International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

Deep Reinforcement Learning for Dynamic Resource Allocation in IoT-enabled Big Data Networks

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Submitted: 06/02/2024 **Revised**: 14/03/2024 **Accepted**: 20/03/2024

Abstract: In the area of Internet of Things (IoT)-enabled big data networks, the dynamic and diverse character of these settings presents a significant problem in terms of the optimal allocation of resources. Deep Reinforcement Learning (DRL) has emerged as a viable technique to overcome this issue by dynamically adjusting resource allocation algorithms depending on changing network circumstances and demands. This approach has the potential to handle other problems as well. The purpose of this study is to provide a complete assessment and analysis of traditional research efforts that revolve around the use of DRL approaches for dynamic resource allocation in big data networks that are enabled by the Internet of Things (IoT). Furthermore, we emphasize the possible advantages and limits of applying DRL in such complex systems by analyzing the techniques, problems, and successes of previous research that have been conducted in this field. We have identified important research gaps and potential for future investigations via this study. These studies are focused at enhancing the efficacy and scalability of DRL-based resource allocation solutions in big data networks that are enabled by the Internet of Things (IoT).

Keywords: *Deep Reinforcement Learning, Dynamic Resource Allocation, IoT, Big Data*

1. Introduction

The combination of Internet of Things (IoT) technology with big data analytics has generated significant interest in improving resource allocation in networks that use both IoT and big data. A very encouraging area of study is using Deep Reinforcement Learning (DRL) methods to dynamically distribute resources in intricate contexts. This strategy seeks to use the capabilities of deep learning and reinforcement learning to dynamically distribute resources according to changing network circumstances and needs. The majority of research in this field has focused on creating and assessing frameworks that use deep reinforcement learning (DRL) to allocate resources in large data networks that are enabled by the Internet of Things (IoT). These studies generally concentrate on boosting the usage of resources, improving the efficiency of networks, and optimizing performance indicators like as throughput, latency, and energy consumption. Although DRL has great promise in this setting, there are still substantial hurdles and restrictions that must be overcome in order to fully appreciate its advantages in real-world application.

The proliferation of Internet of Things (IoT) devices, in conjunction with the exponential expansion of data created by these networked systems, has ushered in a new era of possibilities and problems for network resource management that have never been seen before. In big data networks that are enabled by the Internet of Things (IoT), where enormous volumes of data are created and processed in real time, allocation of resources in an effective manner is of the utmost importance in order to guarantee optimum performance, scalability, and sustainability. Due to the fact that traditional methods of resource allocation often have difficulty dealing with the dynamic and varied character of these systems, there has been a growing interest in the investigation of innovative procedures that are able to adjust to changing situations.

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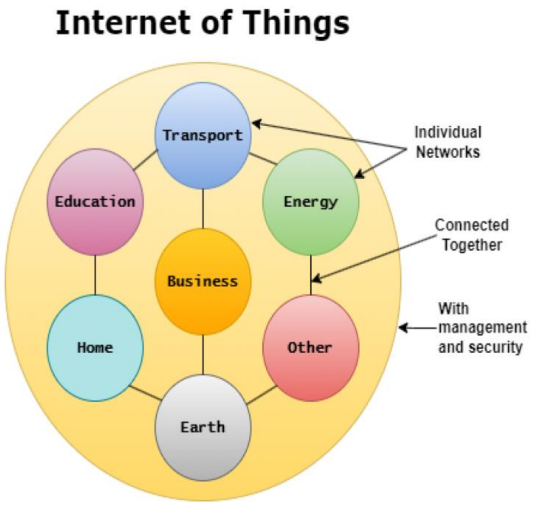

Fig. 1. Proliferation of Internet of Things

Deep Reinforcement Learning, often known as DRL, has emerged as a potentially useful paradigm for resolving the complexity of resource allocation in large data networks that are enabled by the Internet of Things (IoT). Deep reinforcement learning (DRL) provides a strong framework for learning sophisticated decision-making rules in settings that are both dynamic and unpredictable. This framework is achieved by merging deep neural networks with reinforcement learning. This method makes it possible for intelligent agents to independently modify resource allocation tactics in response to input from the surrounding environment, which ultimately results in improved system performance and use of available resources.

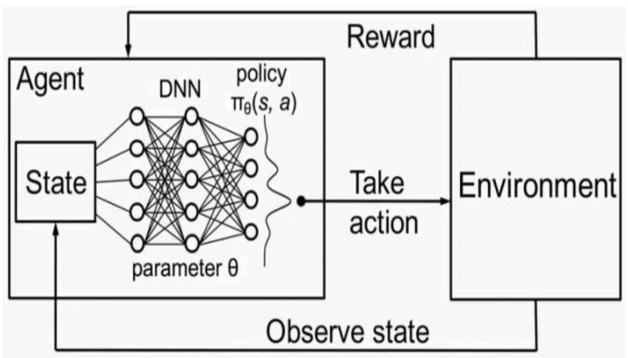

Fig. 2. Deep Reinforcement Learning

Over the last few years, there has been an increasing interest in using DRL approaches in order to address the issues of dynamic resource allocation in large data networks that are enabled by the Internet of Things (IoT). Conventional research efforts have mostly been on the development of frameworks that are based on DRL and are able to dynamically allocate resources like as bandwidth, compute, and storage in response to changing network circumstances and application needs. Through the use of the adaptable capabilities of DRL algorithms, the purpose of this research is to increase the efficiency of the network, improve the Quality of Service (QoS), and reduce the challenges associated with resource contention.

