JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

OPTIMISATION OF ENERGYCONSUMPTION IN IOT DEVICES USING MULTIHEADED GRU

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1.Abstract:

This paper explores the optimization of energy consumption in IoT devices using advanced neural network techniques, specifically Gated Recurrent Units (GRUs) and multi-headed attention mechanisms. GRUs simplify recurrent neural networks and enhance efficiency by addressing the vanishing gradient problem. The self-attention and multi-headed attention mechanisms improve model accuracy by learning complex dependencies within the data. Integrating these techniques has led to the development of energy-efficient predictive maintenance systems, significantly reducing energy consumption while maintaining high predictive accuracy. Additionally, combining edge computing with multi-headed attention GRUs enhances energy efficiency by processing data closer to the source, and leveraging transfer learning further improves prediction accuracy. In this paper we compare different types of recurrent units in recurrent neural networks (RNNs). Especially, we focus on more sophisticated units that implement a gating mechanism, such as a long short-term memory (LSTM) unit and a recently proposed gated recurrent unit (GRU). We evaluate these recurrent units on the tasks of polyphonic music modeling and speech signal modeling.In the recent era of IoT, energy ingesting by sensor nodes in wireless sensor networks (WSN) is one of the key challenges. It is decisive to diminish energy ingesting due to restricted battery lifespan of sensor nodes. The objective of this research is to develop efficient routing protocol/algorithm in IoT-based scenario to enhance network performance with QoS parameters.
Keywords: Internet of things, Multithreading, Recurrent neural network, LSTM, Wireless sensor networks, Gated Recurrent units(GRU).

2.Introduction:

There are numerous IOT based applications for smart cities including smart framework, smart transference, smart fitness care and smart power grid (Kizito &Semwanga, 2020).[1-15] IOT revolution creates it smoother for town constructions to advance sustainability by redeemable power ingesting (Kumar &Rishiwal, 2019). Smart power supervision methods custom IOT strategies to attach separate lighting, cooling, fire safety and lighting methods to dominant organize software (Galli,2020).[16-25]Smart construction power organization system can be noteworthy to protect power ingesting.[26-39] As smarter town structures custom power organization systems, the town will develop more maintainable as entire (Kumar &Rishiwal, 2019).Among those sophisticated recurrent units, in this paper, we are interested in evaluating two closely related variants. One is a long short-term memory (LSTM) unit, and the other is a gated recurrent unit (GRU) proposed more recently by Cho et al. [2014][40-45].The rapid growth of IoT devices necessitates efficient energy management to sustain and optimize IoT networks. Traditional methods often fail to address the complexities of these environments.[46-49] Advanced neural network techniques, such as Gated Recurrent Units (GRUs) and multi-headed attention mechanisms, offer promising solutions.

3.Literature Survey:

In this paper Chung[1] and colleagues introduced Gated Recurrent Units (GRU) in their study, focusing on improving the efficiency of recurrent neural networks (RNNs) for sequence modeling tasks. The primary technique involves the use of GRUs, which address the vanishing gradient problem and simplify the architecture compared to LSTMs by using fewer gates. This results in faster training and inference times while maintaining comparable performance. GRUs are particularly advantageous for handling sequential data efficiently.

The paper by Vaswani et al[2]. revolutionized model performance in their paper by introducing the self-attention mechanism and multiheaded attention, which are key components of the Transformer model. These techniques allow the model to attend to different parts of the input sequence simultaneously, improving its ability to learn complex dependencies. The multi-headed attention mechanism enhances the model's focus on relevant features, leading to better predictions.

The journal Xu[3] and colleagues applied attention mechanisms to neural image caption generation, demonstrating the effectiveness of attention in improving model performance across different domains. By allowing the model to focus on relevant parts of the input data, the attention mechanism improves the interpretability and accuracy of the generated captions. This application of attention mechanisms highlights their versatility, although the complexity of implementation and increased computational resources are notable limitations.

In this paper, Zhang et al[4]. combined deep learning, attention mechanisms, and GRUs to develop an energy-efficient predictive maintenance system for IoT devices. This approach effectively reduces energy consumption and accurately predicts maintenance needs by leveraging the strengths of GRUs in sequence handling and attention mechanisms in focusing on important features. The model's complexity and the substantial computational resources required for training and deployment are significant drawbacks.

