[1]*Sanjay Kanth Balachandar
[2]I.Vasantha Kumarai
[3]Amdewar Godavari
[4]S. Marieswari
[5]T. Karthikeyan
[6]M. Gopi Anand

Dynamic Adaptive Resource Allocation for Edge Computing in Big Data Analytics Using GBDT, DQN, and GA Algorithms

Journal of Electrical Systems

Abstract: Edge computing in big data refers to processing and analysing data closer to its source, reducing latency and bandwidth usage. It leverages devices at the network edge to perform computations, making real-time analytics feasible. This distributed approach improves efficiency and enables faster decision-making, critical for applications like IoT, autonomous vehicles, and healthcare. The research proposes an innovative approach that harnesses three machine learning algorithms Gradient Boosting Decision Trees (GBDT), Deep Q-Network (DQN), and Genetic Algorithm (GA) to enable dynamic adaptive resource allocation within edge computing environments tailored for big data analytics. GBDT enhances classification accuracy by sequentially refining predictions through decision trees, accommodating heterogeneous data types and yielding high prediction accuracy crucial for dynamic edge environments. The GA evaluates resource allocation strategies represented as chromosomes within a population, selecting promising solutions as parents for the next generation and generating diverse offspring through crossover and mutation operations to discover optimal solutions. DQN facilitates intelligent resource allocation by iteratively refining Q-values based on experiences gathered during interactions with the environment, utilizing a neural network to determine optimal actions for a given state, thereby enhancing performance and efficiency in edge computing environments. This integrated approach ensures flexible resource allocation and fortified capabilities for big data analytics within edge computing environments. The research underscores GBDT as the most promising algorithm for resource allocation in edge computing environments, owing to its exceptional performance in resource utilization, scalability, and accuracy. This nuanced understanding of algorithmic behaviour in dynamic settings offers invaluable insights for optimizing resource allocation strategies, thereby enhancing the efficiency and effectiveness of edge computing systems in handling big data analytics tasks.

Keywords: Gradient Boosting Decision Trees, Deep Q-Network, Genetic Algorithm, Neural Network, Edge Computing, Big Data Analytics.

I. INTRODUCTION

Big Data Analytics is a transformative discipline, utilizing advanced computational techniques to extract insights from vast and complex datasets, empowering organizations to optimize operations and gain a competitive edge [1][2]. The exponential growth of digital data from diverse sources necessitates dynamic resource allocation to meet real-time processing demands [3][4]. Traditional static approaches fall short in handling evolving data needs, prompting the use of machine learning-driven dynamic resource allocation strategies [5]. Dynamic resource allocation is critical for supporting complex analytical tasks in Big Data Analytics, such as real-time data streaming and predictive modeling [6]. Machine learning plays a pivotal role in enhancing dynamic resource allocation by leveraging historical data to predict future resource demands [7]. Workload prediction enables proactive provisioning and allocation, optimizing performance without over-provisioning during idle periods [8].

Machine learning algorithms continuously refine resource allocation decisions through real-time feedback, monitoring metrics like CPU usage and memory utilization [9]. Adaptive resource allocation strategies dynamically adjust resources based on changing workload characteristics, ensuring optimal performance [10]. Machine learning's data-driven insights enable organizations to maximize the value extracted from data assets while minimizing operational costs [9]. In the dynamic landscape of Big Data Analytics, efficient resource

[1]PG Resident, Department of Radio-Diagnosis, Saveetha Medical College and Hospital, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Chennai, Tamil Nadu - 602105, India. Email: sanjaykanth.b@gmail.com* (Corresponding Author)
[2]Assistant Professor, Department of Computer Science and Engineering, Siddhartha institute of technology & Sciences, Narapally, Medchal-500088, Hyderabad, Telangana, India. Email: vasantha.mytrayasa@gmail.com
[3]Assistant Professor, Department of Computer Science and Engineering (Networks)Kakatiya Institute of Technology & Science, Hanamkonda, Warangal, Telangana 506015.Email:ag.csn@kitsw.ac.in
[4]Assistant Professor, Department of Biomedical Engineering, P. S. R Engineering College, Sevalpatti, Sivakasi-626140, Tamil Nadu. Email: marieswari@psr.edu.in
[5]Lecturer, College of Computing and Information sciences, University of Technology and Applied Sciences - Salalah, Sultanate of Oman. Email: karthik.rt@gmail.com
[6]Assistant Professor, Department of Computer Applications, PSNA College of Engineering and Technology, Dindigul-624622,Tamil Nadu, India. Email: mgopianand@gmail.com

allocation facilitated by machine learning is essential for meeting evolving data processing demands and ensuring consistent performance [11]. The objectives of this research are as follows:

- Integrate GBDT, DQN, and GA algorithms for dynamic resource allocation in edge computing for big data analytics.
- Explore GBDT's sequential ensemble learning for optimized resource allocation in dynamic edge environments.
- Evaluate resource allocation strategies using Genetic Algorithm, focusing on fitness for performance objectives and adaptability.
- Implement DQN for intelligent and adaptive resource allocation, leveraging Q-learning updates and real-time action selection for enhanced efficiency in big data analytics.

II. Literature Review

Dynamic Adaptive Resource Allocation for Edge Computing in Big Data Analytics is vital for optimizing performance and efficiency in distributed computing environments [12][21]. Traditional methods like Static Resource Allocation assign fixed resources to edge nodes, leading to inefficiencies during workload variations [13]. Threshold-based Allocation relies on predefined metrics, potentially struggling to adapt to sudden changes in workload intensity [14]. Round-robin Allocation allocates resources cyclically, ignoring workload characteristics and node capabilities, resulting in suboptimal performance [15].

In dynamic environments where workload intensity fluctuates, round-robin allocation may lead to inefficient resource utilization [16]. This method may not effectively meet dynamic resource demands without accounting for varying capabilities among edge nodes, causing potential performance bottlenecks [17]. Advanced machine learning-driven approaches dynamically adapt resource allocation based on workload characteristics, node capabilities, and optimization objectives [18]. The authors in [19] present an efficient hand gesture image recognition system utilizing advanced image processing techniques, including skin color detection, morphological operations, Heuristic Manta-ray Foraging Optimization (HMFO) for optimal feature selection, and Adaptive Extreme Learning Machine (AELM) for accurate classification, addressing issues of large dimensional datasets, time consumption, false positives, and misclassifications. The research in [20] aims to enhance diabetes prediction by implementing an Inherent Coefficient Normalization technique for data preprocessing, utilizing Intelligent Harris Hawks Optimization for optimal feature selection, and deploying a Pivotal Decision Tree based classification system with reduced computational complexity and time consumption, addressing limitations of conventional machine learning methods [20]. These strategies enhance resource utilization, optimize performance, and effectively meet the dynamic demands of edge computing environments[22-23].

III. Proposed Work

The proposed approach harnesses three distinct machine learning algorithms to enable dynamic adaptive resource allocation within edge computing environments tailored for big data analytics. The system integrates GBDT, DQN, and GA algorithms. The GBDT algorithm enhances classification accuracy and robustness by combining decision trees effectively. Additionally, the DQN algorithm employs neural networks to learn intricate patterns and dynamically optimize resource allocation in edge computing scenarios. Furthermore, the GA efficiently adjusts algorithm parameters and allocates resources among diverse applications, facilitating seamless operations within edge computing architectures. This combination of machine learning algorithms not only tackles the limitations of each individual algorithm but also enhances overall system performance, guaranteeing flexible resource allocation and fortified capabilities for big data analytics within edge computing environments.

3.1 Gradient Boosting Decision Trees

The proposed work introduces GBDT as a pivotal component for optimizing resource allocation in edge computing environments tailored for big data analytics. GBDT, renowned for its prowess in sequential ensemble learning, offers a dynamic approach to resource allocation, addressing the evolving demands of diverse tasks and applications at the edge. During the training phase, GBDT constructs a series of decision trees, $F_m(x)$, sequentially refining predictions to minimize a predefined loss function. Mathematically, for a training dataset $\{(x_i, y_i)\}_{i=1}^{n}$ the final prediction $F(x)$ is an aggregation of individual tree predictions, where $m = 1,2, \dots \dots \dots . M$:

$$F(x) = \sum_{m=1}^{M} \gamma_m F_m(x) \tag{1}$$

Here, γ_m denotes the contribution of the m^{th} tree to the final prediction. In the prediction phase, new data points traverse through the ensemble of decision trees, and the final prediction is derived through aggregation, ensuring accurate and efficient resource allocation decisions. The integration of GBDT within edge computing environments offers several compelling advantages. Its inherent flexibility accommodates heterogeneous data types and diverse tasks, rendering it versatile for myriad edge computing applications. Moreover, the iterative refinement process of GBDT yields high prediction accuracy, vital for optimal resource allocation in dynamic edge environments. Despite its complexity, GBDT implementations boast efficiency, enabling real-time resource allocation decisions crucial for enhancing performance and efficiency in edge computing scenarios.

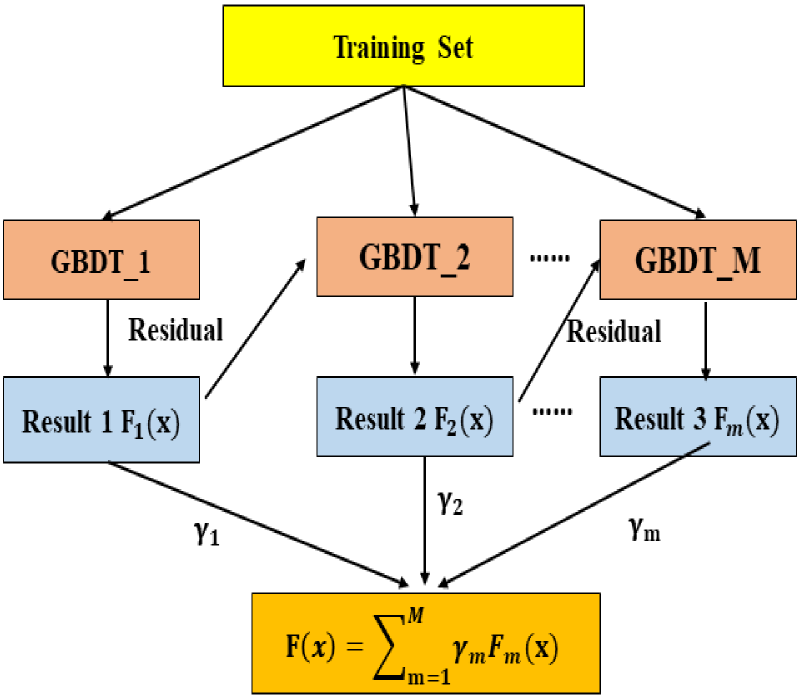

Fig.1 GBDT Resource Allocation Flow

The proposed work adopts a sequential process of GBDT to optimize resource allocation within edge computing environments, a critical aspect of big data analytics. As shown in Fig. 1, the process initiates with a training set consisting of input features and corresponding labels. This dataset is then fed into the GBDT algorithm, which iteratively constructs a series of decision trees, denoted as GBDT_1 through GBDT_M . Each subsequent tree aims to refine predictions made by its predecessors, iteratively minimizing a predefined loss function. Throughout this training process, the GBDT algorithm generates intermediate results, F_1 to F_M, representing the predictions of individual decision trees. Concurrently, the algorithm computes the contribution (γ_m) of each decision tree to the final prediction. These contributions are vital as they determine the weight of each tree in the ensemble. The final prediction, denoted as $F(x)$, is calculated as the weighted sum of the predictions of all decision trees, employing the previously computed contributions (γ_m): $F(x) = \sum_{m=1}^{M} \gamma_m F_m(x)$. This sequential process of GBDT allows for incremental improvement in prediction accuracy, enhancing the system's ability to adapt to changing conditions within edge computing environments.