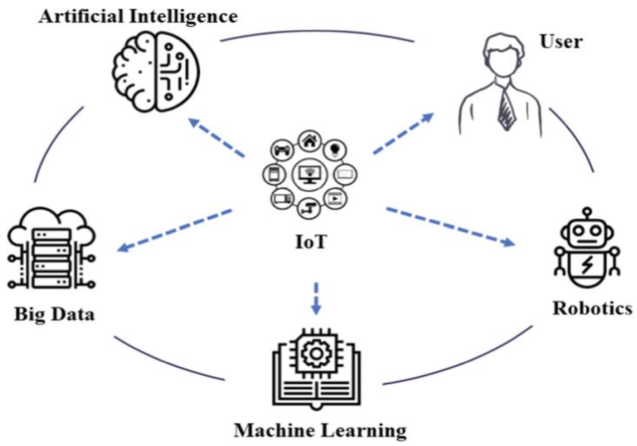

Fig. 3. IoT data analysis by big data

Despite the fact that DRL holds the promise of resource allocation in large data networks provided by the internet of things, there are still a number of obstacles and constraints. There are a number of significant difficulties that need to be solved, some of which include the scalability of DRL algorithms to large-scale networks, the trade-off between exploration and exploitation in dynamic settings, and the resilience of learnt policies against adversarial assaults and uncertainty. Furthermore, the actual implementation of DRL-based solutions in real-world Internet of Things contexts involves careful consideration of problems such as the complexity of the computations involved, the efficiency of the energy consumption, and concerns about privacy.

Within this framework, the purpose of this study is to provide a complete assessment and analysis of traditional research efforts that have been focused on DRL for dynamic resource allocation in large data networks that are enabled by the Internet of Things (IoT). In order to shed light on the present state of the art and suggest prospects for future study, we investigate the techniques, successes, and limits of previous studies that have been conducted in this field. Our goal is to contribute to the development of solutions that are more effective and scalable, and that are capable of fulfilling the needs of new Internet of Things applications. This will be accomplished by gaining a knowledge of the strengths and drawbacks of DRL-based techniques for resource allocation in large data networks that are enabled by the Internet of Things.

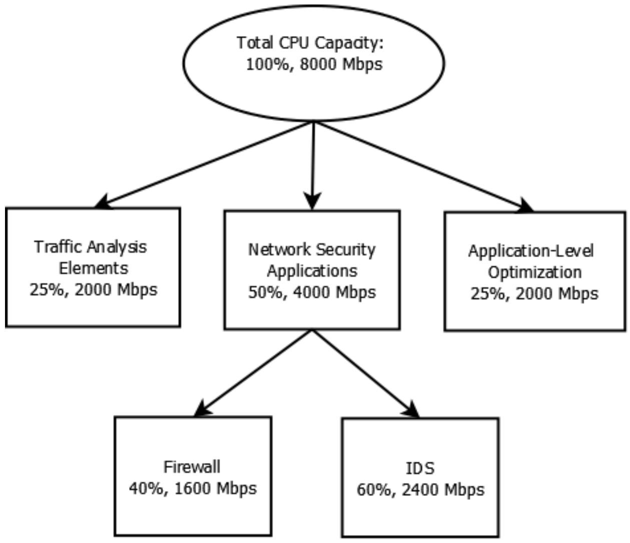

Fig. 4. Example of dynamic resource allocation based on the prediction

2. Literature Review

Y. Hajjaji et al. (2020) investigated the use of big data and Internet of Things (IoT) applications in smart environments. Our objective is to explore prominent applications, trends, data structures, and challenges within these fields. In conclusion, we summarize the most common approaches to big data and IoT in order to provide a foundation for interdisciplinary research on smart cities and the environment [1].

M. Khan et al. (2017) provided a new perspective on the challenges and opportunities of industrial big data in the context of Industry 4.0. The current study assists researchers in determining the threshold for Industry 4.0 systems while developing big data methodologies and approaches [2].

M. Talebkhah et al. (2021) aimed to provide a precise definition for smart cities. This study facilitates more investigation into the challenges and barriers related to the implementation of big data applications in smart cities [3].

T. S. J. Darwish et al. (2018) proposed an architecture for real-time big data analytics in Intelligent Transportation Systems (ITS) based on the Internet of Vehicles (IoV). The paper concludes by outlining the critical obstacles and future research goals that need to be addressed in order to effectively execute the proposed design [4].

M. Stolpe et al. (2016) conducted a comparison between algorithmic cloud-based analysis and decentralized analysis. We explore the promise and challenges of decentralized analytical algorithms that prioritize communication efficiency [5].

I. M. El-Hasnony et al. (2020) conducted a comprehensive analysis of the Internet of Things (IoT) ecosystem by using big data analytics. The study focused on identifying the limitations and issues associated with this technology. The REPtree technique shown superior performance compared to other methods, achieving accuracy levels ranging from 90.66% to 93.6%, which varied depending on the amount of the data. Nevertheless, naïve Bayes outperformed them in terms of the time it took to develop the model, completing the task in a mere 1-18 seconds [6].