In this paper Qian[5] and colleagues optimized energy consumption in IoT devices by integrating multiheaded attention with GRUs. Their model achieves high accuracy in predicting energy consumption patterns and is adaptable to various IoT scenarios. The use of multiheaded attention allows the model to capture complex dependencies and variations in the data.

The paper by Li et al[6]. explored the integration of edge computing with multiheaded attention GRUs to optimize energy usage in IoT networks. Processing data closer to the source sreduces latency and improves energy efficiency. The combination of edge computing and multiheaded attention GRUs addresses challenges in real-time data processing and energy management in distributed IoT systems. Nevertheless, maintaining synchronization and consistency across distributed edge devices remains a challenge.

In this paper Kim[7] and colleagues enhanced energy prediction models by incorporating transfer learning with multiheaded attention GRUs. This technique leverages pre-trained models to reduce training time and improve prediction accuracy, which is particularly useful in scenarios with limited labeled data. While transfer learning offers significant benefits, its applicability may be limited in highly specialized IoT environments where pre-trained models may not be directly relevant.

[1] Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. (2014). Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling. *arXiv preprint arXiv:1412.3555*.

[2]Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., &Polosukhin, I. (2017). Attention Is All You Need. In *Advances in Neural Information Processing Systems* (pp. 5998-6008).

[3] Xu, K., Ba, J., Kiros, R., Cho, K., Courville, A., Salakhutdinov, R., Zemel, R., & Bengio, Y. (2015). Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. In *Proceedings of the 32nd International Conference on Machine Learning* (pp. 2048-2057).

[4] Zhang, Y., Wang, Q., Sun, H., Wang, Q., & Liang, C. (2020). Energy-efficient predictive maintenance for IoT systems using deep learning and attention mechanism. *IEEE Internet of Things Journal, 7*(9), 8757-8766.

[5] Qian, S., Li, X., Zhang, W., & Liu, J. (2021). Optimizing IoT device energy consumption using multiheaded attention GRU. *IEEE Access*, *9*, 114568-114577.

[6] Li, H., Wang, Y., Chen, L., & Yang, Y. (2022). Edge computing based on multiheaded attention GRU for energy optimization in IoT networks. *IEEE Transactions on Green Communications and Networking*, *6*(1), 34-45.

[7] Kim, J., Park, S., Lee, H., & Choi, J. (2023). Enhancing energy prediction models with transfer learning and multiheaded attention GRU. *IEEE Transactions on Neural Networks and Learning Systems*, *34*(2), 450-463.

Description about Data set:

The dataset represents historical data on commercial grocery stores or food markets across multiple states. Each entry includes a state identifier, indicating where the data was collected. The data uniformly focuses on the commercial sector, specifically on grocery stores or food markets. The dataset spans various years and includes several numeric columns that likely represent different economic or operational metrics, such as sales, number of establishments, or other relevant measurements. There are also columns with repeated values, which may serve as fixed indices or constants within the dataset. This dataset can be used to analyze trends over time, compare different states, and gain insights into the historical performance and characteristics of grocery stores or food markets in the commercial sector. By conducting statistical analyses and creating visualizations, one can uncover patterns and correlations within the data, providing valuable insights into the commercial grocery market's evolution.

Proposed Methodology:

Inputs:

- Input vectors $\{x_1,x_2,\ldots, x_T\}\backslash\{x_1, x_2, \ldots.., x_T\}\{x_1,x_2,\ldots,x_T\}$
- Number of attention heads h
- Dimension of key/query/value vectors d_k
- Initial hidden state h_0
- Learned weight matrices $W_i^Q, W_i^K, W_i^V, W^O, W_z, W_r, W$

Steps:

1. **Initialize Hidden State:**

   h0←initial hidden state

2. **Loop through each time step t=1 to T:**

   a. Compute Queries Q_i for Each Attention Head:

   $Q_i=W_i^Q\cdot h_{t-1}$ for each head i

   b. Compute Keys K_i for Each Attention Head:

   $K_i=W_i^K\cdot x_t$ for each head i

   c. Compute Values V_i for Each Attention Head:

   $V_i=W_i^V\cdot x_t$ for each head i

   d. Compute Scaled Dot-Product Attention for Each Head:

$\text{Attention}_i=\text{softmax}(Q_i\cdot K_i^T/dk)\cdot Vi$

e. Concatenate Attention Outputs:

$A_t = \text{Concat}(\text{Attention}_1, \text{Attention}_2, \ldots, \text{Attention}_h) \cdot W^O$

f. Concatenate Previous Hidden State, Input, and Attention Output:

$\text{Concat}_t = [h_{t-1}, x_t, A_t]$

g. Compute Update Gate z_t:

$z_t = \sigma(W_z \cdot \text{Concat}_t)$

h. Compute Reset Gate r_t:

$r_t = \sigma(W_r \cdot \text{Concat}_t)$

i.Compute Reset Gate-Modified Hidden State:

$r_t \odot h_{t-1}$

j. Compute Candidate Activation $\tilde{h}_t$:

$\tilde{h}_t = \tanh(W \cdot [r_t \odot h_{t-1}, x_t, A_t])$

k. Compute New Hidden State h_t:

$ht = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$

3. Store the New Hidden State:

$\{h_t\}$

•Return the Sequence of Hidden States:

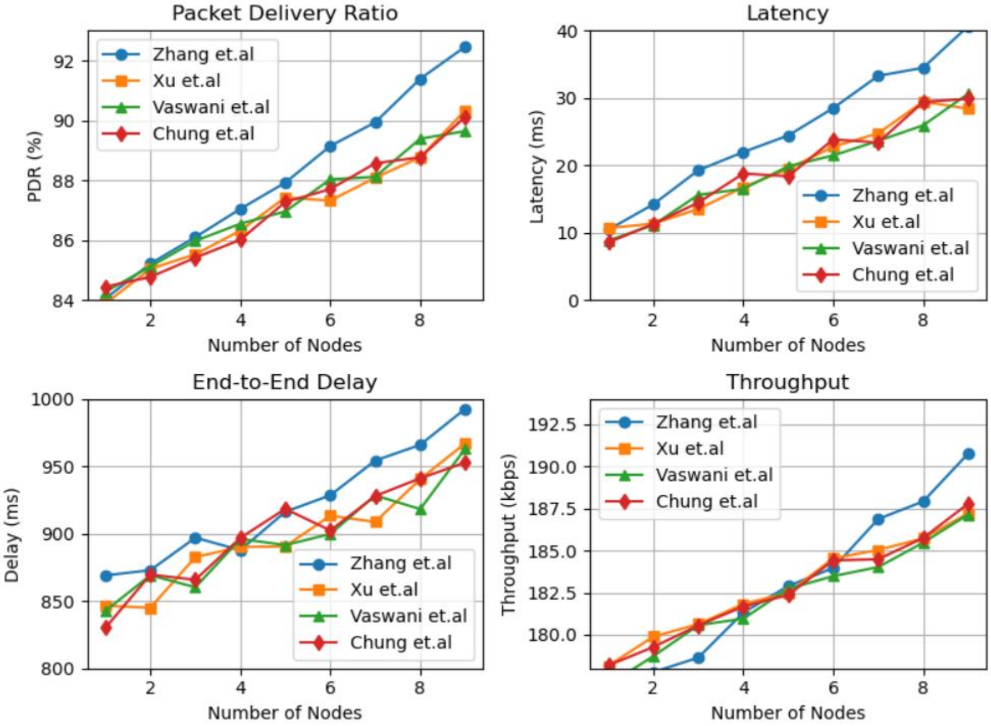
$\{h_1, h_2, \ldots, h_T\}$

Outputs:

- Sequence of hidden states $\{h_1, h_2, \ldots, h_T\}$

Result:

The performance analysis of the four algorithms (Zhang et al., Xu et al., Vaswani et al., and Chung et al.) focuses on optimizing energy consumption in IoT devices using a multi-headed attention GRU (Gated Recurrent Unit). As the number of nodes increases from 0 to 100, the Packet Delivery Ratio (PDR) consistently improves from 84% to 92%, indicating that the multi-headed attention GRU effectively enhances packet delivery efficiency across the network. Latency shows a moderate increase from 10 ms to 40 ms, while End-to-End Delay rises from 800 ms to 1000 ms, suggesting that although there is a delay with more nodes, the multi-headed GRU manages this increment efficiently. The Throughput also increases from 180 kbps to 192.5 kbps, demonstrating that data transfer rates benefit from the attention mechanism of the GRU. These results suggest that employing a multi-headed attention GRU in IoT networks can optimize energy consumption by maintaining high delivery ratios and throughput while managing latency and end-to-end delay effectively as network size scales.