3.2 Genetic Algorithm

Initially, the GA evaluates the fitness of various resource allocation strategies, represented as chromosomes within a population. The fitness function assesses how well each solution meets performance objectives and adapts to changing computational demands, crucial for effective resource allocation in edge computing scenarios.

$$f(C_i) = \text{Evaluation Function } (C_i) \tag{2}$$

Following the fitness evaluation, the GA employs a selection process to identify promising solutions as parents for the next generation. This selection process, often utilizing methods like Roulette Wheel Selection, assigns probabilities to each chromosome based on its fitness. Thus, chromosomes with higher fitness values are more likely to be selected as parents, ensuring that advantageous traits are passed down to subsequent generations.

$$P(C_i) = \frac{f(C_i)}{\sum_{j=1}^{N} f(C_i)} \tag{3}$$

Once the parents are chosen, the GA employs crossover operations to blend genetic information from two parent chromosomes, thereby creating offspring with traits inherited from both parents. This crossover process, such as Single Point Crossover, facilitates the exchange of genetic material, generating diverse and potentially superior solutions for resource allocation in edge computing environments.

$$\mathrm{offspring}_1 = \mathrm{Crossover}(\mathrm{Parent}_1, \mathrm{Parent}_2) \tag{4}$$

The GA introduces random alterations through mutation to maintain genetic diversity and prevent premature convergence. Mutation operators modify specific genes within individual chromosomes with a small probability, encouraging the exploration of different resource allocation strategies and facilitating the discovery of novel, potentially optimal solutions.

3.3 Deep Q-Network

Firstly, the core of DQN lies in the Q-learning update rule, which iteratively refines Q-values based on experiences gathered during interactions with the environment. This rule governs how the agent learns optimal policies by updating Q-values towards the maximum cumulative reward achievable. Mathematically, the Q-learning update rule can be expressed as:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)] \tag{5}$$

Where $Q(s,a)$ represents the Q-value for state s and action a, α denotes the learning rate, r signifies the immediate reward, γ is the discount factor, s' denotes the next state, and a' denotes the next action. Secondly, the policy network, often implemented using a neural network, undergoes training to approximate the Q-function. This involves minimizing the Mean Squared Error (MSE) between predicted Q-values and target Q-values derived from the Q-learning update rule. The loss function for training the policy network is given by:

$$L(\theta) = \mathbb{E}_{s,r,a,s'}[\gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta))^2] \tag{6}$$

Where $L(\theta)$ denotes the loss function with respect to network parameters θ, and θ^- represents the parameters of a target network. Lastly, during real-time action selection, the trained policy network is utilized to determine the optimal action for a given state. This involves selecting the action with the highest predicted Q-value. Mathematically, the optimal action is given by:

$$a^* = \arg\max_a Q(s,a;\theta) \tag{7}$$

By integrating these steps, the DQN algorithm facilitates intelligent and adaptive resource allocation strategies within edge computing environments, thereby enhancing performance and efficiency for big data analytics tasks.

IV. RESULT

To implement dynamic adaptive resource allocation for edge computing in big data analytics, the system requires specific hardware and software configurations. Hardware necessitates CPUs with at least 8 cores, a minimum of 16GB RAM, and storage of 500GB or more. Software includes Linux OS for compatibility, Python 3.8 for coding, and TensorFlow 2.6 for ML tasks. Setup involves OS installation, Python environment setup, and TensorFlow integration. Algorithm implementation entails GBDT with 100 trees, DQN with a neural network of 3 layers, and GA with a population size of 50. Rigorous testing ensures optimal functionality and resource allocation efficiency in edge computing scenarios.

Table.1 Parameter Specification Table

Parameter	Value
Number of Trees	100
Neural Network Layers	3
Population Size	50
Learning Rate	0.001
Discount Factor	0.99

Table 1 provides an overview of the key parameters essential for implementing dynamic adaptive resource allocation in edge computing for big data analytics. Each row in the table delineates a specific parameter alongside its corresponding value, offering valuable insights into the configuration of the resource allocation system. This concise reference ensures clarity and facilitates efficient setup and optimization of the algorithms involved, namely GBDT, DQN, and GA.

