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EDGE & AI BASED HANDOFF MANAGEMENT SCHEME FOR FUTURE NETWORKS

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Abstract:
Bringing artificial intelligence (AI) to operate on the devices which are resource constrained is called AI on the Edge or Edge AI or Edge Intelligence. Artificial Intelligence employs machine learning, deep learning and other techniques for solving complex decision-making problems or for data transmission and computation. One of such large-scale complex systems is Heterogenous Networks (HetNets) which consists of varied access technologies with different properties. And when a device moves across such diverse environment, providing seamless continuity in session and call becomes an issue. Hence, in this paper Edge AI has been employed where an edge node is intelligent enough to make an optimal handoff decision to avoid ping-pong and unnecessary handoffs. Further, a detailed taxonomy of the related AI-based techniques of HetNets is also shown by discussing the pros and cons for various AI-based techniques for different problems in HetNets. Opening research issues and pending challenges are concluded as well, proposed solution is also provided to provide guidelines for future research work.

Keywords: Artificial Intelligence, Edge Computing, Edge Intelligence

1. INTRODUCTION

We all are witnessing the boom in the era being driven by Artificial Intelligence (AI) which have paved the way, for several applications ranging from healthcare to cognitive computing, from automation & robotics to natural language processing (NLP), speech recognition and computer vision [1]. Many applications such as video surveillance, smart home, intelligent personal assistants, etc being used by us have remarkably changed the lifestyle and efficiency [2].

The edge computing is next evolution of Cloud Computing which brings data collecting centers closers to end users in order to save battery life and bandwidth. This phenomenon was restricted to videos & images of all kinds but due to unprecedented growth of mobile users and increased dependency on smart devices has led to emergence of innovative applications of AI. However, bringing AI to the edge of the network also brings concerns of privacy, low performance, and increased cost. Moving data in abundance through Internet may cause delay in transmission, breach of security and more cost is incurred [3].One possible traditional solution to tackle this problem is bring data in bulk to data centers from smart devices [4].

This led to the amalgamation of AI & Edge Computing in a new terminology of Edge Intelligence which supports execution of AI algorithms to be executed on local allowing users to process data in real-time at the edge which is gaining much attention from academia and industry [5]. EI does not comply depend on cloud. EI is utilizing edge resources to achieve better insights of AI. Several initiatives have been undertaken by enterprises such asIBM, Google, Microsoft, and Intel to exhibit the benefits offered byEdge computing in implementing AI. Such projects are paving way for diverse AI applications such as spanning from live video analytics, cognitive assistance to precision agriculture, smart home, and Industrial Internet of Things (IIoT) [6].

This paper is structured as: Section II discusses basics of Edge computing. Section III presents the current applications of edge computing integrating AI. The relation between edge and AI is discussed in Section IV and paper is concluded in Section V.