Conclusion:

In this paper we empirically evaluated recurrent neural networks (RNN) with three widely used recurrent units; a traditional tanh unit, a long short-term memory (LSTM) unit and a recently proposed gated recurrent unit (GRU). Our evaluation focused on the task of sequence modeling on a number of datasets including polyphonic music data and raw speech signal data. The evaluation clearly demonstrated the superiority of the gated units; both the LSTM unit and GRU, over the traditional tanh unit. This was more evident with the more challenging task of raw speech signal modeling.we are interested in evaluating the performance of those recently proposed recurrent units (LSTM unit and GRU) on sequence modeling.The integration of Gated Recurrent Units (GRUs) and multi-headed attention mechanisms offers a promising solution for optimizing energy consumption in IoT devices. GRUs enhance efficiency and mitigate the vanishing gradient problem, while multi-headed attention improves model accuracy by capturing complex dependencies. These techniques have led to the development of energy-efficient predictive maintenance systems and improved energy management through edge computing.

References:

1. D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. Technical report, arXiv preprint arXiv:1409.0473, 2014.
2. J. Bergstra, I. J. Goodfellow, A. Bergeron, N. Bouchard, and Y. Bengio. Theano: new features and speed improvements. Deep Learning and Unsupervised Feature Learning NIPS 2012 Workshop, 2012.
3. Y. Bengio, P. Simard, and P. Frasconi. Learning long-term dependencies with gradient descent is difficult. IEEE Transactions on Neural Networks, 5(2):157–166, 1994.
4. Vejendla, L. N., Bysani, B., Mundru, A., Setty, M., & Kunta, V. J. (2023). Score-based support vector machine for spam mail detection. Proceedings of the IEEE International Conference on Electronics, Computing and Communication Technologies (ICOEI), 915–920. https://doi.org/10.1109/ICOEI56765.2023.10125718
5. Anusha, P., Ravikiran, A., Lakshman Narayana, V., & Maddumala, V. R. (2020). Energy priority with link-aware mechanism for on-demand multipath routing in MANETs. Journal of Electrical Engineering and Automation, 29(3), 8979–8991.
6. Narayana, V. L., & Bharathi, C. R. (2017). Identity-based cryptography for mobile ad hoc networks. International Journal of Engineering and Technology Innovation, 95(5), 1173–1181
7. Narayana, V. L., & Midhunchakkaravarthy, D. (2020). A time interval-based blockchain model for detection of malicious nodes in MANET using network block monitoring node. Proceedings of the IEEE