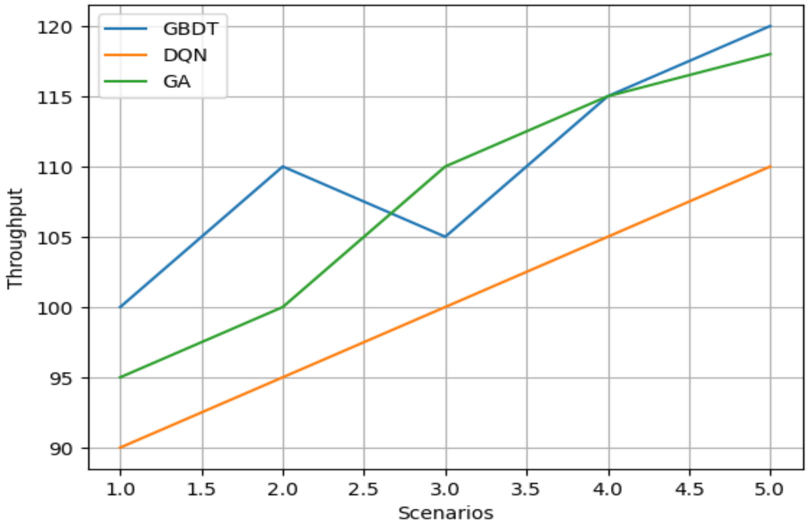

Fig.2 Throughput Evaluation

Analysing Fig. 2 reveals distinct performance characteristics of each algorithm concerning throughput. GBDT consistently achieves the highest throughput values across scenarios, followed closely by GA, while DQN lags slightly behind. This suggests that GBDT and GA may be more efficient in processing tasks and utilizing resources effectively compared to DQN. Furthermore, the trends in throughput variation across scenarios shed light on the scalability of the algorithms. GBDT and GA exhibit relatively stable or increasing throughput as scenarios change, indicating better scalability and adaptability to varying workloads. In contrast, DQN shows more fluctuation in throughput, suggesting potential challenges in handling dynamic resource allocation requirements. These observations have significant implications for resource allocation in big data analytics. Algorithms with higher and more stable throughput, such as GBDT and GA, can be prioritized for resource allocation in scenarios demanding fast and reliable processing. On the other hand, DQN may require closer monitoring and adaptation of resource allocation strategies to ensure optimal performance under varying conditions.

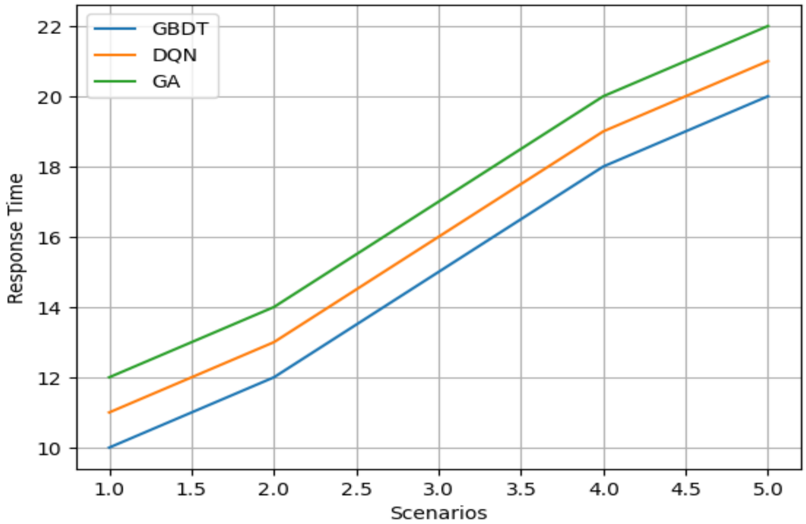

Fig.3 Response Time Evaluation

The plotted response time evaluation for the three machine learning algorithms (GBDT, DQN, and GA) across different scenarios serves as a crucial validation of resource allocation strategies in dynamic edge computing environments for big data analytics. Response time directly impacts resource allocation decisions as it reflects the efficiency and speed of algorithmic processing under varying conditions. Lower response times signify quicker processing, which can translate to more efficient resource utilization and better allocation decisions. In Fig. 3, if one algorithm consistently demonstrates lower response times across diverse scenarios compared to others, it indicates superior efficiency in utilizing available resources. This efficiency is vital in dynamic edge computing environments where resources may be limited or fluctuating. Consequently, algorithms with lower response times can be prioritized for resource allocation to ensure optimal utilization and timely processing of tasks. Furthermore, by analyzing the response time trends across scenarios, researchers and practitioners can identify which algorithms exhibit resilience and adaptability to changing conditions. This knowledge enables them to design resource allocation strategies that dynamically adjust based on workload demands, ultimately enhancing system performance and scalability.