Wazid et al. (2019) investigated network and threat models for cloud-driven IoT-based big data authentication method. The security requirements, issues, and problems of this environment are then analyzed. In this paper, we enumerate and provide a concise analysis of potential areas of future study in developing authentication techniques and security protocols for cloud-driven Internet of Things (IoT)-based big data environments [7].

S. Bebortta et al. (2023) introduced a dynamic integer linear programming approach to optimize task offloading. This technique efficiently assigns resources from the fog computing layer to IoT devices, taking into account limitations on task execution and resource availability. The proposed approach tackles the issues associated with IoT and fog computing, while simultaneously enhancing power efficiency and reducing latency [8].

Y. Yang (2023) presents a methodology that utilizes big data to conceptualize Internet of Things (IoT) networks. Incorporating IoT into business model innovation endeavors is crucial to assure its integration into strategy, business planning, and decision-making at all organizational levels, as supported by modeling and formal descriptions [9].

Kumar et al. (2023) used cryptographic platforms such as H-IoT to safeguard data access in many domains including big data, blockchain, machine learning, deep learning, edge computing, and software-defined networks. This article provides techniques to minimize different types of attacks utilizing the given information. The paper also discusses the concerns about security, scalability, real-time operation, resource restrictions, latency, and power consumption in H-IoT systems [10].

3. Problem Statement

The issue with the usual study on "Deep Reinforcement Learning for Dynamic Resource Allocation in IoT-enabled Big Data Networks" is in its narrow focus and its disadvantages. Although deep reinforcement learning (DRL) shows potential in solving intricate decision-making issues, its implementation in the dynamic resource allocation of IoT-enabled big data networks may face difficulties. These obstacles include scalability concerns, as the dimensions of the network and its intricacy grow, resulting in lengthier training durations and more processing demands. Moreover, the use of historical data to train DRL models may not sufficiently reflect the ever-changing characteristics of IoT contexts. In addition, traditional research in this field may fail to recognize the significance of immediate adjustment and resilience to evolving network circumstances, which are crucial for guaranteeing the most efficient distribution of resources in dynamic settings. Therefore, it is necessary for future studies to overcome these constraints and create more effective and resilient DRL-based solutions that are customized to the unique needs of IoT-enabled big data networks.

4. Challenges

There are a number of obstacles that Deep Reinforcement Learning (DRL) for Dynamic Resource Allocation in Internet of Things (IoT)-enabled Big Data Networks must overcome because of the complexity and changes that occur in these settings. These are some of the most significant challenges:

1. Internet of Things (IoT)-enabled big data networks produce enormous volumes of data from a large number of linked devices, which results in high-dimensional state and action spaces. In order to train DRL agents to successfully explore these complex landscapes, it is necessary to overcome challenges associated with the curse of dimensionality and challenges related to scalability.

2. The Internet of Things (IoT) ecosystems are dynamic and prone to quick changes, such as variations in data traffic, device failures, and shifting network conditions. The process of adapting DRL rules to contexts that are constantly changing while yet providing stability and convergence is a substantial challenge.

3. Because Internet of Things devices often have limited processing resources, memory, and energy, it is difficult to install and run DRL algorithms directly on edge devices. It is of the utmost importance to design lightweight DRL designs and algorithms that are capable of functioning effectively inside resource-constrained Internet of Things scenarios.

4. Internet of Things networks are made up of a wide variety of devices, each of which has a unique set of capabilities, communication protocols, and data formats. It is a difficult effort to design DRL-based resource allocation techniques that are capable of accommodating variety and diversity while simultaneously improving performance and keeping justice in mind.

5. Scalability is a critical difficulty when adopting DRL for resource allocation in large-scale Internet of Things networks that include hundreds or millions of devices. Both scalability and efficiency are problems that must be overcome, including the training of DRL agents at scale and the guaranteeing of effective communication and coordination across devices.

6. In dynamic Internet of Things settings, it may be difficult to strike a balance between exploration, which involves uncovering new methods, and exploitation, which involves utilizing techniques that are already known. In order to optimize long-term benefits, DRL agents are required to investigate novel resource distribution strategies while simultaneously making efficient use of the information they have acquired.

7. It is crucial to ensure the safety and reliability of DRL-based resource allocation choices in mission-critical Internet of Things applications, such as those in the healthcare and industrial automation industries. When it comes to adoption, the development of methods to evaluate and validate DRL rules and reduce the risk of catastrophic failures is absolutely necessary.

8. Considerations about Privacy and Security Internet of Things networks often deal with sensitive data, which raises issues about privacy and security. In order to safeguard sensitive information while simultaneously maintaining secure communication and authentication in Internet of Things contexts, DRL algorithms need to address strategies that preserve privacy throughout training and data inference.

9. In order to successfully implement DRL-based resource allocation solutions at scale, it is essential to achieve compatibility and standardization across a wide variety of Internet of Things devices, platforms, and protocols. It is vital to provide standard frameworks, protocols, and application programming interfaces (APIs) that allow smooth integration and communication.

