Patgiri, 6G Communication Technology: AÂ˘aVi-sion on Intelligent Healthcare, Springer Singapore, Singapore, 2021, pp. 1–18.
[61]. J. Yao, T. Han, N. Ansari, On mobile edge caching, IEEE Com-munications Surveys & Tutorials 21 (3) (2019) 2525–2553
[62]. J. Zhang, F. Wang, K. Wang, W. Lin, X. Xu, C. Chen, Data-driven intelligent transportation systems: A survey, IEEE Transactions on Intelligent Transportation Systems 12 (4) (2011) 1624–163
[63]. S. A. Boyer, SCADA: supervisory control and data acquisition, International Society of Automation, 2009.
[64]. Y. Zhou, L. Liu, L. Wang, N. Hui, X. Cui, J. Wu, Y. Peng,Y. Qi, C. Xing, Service-aware 6g: An intelligent and open net-work based on the convergence of communication, computing and caching, Digital Communications and Networks 6 (3) (2020) 253–260.
[65]. S. Nayak, R. Patgiri, 6g communications: A vision on the poten-tial applications (2020)
[66]. Sabuzima Nayak, Ripon Patgiri, Lilapati Waikhom, Arif Ahmed,A review on edge analytics: Issues, challenges, opportunities, promises, future directions, and applications,Digital Communications and Networks,2022,ISSN 2352-864 https://doi.org/10.1016/j.dcan.2022.10.016.