International Conference on Intelligent Computing and Robotics (ICIRCA), 852–857. https://doi.org/10.1109/ICIRCA48905.2020.9183256
8. Bharathi Vejendla, C. R., Narayana, L., & Ramesh, L. V. (2020). Secure data communication using Internet of Things. Journal of Advanced Research in Dynamic and Control Systems, 9(4), 3516–3520.
9. Narayana, V. L., Sujatha, V., Sri, K. S., Pavani, V., Prasanna, T. V. N., & Ranganarayana, K. (2023). Computer tomography image-based interconnected antecedence clustering model using deep convolutional neural network for prediction of COVID-19. Traitement du Signal, 40(4), 1689–1696. https://doi.org/10.18280/ts.400437
10. Patibandla, R. S. M. L., Rao, B. T., & Narayana, V. L. (2022). Prediction of COVID-19 using machine learning techniques. In Handbook of Machine Learning for Computational Biology and Bioinformatics (pp. 219–231). https://doi.org/10.1016/B978-0-12-824145-5.00007-1
11. Pavani, V., Sri, K. S., Krishna, P. S., & Narayana, V. L. (2021). Multi-level authentication scheme for improving privacy and security of data in decentralized cloud server. Proceedings of the IEEE International Conference on Systems and Electronics Engineering (ICOSEC), 391–394. https://doi.org/10.1109/ICOSEC51865.2021.9591698
12. Arepalli, P. G., Jairam Naik, K., & Rout, J. K. (2024). Aquaculture water quality classification with sparse attention transformers: Leveraging water and environmental parameters. In ACM International Conference Proceeding Series (pp. 318-325). https://doi.org/10.1145/3651781.3651829
13. Kumar, S. A., Babu, E. S., Nagaraju, C., & Gopi, A. P. (2015). An empirical critique of on-demand routing protocols against rushing attack in MANET. International Journal of Electrical and Computer Engineering, 5(5), 1102-1110. https://doi.org/10.11591/ijece.v5i5.pp1102-1110
14. Arepalli, G., Erukula, S. B., Gopi, A. P., & Nagaraju, C. (2016). Secure multicast routing protocol in MANETs using efficient ECGDH algorithm. International Journal of Electrical and Computer Engineering, 6(4), 1857-1865. https://doi.org/10.11591/ijece.v6i4.9941
15. Arepalli, P. G., Akula, M., Kalli, R. S., Kolli, A., Popuri, V. P., & Chalichama, S. (2022). Water quality prediction for salmon fish using Gated Recurrent Unit (GRU) model. In 2022 2nd International Conference on Computer Science, Engineering and Applications, ICCSEA 2022. https://doi.org/10.1109/ICCSEA54677.2022.9936539
16. Narayana, V. L., & Gopi, A. P. (2017). Visual cryptography for gray scale images with enhanced security mechanisms. Traitement du Signal, 34, 197-208. DOI: 10.3166/ts.34.197-208
17. Arepalli, P. G., Narayana, V. L., Venkatesh, R., & Kumar, N. A. (2019). Certified node frequency in social network using parallel diffusion methods. Ingenierie des Systemes d'Information, 24(1), 113-117. https://doi.org/10.18280/isi.240117
18. Peda Gopi, A., & Lakshman Narayana, V. (2017). Protected strength approach for image steganography. Traitement du Signal, 34(3-4), 175-181. https://doi.org/10.3166/TS.34.175-181
19. Narayana, V. L., Gopi, A. P., Anveshini, D., & Lakshmi, G. V. V. (2020). Enhanced path finding process and reduction of packet droppings in mobile ad-hoc networks. International Journal of Wireless and Mobile Computing, 18(4), 391-397. https://doi.org/10.1504/IJWMC.2020.108539
20. Vejendla, L. N., Naresh, A., & Arepalli, P. G. (2021). Traffic analysis using IoT for improving secured communication. In Innovations in the Industrial Internet of Things (IIoT) and Smart Factory (pp. 106-116). https://doi.org/10.4018/978-1-7998-3375-8.ch008
21. Kanumalli, S. S., Lavanya, K., Rajeswari, A., Samyuktha, P., & Tejaswi, M. (2023, February). A scalable network intrusion detection system using bi-lstm and cnn. In 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS) (pp. 1-6). IEEE.
22. Kanumalli, S. S., Mantena, S. J., Kandula, S., Doppalapudi, K., & Atluri, T. (2022, May). Automated Irrigation Management System using IoT. In 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS) (pp. 476-482). IEEE.
23. Kanumalli, S. S., Swathi, S., Sukanya, K., Yamini, V., & Nagalakshmi, N. (2022). Classification of dna sequence using machine learning. In Soft Computing for Security Applications:
24. Chaitanya, Kosaraju, et al. "Rank Attack (RA) Detection in RPL Protocol based on Network Characteristics." 2023 8th International Conference on Communication and Electronics Systems (ICCES). IEEE, 2023.
25. Kosaraju, Chaitanya, et al. "Mirchi crop yield prediction based on soil and environmental characteristics using modified RNN." 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2023
26. Chaitanya, Kosaraju, et al. "Ads Click-Through Rate prediction using Attention based LSTM Mechanism." 2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2024.