10. Decisions about resource distribution that are based on DRL may have ethical consequences, such as fairness, accountability, and openness. When it comes to responsible deployment, it is very necessary to address ethical and legal factors, such as the reduction of prejudice, the capacity to clarify information, and compliance with data protection rules.

Research initiatives that combine skills in machine learning, optimization, networking, and Internet of Things systems are required in order to address these difficulties which need multidisciplinary research activities. For the purpose of overcoming these problems and realizing the full potential of DRL for dynamic resource allocation in Internet of Things (IoT)-enabled big data networks, collaborative activities including academics, industry, and government are required.

5. Need of Research

The necessity for Deep Reinforcement Learning (DRL) in dynamic resource allocation inside Internet of Things (IoT)-enabled Big Data Networks is a result of many main issues and needs that are intrinsic to these complex settings.

1. The Internet of Things (IoT) networks are not static; rather, they are dynamic since they are made up of a myriad of networked devices that produce enormous volumes of data in real time. When it comes to adapting to the quick changes in network circumstances, such as fluctuating data traffic, device connection, and variable application needs, traditional resource allocation approaches have a difficult time doing so. By providing autonomous decision-making processes that are able to swiftly change resource allocations in response to changing conditions, DRL provides a solution to the problem.
2. IoT enabled Big Data Networks are distinguished by the presence of heterogeneous devices that possess a wide range of capabilities, communication protocols, and resource needs. To add insult to injury, the scope of these networks may be enormous, spanning hundreds or even millions of devices. The management of such heterogeneity and size calls for the implementation of complex allocation algorithms that are able to make effective use of resources while simultaneously catering to a wide range of requirements. Through the process of learning adaptive resource allocation strategies that are adapted to the particular features of the network, DRL approaches have the ability to overcome these difficulties.
3. To distribute resources, traditional optimization algorithms often depend on heuristics or established rules, which may not adequately represent the complexity of Internet of Things settings. DRL, on the other hand, does very well when it comes to learning optimum decision-making strategies from raw data via interaction with the whole environment. Because of this capabilities, DRL algorithms are able to discover detailed patterns and relationships inside the network, which ultimately results in more efficient techniques for resource allocation.
4. In Internet of Things (IoT)-enabled Big Data Networks, the capability to adjust to dynamic situations in real-time is essential for preserving performance and responsiveness. It is possible for DRL algorithms to continually learn and update their resource allocation criteria depending on input from the environment. This allows for rapid adjustments to changing network dynamics, traffic patterns, and application needs.
5. In Internet of Things (IoT) networks, it is vital to allocate resources effectively in order to optimize resource usage, minimize latency, maximize throughput, and reduce energy consumption. By repeatedly improving allocation rules using reinforcement learning processes, DRL-based techniques have showed the power to achieve near-optimal resource allocation. This capability has been demonstrated.

The implementation of DRL for dynamic resource allocation in Internet of Things (IoT)-enabled Big Data Networks meets the need for allocation techniques that are adaptable, scalable, and efficient, and that are able to deal with the complexity and problems that are inherent to these dynamic settings.

6. Proposed Work

Deep reinforcement learning (DRL) is a process flow that incorporates many important processes for dynamic resource allocation in Internet of Things (IoT)-enabled Big Data Networks. These steps are as follows:

1. Observation: The DRL agent makes an observation on the present status of the environment of the Internet of Things network. These include things like the amount of traffic on the network, the state of the device, the availability of resources, and the needs of the application. There are a few different ways that observations may be gathered: directly from Internet of Things devices, network sensors, or via dialogue with network components.

2. State Representation: The information that has been seen is processed and changed into a representation that is acceptable for input to the DRL algorithm. This is referred to as the state representation. It is possible that this will include encoding the state variables into a structured format, such as feature vectors or tensors, in order to facilitate effective learning and decision-making.

3. Action Selection: The DRL agent chooses an action from a collection of accessible actions that indicate choices about resource allocation based on the context in which the environment is now located. In order to maximize performance metrics like as throughput, latency, or energy consumption, among the actions that may be taken are the allocation of computer resources, bandwidth, and storage, as well as the modification of network topologies.

4. Reward Computation: Following the completion of an action, the DRL agent is provided with input from the environment in the form of a reward signal. The reward signal provides a quantitative measure of the efficiency with which the agent executed the action in order to accomplish the specified goals. The definition of rewards may be based on predetermined performance indicators, or they can be dynamically updated depending on the circumstances of the network at the specified time.

5. Policy Update: The DRL agent revises its policy or decision-making approach in accordance with the observed state, the action that was chosen, and the reward that was obtained. In order to enhance the agent's capacity for future

decision-making, this entails modifying the parameters of the neural network model or bringing the Q-values in Q-learning-based techniques up to date.

6. Learning and Exploration: DRL agent learns to optimize resource allocation rules via a process of trial and error. This is accomplished by repeated interactions with the environment. In order to determine the most effective methods, the agent investigates a variety of actions, while simultaneously using the information it has acquired to exploit promising behaviors.

7. Deployment and Evaluation: Once the DRL agent has been trained, the resource allocation policy is deployed in the context of the Internet of Things-enabled Big Data Network. The effectiveness of the policy that has been implemented is assessed based on its capacity to accomplish the goals that have been set and to adjust to the ever-changing circumstances of the network. Network throughput, latency, energy efficiency, fairness, and scalability are some examples of measurements that might be used for evaluation.