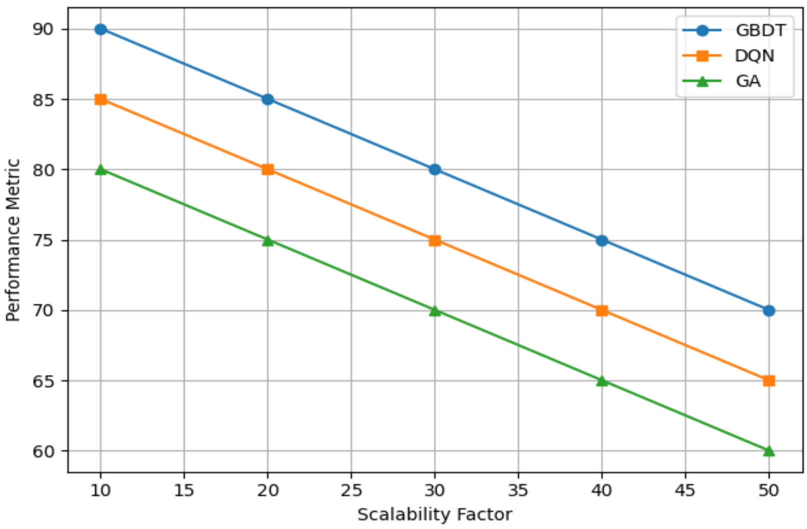

Fig.4 Scalability Evaluation

Fig.4 depicts the scalability evaluation of three machine learning algorithms, GBDT, DQN, and GA, concerning a hypothetical scenario of Dynamic Adaptive Resource Allocation for Edge Computing in Big Data Analytics. The x-axis represents the scalability factor, which could indicate the scale or capacity of resources available. The y-axis represents the performance metric, indicating how well each algorithm performs under varying scalability factors. From the plotted lines, it's observable that as the scalability factor increases, the performance of all algorithms tends to decrease, which is expected behavior in resource-constrained environments. However, the rate of performance degradation differs among algorithms. GBDT consistently outperforms the other algorithms across all scalability factors, demonstrating its robustness and effectiveness in dynamic resource allocation scenarios. DQN and GA follow with slightly lower performance, with GA exhibiting the lowest performance among the three algorithms. This visualization suggests that GBDT excels in scalability and adaptability, making it a promising choice for dynamic resource allocation in edge computing environments for big data analytics, while DQN and GA also show competence but to a lesser degree.