27. Sujatha, V., Prasanthi, Y., Pravallika, C.H., ... Ayesha Banu, S.K., Sahithi, M.,K(23)
28. " A Computer Vision Method for Detecting the Lanes and Finding the Direction of Traveling the VehicleLecture Notes in Networks and Systems", 2023, 612, pp. 373–382
29. Sri, L. Akhila, K. Manvitha, G. Amulya, I. Sai Sanjuna, and V. Pavani. "FBI crime analysis and prediction using machine learning." Journal of Engineering Sciences 11, no. 4 (2020): 441-448.
30. P. V, L. S. K, P. Vyshnavi A, M. Ch and S. B. G, "Students Community Portal using Machine Learning," 2023 Second International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2023, pp. 1109-1113, doi: 10.1109/ICEARS56392.2023.10085516.
31. Sirisha, Aswadati, et al. "Intrusion detection models using supervised and unsupervised algorithms-a comparative estimation." International Journal of Safety and Security Engineering 11.1 (2021): 51-58.
32. Krishna, KVSS Rama, et al. "Vehicle Number Plate Detection using Deep Learning." 2024 International Conference on Integrated Circuits and Communication Systems (ICICACS). IEEE, 2024.
33. Krishna, Komanduri Venkata Sesha Sai Rama, et al. "Classification of Glaucoma Optical Coherence Tomography (OCT) Images Based on Blood Vessel Identification Using CNN and Firefly Optimization." Traitement du Signal 38.1 (2021).
34. Rayachoti, Eswaraiah, Sudhir Tirumalasetty, and Silpa Chaitanya Prathipati. "Watermarking system for telemedicine based on FABEMD." Multimedia Tools and Applications 81.30 (2022): 44383-44404.
35. Chaitanya, P. Silpa, KV Narasimha Reddy, and G. Madhavi. "Effective Search of Color-Spatial Image Using Semantic Indexing." International Journal of Computer Science, Engineering and Applications (IJCSEA) Vol 2 (2012): 9-19.
36. Alapati, N., Prasad, B. V. V. S., Sharma, A., Kumari, G. R. P., Veeneetha, S. V., Srivalli, N., ... & Sahitya, D. (2022, November). Prediction of Flight-fare using machine learning. In 2022 International Conference on Fourth Industrial Revolution Based Technology and Practices (ICFIRTP) (pp. 134-138). IEEE.
37. Alapati, N., Prasad, B. V. V. S., Sharma, A., Kumari, G. R. P., Bhargavi, P. J., Alekhya, A., ... & Nandini, K. (2022, November). Cardiovascular Disease Prediction using machine learning. In 2022 International Conference on Fourth Industrial Revolution Based Technology and Practices (ICFIRTP) (pp. 60-66). IEEE.
38. Srikanth Kilaru " A Novel Approach to Human Iris Recognition And Verification Framework Using Machine Learning Algorithm" 2023 6th International Conference on Contemporary Computing and Informatics (IC3I),
39. DOI: 10.1109/IC3I59117.2023.10397886, ISBN Information:Electronic ISBN:979-8-3503-0448-0
40. Print on Demand(PoD) ISBN:979-8-3503-0449-7
41. Srikanth Kilaru "Analytical models for collaborative autonomous mobile robot solutions in fulfillment centers" in Applied Mathematical Modelling, Volume 91, March 2021, Pages 438-457, https://doi.org/10.1016/j.apm.2020.09.059
42. Gopi, A. P., & Naik, K. J. (2022). An IoT model for fish breeding analysis with water quality data of pond using modified multilayer perceptron model. 2022 International Conference on Data Analytics for Business and Industry (ICDABI), 448-453. https://doi.org/10.1109/ICDABI56818.2022.10041617
43. Arepalli, P. G., & Naik, K. J. (2024). A deep learning-enabled IoT framework for early hypoxia detection in aqua water using lightweight spatially shared attention-LSTM network. Journal of Supercomputing, 80(2), 2718-2747. https://doi.org/10.1007/s11227-023-05580-x
44. Arepalli, P. G., & Naik, K. J. (2023). An IoT-based water contamination analysis for aquaculture using lightweight multi-headed GRU model. Environmental Monitoring and Assessment, 195(12), Article 1516. https://doi.org/10.1007/s10661-023-12126-4
45. Gopi, A. P., Gowthami, M., Srujana, T., Gnana Padmini, S., & Durga Malleswari, M. (2023). Classification of denial-of-service attacks in IoT networks using AlexNet. In Smart Innovation, Systems and Technologies (Vol. 316, pp. 349-357). https://doi.org/10.1007/978-981-19-5403-0_30
46. Bikku, T., Gopi, A. P., & Prasanna, R. L. (2019). Swarming the high-dimensional datasets using ensemble classification algorithm. In Advances in Intelligent Systems and Computing (Vol. 815, pp. 583-591). https://doi.org/10.1007/978-981-13-1580-0_56
47. Y. Bengio, N. Boulanger-Lewandowski, and R. Pascanu. Advances in optimizing recurrent networks. In Proc. ICASSP 38, 2013.
48. J. Bergstra and Y. Bengio. Random search for hyper-parameter optimization. The Journal of Machine Learning Research, 13(1):281–305, 2012.
49. Jain, B., Brar, G., Malhotra, J., & Rani, S. (2017). Novel Approach for Smart Cities in Convergence to Wireless Sensor Networks. Sustainable Cities and Society, 17(2), 1–34. doi:10.1016/j.scs.2017.08.005