8. Feedback and Iteration: The deployment phase offers useful input that can be utilized to refine and enhance the resource allocation policy of the DRL agent. This feedback may be used to iterate and improve the policy. This iterative process entails continually monitoring the performance of the network, collecting data, retraining the DRL model, and adjusting the resource allocation policy in order to accommodate the ever-changing needs and dynamics of the network.

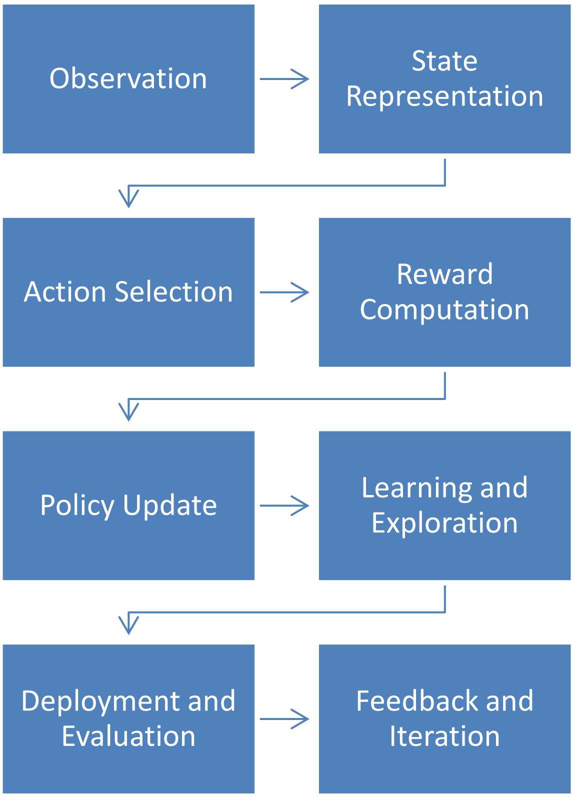

Fig. 5. Process flow of Work

In general, the process flow of DRL for dynamic resource allocation in Internet of Things (IoT)-enabled Big Data Networks involves continuous interaction between the DRL agent and the network environment. The objective of this interaction is to autonomously learn and optimize resource allocation strategies in order to maximize network efficiency and performance.

7. Result and Discussion

There are a few phases involved in the process of developing a Python-based simulation intended to depict Deep Reinforcement Learning (DRL) for the purpose of dynamic resource allocation in Internet of Things-enabled Big Data Networks. In the following paragraphs, I will provide an overview of a fundamental simulation framework that makes use of Python libraries such as NumPy and Matplotlib, and the DRL algorithms may be implemented using TensorFlow or PyTorch. For purposes of illustration, this simulation will concentrate on a simplified situation, which is as follows:

- Environment Setup: Define the Internet of Things (IoT)-enabled Big Data Network environment, which includes IoT devices, network infrastructure, resource types (such as CPU, memory, and bandwidth), and performance indicators (such as throughput and latency).
- State Representation: Specify the manner in which the current state of the environment is shown. This may comprise characteristics such as the state of the device, the traffic on the network, the usage of resources, and the needs of applications.
- Action Space: Define the action space, which is a representation of the many options that might be made about resource allocation. A few examples of such actions include assigning resources to certain devices or modifying the setups of several networks.
- Reward Function: Define a reward function that quantifies the success of choices about resource allocation based on preset performance metrics or goals (for example, maximizing throughput and decreasing latency).
- Deep Reinforcement Learning Model: It is possible to implement a DRL model by making use of frameworks such as TensorFlow or PyTorch. Deep Q-Networks (DQN), Policy Gradient methods (such as REINFORCE), and Actor-Critic methods are some examples of the approaches that might be used in this context.
- Training Loop: The training loop involves training the DRL model by interacting with the environment, choosing actions depending on the current state, getting rewards, and updating the model parameters in

accordance with the results of these interactions. This requires going through a process of exploration and exploitation in an iterative manner in order to determine the most effective strategies for resource allocation.

- Visualization: When it comes to visualization, you may make use of Matplotlib or other visualization tools to generate interactive plots or animations that depict the network environment, choices about resource allocation, and performance metrics in real time or at various time steps throughout training.
- Evaluation: Evaluate the performance of the trained DRL model on data that it has not previously seen or in a validation environment that is independent from the training environment in order to determine its capacity to generalize and achieve efficient resource allocation choices.

Simulation for dynamic resource allocation using deep reinforcement learning considers 30 epochs to find training, validation, testing accuracy.