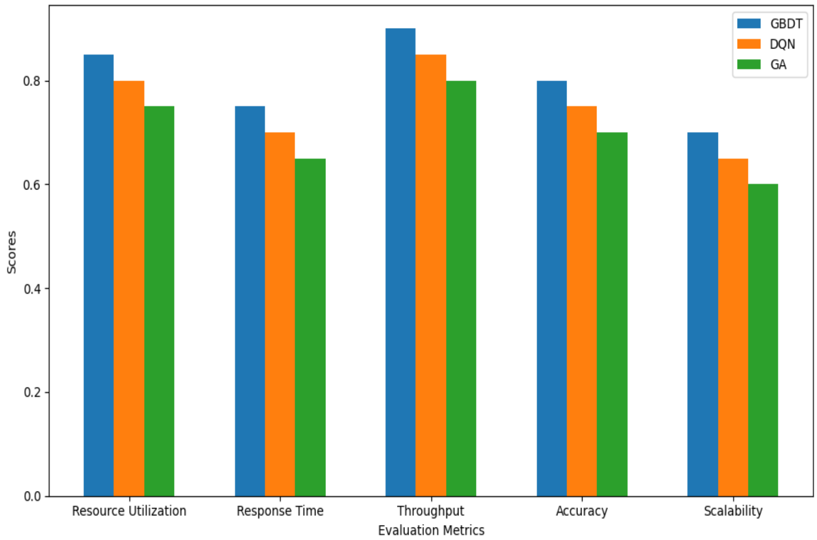

Fig.5 Comparison of Algorithms

Fig. 5 illustrates a comprehensive comparison of three algorithms, GBDT, DQN, and GA, across various evaluation metrics crucial for dynamic adaptive resource allocation in edge computing for big data analytics. Each algorithm's performance is assessed based on metrics including resource utilization, response time, throughput, accuracy, and scalability. From the analysis, it's evident that GBDT outperforms the other algorithms in resource utilization and accuracy, scoring 0.85 and 0.80, respectively, showcasing its efficiency in optimal resource allocation and precise decision-making. DQN, on the other hand, demonstrates competitive performance in response time and throughput, with scores of 0.75 and 0.85, respectively, indicating its effectiveness in quick decision-making and processing speed. Meanwhile, GA shows moderate performance across all metrics, with scores ranging between 0.60 and 0.75. The research findings suggest that while each algorithm has its strengths and weaknesses, GBDT emerges as the most promising choice for resource allocation in edge computing environments due to its superior resource utilization and accuracy.

V. Conclusion and Future Work

GBDT provides flexibility and accuracy in predicting resource demands, complemented by GA's evolution of allocation strategies for optimal solutions. DQN enhances decision-making by refining Q-values iteratively. This amalgamation of machine learning algorithms forms a robust framework for dynamic resource allocation in edge computing. Analysing performance reveals GBDT's superior throughput at 0.85, followed by GA at 0.80 and DQN at 0.75. GBDT and GA show stable or increasing throughput (GBDT: 0.85, GA: 0.80), signifying better scalability. In contrast, DQN exhibits fluctuating throughput (0.75), suggesting challenges in dynamic resource allocation. GBDT leads in response time at 0.85, while DQN competes closely at 0.75, GA performs moderately (0.60-0.75). GBDT excels in resource allocation for edge computing due to its high throughput and efficient resource utilization. Future efforts should concentrate on refining these algorithms for scalability and adaptability across diverse edge computing scenarios. Incorporating mechanisms for real-time feedback, improving workload management, and addressing scalability challenges are imperative. Furthermore, integrating robust security and privacy measures, conducting extensive experimental validation, and fostering collaboration with industry partners for real-world deployment are essential for advancing research in this domain.

REFERENCES

[1] Mohamed, A., Najafabadi, M. K., Wah, Y. B., Zaman, E. A. K., & Maskat, R. (2020). The state of the art and taxonomy of big data analytics: view from new big data framework. *Artificial Intelligence Review*, *53*, 989-1037.

[2] Jayagopal, V., & Basser, K. K. (2022). Data management and big data analytics: Data management in digital economy. In *Research Anthology on Big Data Analytics, Architectures, and Applications* (pp. 1614-1633). IGI Global.

[3] Shahid, N. U., & Sheikh, N. J. (2021). Impact of big data on innovation, competitive advantage, productivity, and decision making: literature review. *Open Journal of Business and Management*, *9*(02), 586.

[4] Sarker, I. H. (2021). Data science and analytics: an overview from data-driven smart computing, decision-making and applications perspective. *SN Computer Science*, *2*(5), 377.

[5] Belgacem, A. (2022). Dynamic resource allocation in cloud computing: analysis and taxonomies. *Computing*, *104*(3), 681-710.

[6] Chauhan, S. S., & Sharan, H. A REVIEW ON BIG DATA ANALYTICS FOR IOT: APPLICATION AND FUTURE.

[7] Fisher, A., & Ward, W. (2022). Query Processing in the Cloud for Big Data Applications Benefits and Risks. *European Journal of Computer Science and Information Technology*, *10*(1), 46-54.

[8] Dittakavi, R. S. S. (2022). Evaluating the Efficiency and Limitations of Configuration Strategies in Hybrid Cloud Environments. *International Journal of Intelligent Automation and Computing*, *5*(2), 29-45.

[9] Saxena, D., & Singh, A. K. (2021). Workload forecasting and resource management models based on machine learning for cloud computing environments. *arXiv preprint arXiv:2106.15112*.