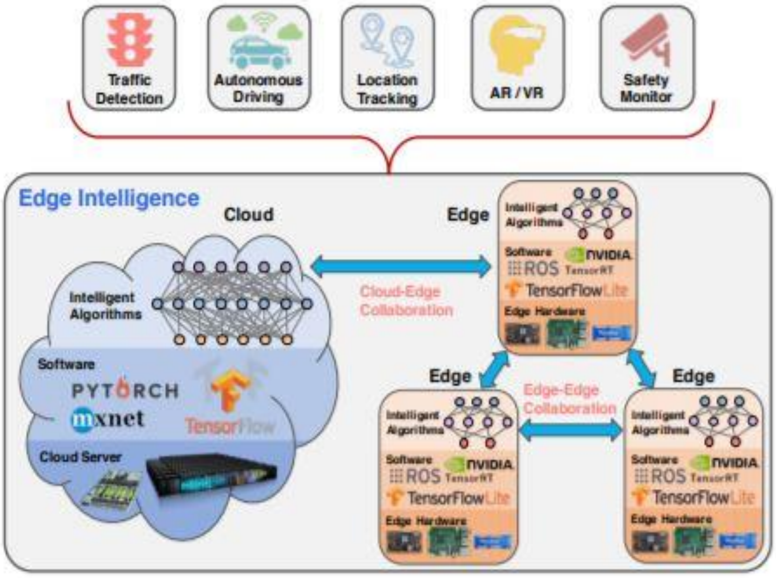

Figure 1: Edge Intelligence

1.1 EDGE COMPUTING AND AI: CORRELATION

The convergence of AI and edge computing becomes predictable with the advancements. Both are interactive in each other. AI facilitates more technologies in edge computing and in turn, edge computing provides scalability, thus making AI suitable for several diverse applications. " Edge Computing is a distributed computing paradigm, where software-defined networks are built to decentralize data and provide services with robustness and elasticity. "It is severely impacted by allocation of resources in layers, such as "CPU cycle frequency, access jurisdiction, radio-frequency, bandwidth," and so on [7]. It requires improved efficiency of the system. To ensure efficiency, AI models can tackle it. Basically, these model employ Stochastic Gradient Descent (SGD) techniques to attain high optimization.

Nowadays, it is gradually becoming possible that AI chips with computational acceleration such as Field Programmable Gate Arrays (FPGAs), Graphics Processing Units (GPUs), Tensor Processing Units (TPUs) and Neural Processing Units (NPUs) are integrated with intelligent mobile devices [8]. More corporations participate in the design of chip architectures to support the edge computation paradigm and facilitate DNN acceleration on resource-limited IoT devices. The hardware upgrade on edge also injects vigor and vitality into AI."

1.2 CURENT TRENDS IN EDGE INTELLIGENCE

Recently, edge computing superseded services facilitated by AI for advances in 5G and empowered AI to facilitate at the edge of the network. Thus, the role of edge-AI is divided as follows [9]:

- AI for edge computing (for instance, edge AI over wireless systems, AI-powered network management and many more).
- Edge computing for AI (for instance, smart energy, smart transportation, smart healthcare, tactile sensing services, smart agriculture, virtual reality, etc.)[10]. To achieve these scalable services reliably in the edge, "Artificial Intelligence-As-A-Service (AIaaS)" is vital for edge computing.

The compound annual growth rate (CAGR) is estimated to be 56.7% by 2025, whereas the projected market size is nearly $77, 047.7 million [11]. There is significant shift from cloud to fog and edge [12] due to AIaaS. Additionally, the potentiality of edge AI services have been considered as "infrastructure and service providers such as content caching in the edge [13], smart energy management for the wireless network [14], autonomous driving [15], federated learning model [16]for wireless network, etc."