Table 1 Simulation for training, validation and testing accuracy

Epoch	Training accuracy	Validation accuracy	Testing accuracy
1	92.8894	93.0279	93.2137
2	92.94813	92.95643	92.98559
3	93.03837	93.15892	93.28999
4	93.06008	93.11955	93.2378
5	93.11582	93.17972	93.30031
6	93.16383	93.32534	93.51085
7	93.17278	93.36165	93.42779
8	93.20848	93.39889	93.54006
9	93.30708	93.40894	93.42456
10	93.31641	93.50985	93.64495
11	93.36442	93.55172	93.7369
12	93.44948	93.58227	93.67409
13	93.48208	93.59152	93.77283
14	93.52147	93.55855	93.6482
15	93.56568	93.68008	93.72754
16	93.62777	93.78965	93.88174
17	93.68448	93.69752	93.73305
18	93.73339	93.75926	93.91116
19	93.79026	93.90342	93.95153
20	93.80849	93.96042	94.1332
21	93.83166	93.83397	93.91004
22	93.87067	93.91484	93.94436
23	93.89439	94.08645	94.14299
24	93.94044	93.97743	94.01247
25	94.00547	94.09062	94.12274
26	94.09933	94.18703	94.1932
27	94.1193	94.12054	94.31276
28	94.15085	94.18576	94.2768
29	94.17793	94.18717	94.24275
30	94.25637	94.38865	94.57785

Considering above table accuracy chart has been plotted below

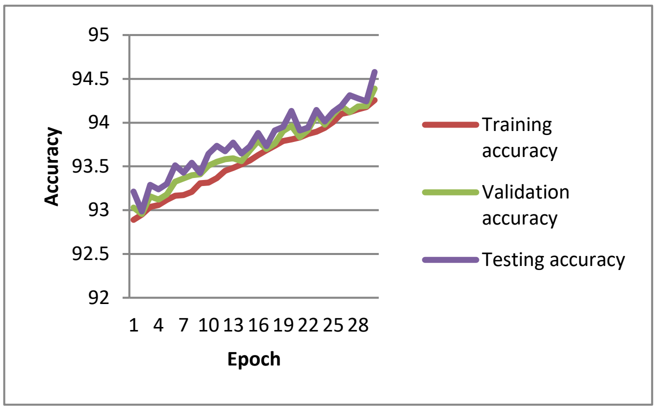

Fig.6. Accuracy for training, validation and testing accuracy

It has been observed that proposed model is providing better accuracy as compared to conventional reinforcement learning models.

Table 2 Comparison of testing accuracy of proposed and convention work

Model	Conventional ANN model	Conventional LSTM model	Proposed work Deep reinforcement learning model
Accuracy	91.34	93.21	94.57

Considering table 2, comparison graph has been plotted to visualize the accuracy difference in case of conventional deep learning model and deep reinforcement learning.

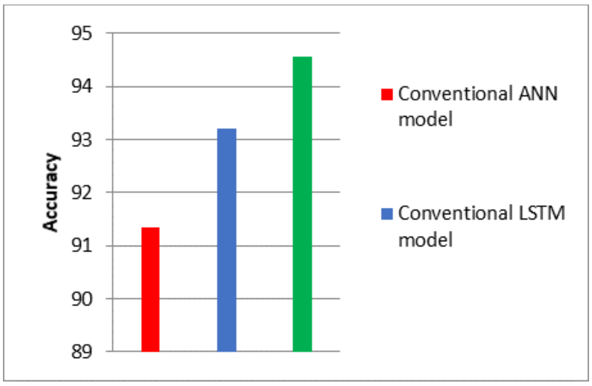

Fig.7. Comparison of accuracy for different models

8. Conclusion

Dynamic resource allocation has been made considering deep reinforcement learning in IoT enabled big data network. However training and testing of such model is complex and time consuming operation but simulation results conclude that accuracy for training, validation and testing is lying between 93% and 94.5%.

9. Future Scope

IoT-enabled Big Data Networks may benefit from Deep Reinforcement Learning (DRL) for dynamic resource allocation. Data expansion, IoT devices, and technology need sophisticated resource management. DRL has numerous R&D choices.First, DRL algorithm advances such attention mechanisms, meta-learning, and multi-agent reinforcement learning may improve resource allocation policy flexibility, scalability, and efficiency. DRL agents may learn more complicated decision-making processes, optimize resource utilization across heterogeneous IoT devices, and decrease network uncertainties and dynamic changes.Second, edge computing, federated learning, and blockchain solve distributed IoT resource allocation issues with DRL. DRL-based edge computing systems may distribute resources locally in real time, decreasing latency and bandwidth. Federated learning may train distributed IoT device models data-protected. Blockchain may provide decentralized, transparent, and auditable IoT resource allocation.In addition to networking, DRL invests in smart cities, healthcare, industrial automation, and autonomous cars. DRL algorithm adaption for these applications opens new research avenues for domain-specific resource allocation solutions that fulfill performance, reliability, safety, and regulatory compliance. Future study must address DRL-based resource allocation system scalability, robustness, and interpretability. Actual DRL implementations include managing massive IoT networks, responding to changing environmental circumstances, and justifying decision-making. Finally, DRL for dynamic resource allocation in IoT-enabled Big Data Networks will establish, collaborate, and use research to improve efficiency, service quality, and IoT ecosystem capabilities. Studies and DRL strategies for IoT network resource allocation may benefit society, industry, and the economy.

References

[1] Y. Hajjaji, W. Boulila, I. R. Farah, I. Romdhani, and A. Hussain, “Big data and IoT-based applications in smart environments: A systematic review,” Computer Science Review, vol. 39. Elsevier BV, p. 100318, Feb. 2021. doi: 10.1016/j.cosrev.2020.100318.