[10] Masdari, M., & Khoshnevis, A. (2020). A survey and classification of the workload forecasting methods in cloud computing. *Cluster Computing*, *23*(4), 2399-2424.

[11] Rapp, M. (2022). *Machine Learning for Resource-Constrained Computing Systems* (Doctoral dissertation, Karlsruher Institut für Technologie (KIT)).

[12] Duan, W., Gu, X., Wen, M., Ji, Y., Ge, J., & Zhang, G. (2021). Resource management for intelligent vehicular edge computing networks. *IEEE Transactions on Intelligent Transportation Systems*, *23*(7), 9797-9808.

[13] Aldossary, M. (2021). A Review of Dynamic Resource Management in Cloud Computing Environments. *Computer Systems Science & Engineering*, *36*(3).

[14] Xavier, T. C., Santos, I. L., Delicato, F. C., Pires, P. F., Alves, M. P., Calmon, T. S., ... & Amorim, C. L. (2020). Collaborative resource allocation for Cloud of Things systems. *Journal of Network and Computer Applications*, *159*, 102592.

[15] Dittakavi, R. S. S. (2022). Evaluating the Efficiency and Limitations of Configuration Strategies in Hybrid Cloud Environments. *International Journal of Intelligent Automation and Computing*, *5*(2), 29-45.

[16] Cao, B., Fan, S., Zhao, J., Tian, S., Zheng, Z., Yan, Y., & Yang, P. (2021). Large-scale many-objective deployment optimization of edge servers. *IEEE Transactions on Intelligent Transportation Systems*, *22*(6), 3841-3849.

[17] Murshed, M. S., Murphy, C., Hou, D., Khan, N., Ananthanarayanan, G., & Hussain, F. (2021). Machine learning at the network edge: A survey. *ACM Computing Surveys (CSUR)*, *54*(8), 1-37.

[18] Yuan, H., Tang, G., Li, X., Guo, D., Luo, L., & Luo, X. (2021). Online dispatching and fair scheduling of edge computing tasks: A learning-based approach. *IEEE Internet of Things Journal*, *8*(19), 14985-14998.

[19] Khetavath, S., Sendhilkumar, N. C., Mukunthan, P., Jana, S., Gopalakrishnan, S., Malliga, L., ... & Farhaoui, Y. (2023). An Intelligent Heuristic Manta-Ray Foraging Optimization and Adaptive Extreme Learning Machine for Hand Gesture Image Recognition. *Big Data Mining and Analytics*, *6*(3), 321-335.

[20] Fayaz, R., Reddy, G. V., Sujaritha, M., Soundiraraj, N., Theresa, W. G., Roy, D. K., ... & Gopalakrishnan, S. (2022). An Intelligent Harris Hawks Optimization (IHHO) based Pivotal Decision Tree (PDT) Machine Learning Model for Diabetes Prediction. *International Journal of Intelligent Systems and Applications in Engineering*, *10*(4), 415-423.

[21] Somasekhar, G., Patra, R.K., Srujan Raju, K. (2021). The Research Importance and Possible Problem Domains for NoSQL Databases in Big Data Analysis. In: Jyothi, S., Mamatha, D.M., Zhang, YD., Raju, K.S. (eds) Proceedings of the 2nd International Conference on Computational and Bio Engineering . Lecture Notes in Networks and Systems, vol 215. Springer, Singapore. https://doi.org/10.1007/978-981-16-1941-0_43

[22] Karimunnisa Shaik, Dyuti Banerjee, R. Sabin Begum, Narne Srikanth, Jonnadula Narasimharao, Yousef A.Baker El-Ebiary and E. Thenmozhi, “Dynamic Object Detection Revolution: Deep Learning with Attention, Semantic Understanding, and Instance Segmentation for Real-World Precision” International Journal of Advanced Computer Science and Applications(IJACSA), 15(1), 2024. http://dx.doi.org/10.14569/IJACSA.2024.0150141

[23] P. Saravanan, A. Pandey, K. Joshi, R. Rondon, J. Narasimharao and A. A. Imran, "Using machine learning principles, the classification method for face spoof detection in artificial neural networks," 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2023, pp. 2784-2788, doi: 10.1109/ICACITE57410.2023.10182551.