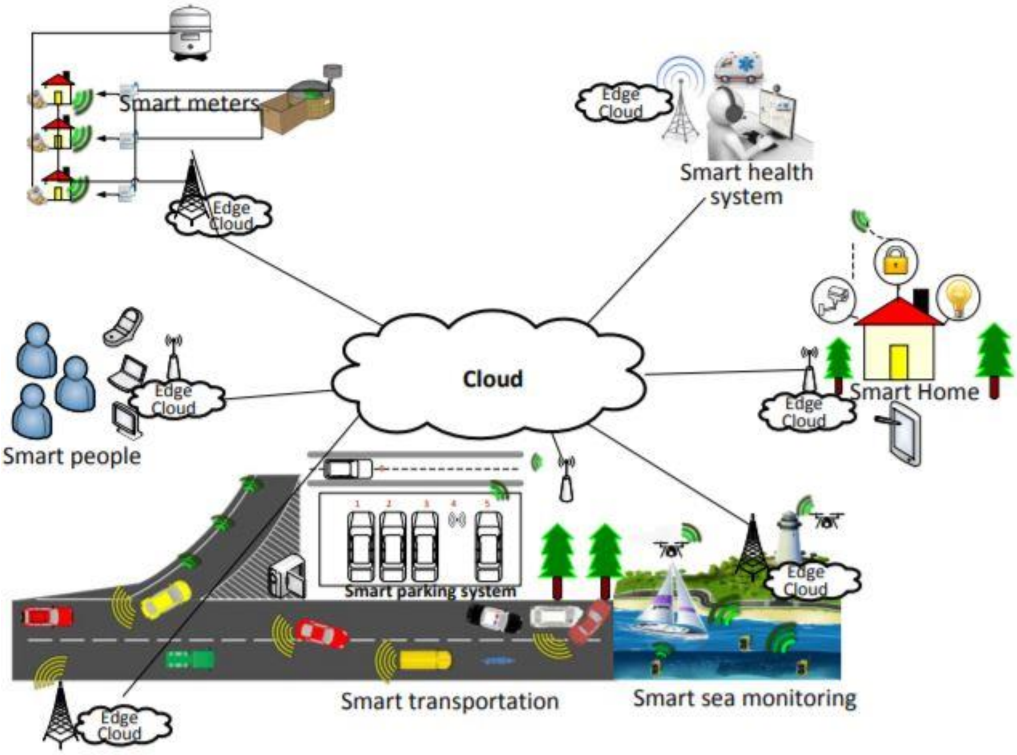

Figure 2: Applications of Edge Computing

2. RELATED WORK

2.1 PRIMER ON EDGE COMPUTING

Edge computing is an emerging technology which permits computation at the edge of the network, upstream data on behalf of IoT services and on downstream data on behalf of cloud services. "Edge" is a computational network resource which establishes connection between data sources and cloud data centers. Edge computing incorporates location awareness, mobility support, and ultra-low latency thus making it highly suitable for future applications such as virtual reality, sea monitoring smart home and industrial automation as shown in Figure 1 [8].

2.1.1 Edge Intelligence

The development of Edge Intelligence (EI) originates from two phases [9]. Firstly, the vast data being produced from physical devices connected through internet must be processed at the edge. Secondly, this data must be handled in real time such as video monitoring, autonomous driving, etc. EI with the help of AI, sensor networks, etc. has the potential to tackle this edge data intelligently.

2.1.2 Heterogeneous Networks

A heterogeneous network is a network connecting devices like computers, laptops, PDAs, wearable devices etc. that are manufactured by different manufacturers and are using distinct operating systems and protocols. For example, local area networks (LANs) that connect Microsoft Windows and Linux based personal computers with Apple Macintosh computers are heterogeneous.

2.2 Related Work

In this section, we review the existing work done by various authors on Decision making process pertaining to various networks around looking into the different metrics of mobility management for seamless connectivity.

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Reference	Method/ Tool Adopted	Parameters considered	QoS	Real Time Scenario	Limitations & Challenges	Future Directions
[17]	Ant Colony Optimization using Brute Force (BF) Algorithm	Latency, Energy consumption & Computation price	X	X	Not considered different types of application & Bandwidth and Network load not considered	Application for IoT Networks and to investigate another set of intelligent algorithms
[18]	Evolutionary Algorithms	Computation complexity, Application Delay & Power	X	√	Computational and storage constraints, scalability and security needs great attention.	More technologies for integrating MEC servers & cloud servers need to be developed
[19]	Lyapunov optimization Technique	Latency & Migration Cost	√	X	Needs to incorporate the network load for traffic steering.	Incorporating Device to device collaboration.
[20]	Lyapunov & Multi Armed Bandit (MAB) Theory	Load & Energy Consumption	X	X	Lack of accurate information related to computational Load Unavailability of future information Dynamic network requirements	To design a framework for dense scenarios.
[21]	Artificial fish swarm–based cluster formation	Energy & RSSI	X	X	Increased in energy consumption due to the delay in selecting	To develop more innovative routing protocols based on Distance Vector for limiting time in selecting CH.

					Cluster Head (CH)	
[22]	TOPSIS VIKOR PROMETHEE	Energy & Bandwidth	X	√	Limited to ten features of product	Attributes can be increased
[23]	ns-2 tool	Packet Loss, User Satisfaction	√	√	reducing the loss of packets and the time periods during which the minimum requirements are not satisfied as well as the number of useless handovers.	Improvement in Packet loss
[24]	COPRAS SAW PROMETHEE	BER, Load	√	√	Constraints on the variables of the above-listed and new MADM methods and will concentrate on the properties of the objective functions and their limitations	Analyzing the sensitivity of fuzzy AHP methods by fluctuating the data and on investigating several algorithms of FAHP methods.