[2] M. Khan, X. Wu, X. Xu and W. Dou, "Big data challenges and opportunities in the hype of Industry 4.0," 2017 IEEE International Conference on Communications (ICC), Paris, France, 2017, pp. 1-6, doi: 10.1109/ICC.2017.7996801.

[3] M. Talebkhah, A. Sali, M. Marjani, M. Gordan, S. J. Hashim and F. Z. Rokhani, "IoT and Big Data Applications in Smart Cities: Recent Advances, Challenges, and Critical Issues," in IEEE Access, vol. 9, pp. 55465-55484, 2021, doi: 10.1109/ACCESS.2021.3070905.

[4] T. S. J. Darwish and K. Abu Bakar, "Fog Based Intelligent Transportation Big Data Analytics in The Internet of Vehicles Environment: Motivations, Architecture, Challenges, and Critical Issues," in IEEE Access, vol. 6, pp. 15679-15701, 2018, doi: 10.1109/ACCESS.2018.2815989.

[5] M. Stolpe, “The Internet of Things,” ACM SIGKDD Explorations Newsletter, vol. 18, no. 1. Association for Computing Machinery (ACM), pp. 15–34, Aug. 2016. doi: 10.1145/2980765.2980768.

[6] I. M. El-Hasnony, R. R. Mostafa, M. Elhoseny, and S. I. Barakat, “Leveraging mist and fog for big data analytics in <scp>IoT</scp> environment,” Transactions on Emerging Telecommunications Technologies, vol. 32, no. 7. Wiley, Jul. 27, 2020. doi: 10.1002/ett.4057.

[7] M. Wazid, A. K. Das, R. Hussain, G. Succi, and J. J. P. C. Rodrigues, “Authentication in cloud-driven IoT-based big data environment: Survey and outlook,” Journal of Systems Architecture, vol. 97. Elsevier BV, pp. 185–196, Aug. 2019. doi: 10.1016/j.sysarc.2018.12.005.

[8] S. Bebortta, S. S. Tripathy, U. M. Modibbo, and I. Ali, “An optimal fog-cloud offloading framework for big data optimization in heterogeneous IoT networks,” Decision Analytics Journal, vol. 8. Elsevier BV, p. 100295, Sep. 2023. doi: 10.1016/j.dajour.2023.100295.

[9] Y. Yang, “Business ecosystem model innovation based on Internet of Things big data,” Sustainable Energy Technologies and Assessments, vol. 57. Elsevier BV, p. 103188, Jun. 2023. doi: 10.1016/j.seta.2023.103188.

[10] M. Kumar et al., “Healthcare Internet of Things (H-IoT): Current Trends, Future Prospects, Applications, Challenges, and Security Issues,” Electronics, vol. 12, no. 9. MDPI AG, p. 2050, Apr. 28, 2023. doi: 10.3390/electronics12092050.

[11] J. Teixeira, “Developing a Cloud Computing Platform for Big Data : The OpenStack Nova case,” pp. 67–69, 2014.

[12] Y. Wang, “Transplantation of Data Mining Algorithms to Cloud Computing Platform when Dealing Big Data,” 2014.

[13] M. Kaur and H. Singh, “A Review of Cloud

Computing Security Issues,” Int. J. Educ. Manag. Eng., vol. 5, no. 5, p. 32, 2015.

[14] Karun Handa, Uma Singh, “Data Security in Cloud Computing using Encryption and Steganography”, International Journal of Computer Science and Mobile Computing, IJCSMC, Vol. 4, Issue. 5, May 2015, pg.786 – 791.

[15] M. Ahmed and M. Ashraf Hossain, “Cloud Computing and Security Issues in the Cloud,” Int. J. Netw. Secur. Its Appl., vol. 6, no. 1, pp. 25–36, 2014.

[16] Chirag M. Shah,et al, “Smart Security Solutions based on Internet of Things (IoT),” International Journal of Current Engineering and Technology, Volume 4, pp. 3401–3404, 2014.

[17] S. Marston, Z. Li, S. Bandyopadhyay, J. Zhang, and A. Ghalsasi, “Cloud computing — The business perspective ☆,” Decis. Support Syst., vol. 51, no. 1, pp. 176–189, 2014.

[18] K. A. H. Ahmed ElShafee, “Design and Implementation of a WiFi Based Home Automation System,” International Journal of Computer Electronc Automation Control Inf. Eng.. Volume 6,2012.

[19] Amol C. Adamuthe, Vikram D. Salunkhe, Seema H. Patil (2015) Cloud Computing – A market Perspective and Research Directions I.J. Information Technology and Computer Science, 2015

[20] Raj Kumar(2015) Research on Cloud Computing Security Threats using Data Transmission International Journal of Advanced Research in Computer Science and Software Engineering Volume 5, Issue 1, January 2015 ISSN: 2277 128X

[21] P. R. Kshirsagar, D. H. Reddy, M. Dhingra, D. Dhabliya and A. Gupta, "Detection of Liver Disease Using Machine Learning Approach," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1824-1829, doi: 10.1109/IC3I56241.2022.10073425.

[22] D. Mandal, A. Shukla, A. Ghosh, A. Gupta and D. Dhabliya, "Molecular Dynamics Simulation for Serial and Parallel Computation Using Leaf Frog Algorithm," 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC), Solan, Himachal Pradesh, India, 2022, pp. 552-557, doi: 10.1109/PDGC56933.2022.10053161.

[23] P. R. Kshirsagar, D. H. Reddy, M. Dhingra, D. Dhabliya and A. Gupta, "A Review on Application of Deep Learning in Natural Language Processing," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1834-1840, doi: 10.1109/IC3I56241.2022.10073309.

[24] M. Dhingra, D. Dhabliya, M. K. Dubey, A. Gupta and D. H. Reddy, "A Review on Comparison of Machine Learning Algorithms for Text Classification," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1818-1823, doi: 10.1109/IC3I56241.2022.10072502.

[25] V. Jain, S. M. Beram, V. Talukdar, T. Patil, D. Dhabliya and A. Gupta, "Accuracy Enhancement in Machine Learning During Blockchain Based Transaction Classification," 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC), Solan, Himachal Pradesh, India, 2022, pp. 536-540, doi: 10.1109/PDGC56933.2022.10053213.

[26] V. Talukdar, D. Dhabliya, B. Kumar, S. B. Talukdar, S. Ahamad and A. Gupta, "Suspicious Activity Detection and Classification in IoT Environment Using Machine Learning Approach," 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC), Solan, Himachal Pradesh, India, 2022, pp. 531-535, doi: 10.1109/PDGC56933.2022.10053312.

[27] P. R. Kshirsagar, D. H. Reddy, M. Dhingra, D. Dhabliya and A. Gupta, "A Scalable Platform to Collect, Store, Visualize and Analyze Big Data in Real- Time," 2023 3rd International Conference on Innovative Practices in Technology and Management (ICIPTM), Uttar Pradesh, India, 2023, pp. 1-6, doi: 10.1109/ICIPTM57143.2023.10118183.

[28] V. V. Chellam, S. Praveenkumar, S. B. Talukdar, V. Talukdar, S. K. Jain and A. Gupta, "Development of a Blockchain-based Platform to Simplify the Sharing of Patient Data," 2023 3rd International Conference on Innovative Practices in Technology and Management (ICIPTM), Uttar Pradesh, India, 2023, pp. 1-6, doi: 10.1109/ICIPTM57143.2023.10118194.

[29] Talukdar, S. B., Sharma, K., & Lakshmi, D. (2024). A Review of AI in Medicine. In W. Jaber (Ed.), Artificial Intelligence in the Age of Nanotechnology (pp. 233-259). IGI Global. https://doi.org/10.4018/979-8-3693-0368-9.ch012

[30] P. R. Kshirsagar, D. H. Reddy, M. Dhingra, D. Dhabliya and A. Gupta, "A Review on Comparative study of 4G, 5G and 6G Networks," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1830-1833, doi:

10.1109/IC3I56241.2022.10073385.

[31] S. Z. D. Babu et al., “Analysation of Big Data in Smart Healthcare,” Artificial Intelligence on Medical Data. Springer Nature Singapore, pp. 243–251, Jul. 24, 2022. doi: 10.1007/978-981-19-0151-5_21.

[32] K. Dushyant, G. Muskan, Annu, A. Gupta, and S. Pramanik, “Utilizing Machine Learning and Deep Learning in Cybesecurity: An Innovative Approach,” Cyber Security and Digital Forensics. Wiley, pp. 271–293, Jan. 14, 2022. doi: 10.1002/9781119795667.ch12.

[33] Vandana, C. P., Chaturvedi, A., Ambala, S., Dineshkumar, R., Ramesh, J. V. N., & Alfurhood, B. S. (2023). Optimizing residential DC microgrid energy management system using artificial intelligence. Soft Computing, 1-8.

[34] Borkar, P., Wankhede, V. A., Mane, D. T., Limkar, S., Ramesh, J. V. N., & Ajani, S. N. (2023). Deep learning and image processing-based early detection of Alzheimer disease in cognitively normal individuals. Soft Computing, 1-23.

[35] Reddy, B. N. K., Suresh, N., Ramesh, J. V. N., Pavithra, T., Bahulya, Y. K., Edavoor, P. J., & Ram, S. J. (2015, August). An efficient approach for design and testing of FPGA programming using Lab VIEW. In 2015 international conference on advances in computing, communications and informatics (ICACCI) (pp. 543-548). IEEE.

[36] Rao, K. R., Rao, P. P., Ramesh, J. V. N., Reddy, P. S., Velivela, S. S. K., & Rajesh, T. (2015). Development of RLS algorithm for localization in wireless sensor networks. Procedia Computer Science, 65, 58-64.

[37] Ramesh, J. V. N., Reddy, B. N. K., Krishna, V. M., Gandhi, B. K., Shiva, V., & Devi, M. D. (2015). An Effective Self-test Scheduling for Realtime Processor based System. International Journal of Smart Home, 9(3), 101-112.

[38] Bhanu, B. B., Rao, K. R., Ramesh, J. V. N., & Hussain, M. A. (2014, September). Agriculture field monitoring and analysis using wireless sensor networks for improving crop production. In 2014 Eleventh international conference on wireless and optical communications networks (WOCN) (pp. 1-7). IEEE.