4. Design and Implementation of the multi decision making algorithm proposed (EMDMA)algorithm

In this section, the conceptual design and implementation of the proposed AI based solution is provided. The algorithm uses non fuzzy and fuzzy method for assigning weights and ranking of the networks. Firstly, the model and the parameters being used in the framework are being discussed. Traditionally, RSSI based schemes were used for decision making and slowly many additional and adaptive approaches were incorporated with RSSI to make it more optimal for decision making but

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the dynamic nature of the network deployed across the area is challenging. Further, many other unpredictable issues such as call drop, call block, ping-pong, corner effect, etc. effects the results.
Many conventional algorithms based on RSSI or RSSI with threshold and hysteresis, RSSI with dwell timer, etc.[25] were discussed and many results related to decision making have been derived from them.
In this proposed edge based multi decision making algorithm proposed (EMDMA)algorithm, RSSI has been used along with other network, user and mobile related parameters to provide seamless session and call continuity to edge nodes.
The proposed scheme consists of following subsystems:

1. ***Data Collection***.
2. ***Employing machine learning algorithms for Handoff Initialization***
3. ***Weight Assigning***
4. ***Network Ranking***

Data Collection: There are numerous parameters used in mobile communication such as load, power, transmission rate, receiver transmitter power, SINR, RSSI, delay, jitter, path loss, frequency, etc. For data collection and deciding which parameters must be selected for the proposed study, a survey from 50 experts was taken. On analysis of this survey, following parameters were selected with the following allowed values:

Attribute	**Range**
RSSI (dbm)	-3 to -55 dbm
	-55 to -75 dbm
	-75 to -99 dbm
Bandwidth (mbps)	20 to 30 mbps
	10 to 20 mbps
	0 to 10 mbps
Packet Loss (%age)	Less than 1 %
	1 to 25 %
	More than 25 %
Network Latency (ms)	150 to 100 ms
	99 to 50 ms
	Below 50 ms

Dataset for the handoff initialization has been attached in Appendix 1.
Gather relevant data for training the machine learning model. This data may include information on signal strength, device location, network congestion, mobility patterns, and other relevant features. Historical handoff events and their context should be part of the dataset.
2. **Employing machine learning algorithms for Handoff initialization**
Applying machine learning to predict event delivery in wireless communication systems uses historical and real-time data to train models to predict when handshakes are likely to be delivered Steps in machine learning to execute use to predict handshakes here.

1. **Data preprocessing:** Clean and preprocess data to deal with missing values and outliers, and ensure accuracy.
2. **Labeling:** Label data instances based on whether or not a handoff event occurred at a particular point in time.
3. **Model selection:** Select the appropriate machine learning model for the prediction task. Common algorithms for binary classification tasks such as handover prediction include logistic regression, decision trees, random forests, support vector machines, and neural networks.

4. **Training the model:** Divide the data set into training and validation sets. Train a machine learning model on the training set, changing the model parameters to reduce the prediction error. Validate the model in a separate validation set to ensure adequate generalization to new.

3. Weight Assigning

An appropriate MADM method, such as Analytic Hierarchy Process (AHP) or Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), or FAHP (Fuzzy analytic Hierarchy Process) is selected to calculate weights objectively or conceptually Under each criterion, a decision matrix is formed, which shows the normalized values of each parameter. The selected MADM method is weighted, validated by expert feedback, and adjusted as necessary. These assigned weights are then added to the decision-making process, which affects the algorithm or decision rule. Continuous improvement is emphasized, prompting regular review and updating of loads to adapt to changing network environments and user behaviors.

4. ***Network Ranking***

The ranking of networks using traditional multi-decision-making (MADM) methods and their simple extensions, such as ELECTRE, PROMETHEE, TOPSIS, FTOPSIS, VIKOR, and FVIKOR, is a comprehensive analysis of network performance at different levels under Pairwise comparison of decision making, preferred use and implementation TOPSIS ranks the alternatives based on how close they are to the optimal solution and against the ideal solution.

Extending to unlikely MADM methods such as FTOPSIS, VIKOR, and FVIKOR, the analysis accounts for the uncertainties and ambiguities of decision-making and introduces numerical ambiguities and linguistic variations included to represent less ambiguity. FTOPSIS modifies the TOPSIS approach to deal with ambiguity, while VIKOR and FVIKOR consider contract breaking solutions for group decision under uncertainty

The choice between traditional MADM and fuzzy MADM methods depends on the quality and uncertainty of the data. Fuzzy extensions are particularly useful when dealing with ambiguous or incomplete information. Continuous monitoring and periodic updates to the rankings enable adaptation to changing network conditions and evolving requirements over time.

5. Edge Related Issues and Challenges

The growth in wireless technology and mobile devices has led to popularity of Edge Computing. Furthermore, applications employing AI are making technological advancements through deep learning and hardware. The huge data being produced at network edge is creating need for efficient processing of data. Hence, it necessitates to integrate AI and Edge computing this, creating Edge intelligence. Both AI and edge computing complements each other as AI helps resolves problems of edge and edge helps in developing AI models on the edge.

6. Conclusion

Proposed algorithm aims at providing better results when AI is incorporated to edge computing for performing mobility tasks in heterogeneous networks. This era is facing tremendous technology boom due to which many new techniques are flourishing to tackle the uncertainty of wireless environment. Hence, an effort is being made to make best use of fuzzy logic and predictive analytics to analyze the need of handoff and decision-making process. Future work may include datasets related to signal system of various transmitters and receivers and based on their data, handoff may be predicted.

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Appemdix I

S. NO.	RSSI (dbm)		Network Load (No. of users)		Handoff		Bandwidth (mbps)		Packet Loss (%age)		Handoff		Handoff (Requird/Not Requied)	
1	-98	low	11	Low	0.734	Yes	2	Low	1.15	Low	0.4	No	0.1	No
2	-96	low	18	Low	0.734	Yes	3		2.06	Medium	0.5	Yes	0.1	No
3	-86	low	28	High	0.734	Yes	4	Low	1.92	Medium	0.4	No	0.1	No
4	-80.1	low	21	Medium	0.734	Yes	5	Low	1.29	Low	0.4	No	0.1	No
5	-78	low	18	Low	0.734	Yes	7	Low	1.58	Medium	0.3	No	0.1	No
6	-70.7	Average	17	Low	0.116	No	7	Low	2.11	Medium	0.4	No	0.1	No
7	-68.6	Average	8	Low	0.253	No	7	Low	1.87	Medium	0.2	No	0.1	No
8	-66	Average	8	Low	0.253	No	8	Low	1.48	Low	0.4	No	0.5	Yes
9	-63.3	Average	18	Low	0.116	No	9	Low	1.66	Medium	0.3	No	0.1	No
10	-57	Average	7	Low	0.253	No	10	Medium	2.58	High	0.6	Yes	0.5	Yes
11	-56	Average	18	Low	0.116	No	10	Medium	2.18	Medium	0.3	No	0.1	No
12	-55	Strong	15	Low	0.116	No	11	Medium	2.38	Medium	0.4	No	0.1	No
13	-52	Strong	1	Low	0.253	No	11	Medium	1.3	Low	0.4	No	0.1	No
14	-51.9	Strong	26	Medium	0.116	No	11	Medium	1.41	Low	0.3	No	0.5	Yes
15	-51	Strong	15	Low	0.116	No	12	Medium	2.66	High	0.4	No	0.1	No
16	-49.2	Strong	6	Low	0.253	No	13	Medium	1.95	Medium	0.6	Yes	0.5	Yes
17	-44	Strong	12	Low	0.116	No	13	Medium	1.86	Medium	0.6	Yes	0.5	Yes
18	-40.7	Strong	12	Low	0.116	No	14	Medium	1.68	Medium	0.4	No	0.5	Yes
19	-38	Strong	30	High	0.116	No	15	Medium	2	Medium	0.4	No	0.5	Yes
20	-36	Strong	2	Low	0.253	No	16	Medium	1.78	Medium	0.5	No	0.1	No
21	-32	Strong	12	Low	0.116	No	18	Medium	2.5	High	0.6	Yes	0.5	Yes
22	-30.7	Strong	12	Low	0.116	No	20	High	2.15	Medium	0.6	Yes	0.5	Yes
23	-29.9	Strong	9	Low	0.253	No	23	High	2.81	High	0.6	Yes	0.5	Yes
24	-21.9	Strong	5	Low	0.253	No	25	High	1.95	Medium	0.4	No	0.1	No