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RESEARCH ARTICLE

Intellectual Data Aggregation Using Independent Cluster based Medicaid Method for Network Functionality Fabrication

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Abstract

Objectives: Network functionality-based tracking is difficult for the fabrication processing under the various environment condition. In order to achieve the efficient result Intellectual data cluster-based Medicaid aggregation method applied for the network functionality analysis of the attack on network entities aggregate the fabrication process for balancing the network to normal flow. **Methods:** The proposed Independent Cluster based Medicaid Intellectual Data Aggregation (ICAMA) is compared with the K-means and GSVM, DBSCAN algorithm for classification of the attack entities to understand the response and reinforcement of the network functionality against the interconnection nodes by using energy and weighted aggregation, accuracy metrics on the CIC-IDS 2019 dataset. **Findings:** The Experiment studies provide the 15.23% lower energy consumption for interconnection of nodes comparing with the DBSCAN and 17.18% against the K-means algorithms. The network functional fabrication progress of proposed method has the weighted aggregation15.07%,8.32%, 6.41%, 5.12%, 5.52%, 8.08% and 2.21% against the given K-means, DBSCAN, GSVM, SOM, PCA, ocSVM and ICA methods and also improves accuracy to 11.07% compared with the GSVM method. ICAMA applies the intellectual functionality based on the distribution of entities in the network as a cluster or a single fabrication process. **Novelty:** In order to restore the regular network progress, ICAMA continuously runs the dynamic collection of network analysis by employing intellectual functional support to identify various types of network anomalies.

Keywords: Clustering; Data aggregation; Energy consumption; Fabrication; Network attacks

1 Introduction

The network analytics process to find the decaying network entities avoiding the normal flow and progress of network utilized for a variety of purposes, including finding connected endpoints, identifying bottlenecks, assessing device health, resolving issues, and probing for potential security flaws also determines how to optimize operations by comparing incoming data with pre-programmed models[1]. The aggregation approaches often makes discrete steps with time interval steps with a single piece of linear function or mixture of functions significantly on samples per object than a greater number of objects[2]. To finds the lag of service time the network functionalities directly measure similarity between the synchronizing methods or the methods that aggregate multiple imputations used for clustering time-series of data with the transmission constraints[3]. The damage tolerance of network distribution functionalities based on the demands for reliable and robust network monitoring procedure and the dynamic allocation of new sources is difficult for the trusted identification in nature[4].

Dash L et al.[5] developed a novel machine learning-based approach to data redundancy reduction with an aggregation tree is built using a specific number of nodes. The Genetic Support Vector Machine (SVM) method is used to remove the unnecessary data from the tree and additionally, Locality Sensitive Hashing (LSH) removes incorrect data on likeness and masses non-redundant facts to the higher node[6,7]. Inayat Ali et al.[8] mentioned a Correlation Degree based on Data Density (DDCD) clustering approach for the network's sink nodes in order to compute the locally available data for those nodes. The sampled data can only be seen through its spatial correlation to the sink node. No standards set for the temporal redundancy of the sampled data computes surrounding sensor nodes that correlate with the least amount of distortion.

Yadav S et al.[9] mentioned servicing in hospital environments sometimes to damage the concurrent multiple node failures in the density area cause network partitioning. The autonomous network recovery in harsh environments is challenging because the nodes in different partitions cannot determine the scope of the damage. Forbush, K et al.[10] suggests the RAG (Real-Time Data Aggregation) routing algorithm for static nodes in WSNs, which makes use of the time-based and topographical conjunction of the data packets. the delayed data packets based on the any-casting policy and makes use of the available data via the waiting policy while using real-time data at the network's Medium Access Control (MAC) layer.

Migenda N et al.[11] have suggested dimensionality lessening methods like PCA with numerical controller charts for guided wave-based unsupervised damage assessment. This method makes use of PCA as a feature separator to decrease the dimensionality of the input space. ICA and artificial neural networks are combined with artificial neural networks (ANN), Zhang et al.[12] have developed a method for unsupervised damage identification in satellite antennas and railway wheels using vibration signals. For dimensionality reduction technique known as the Self-Organizing Map (SOM)[13] can give us insights into highly complex data. Self-Organizing Maps are helpful for exploratory data analysis, clustering problems, and high dimensional dataset visualization.

Khoa et al.[14] have suggested PCA for feature extraction with one-class SVM (ocSVM) for anomaly identification in building-like structures. Wang & Cha[15] merged auto encoders with SVM on numerical and investigational structures for damage detection. The aforesaid research indicates that both ML and DL for feature-learning approaches are preferred for anomaly detection in network structures. Zhao etal[16] investigation into the Computing paradigm's application in the healthcare industry highlighted its significant offspring in terms of network usage, latency, and power consumption. The authors have created a assisted health monitoring system and conducted a performance evaluation based on the previously listed metrics. As in[17] data were locally analyzed, the results showed how this model might be improved to minimize data traffic inside the network. Additionally, healthcare data security was improved, which may offer more accurate understanding of the patient's health situation.

In[18], it is suggested that communication science should separate the communication effect into three levels. According to the logical order or performance stage of its occurrence, it can be separated into external information working on people's intuition and memory system creating a gain in people's knowledge and a change in knowledge composition[19]. The psychological and attitudinal levels are affected by these impacts on the cognitive level since they have an impact on how people think or value things[20]. People's actions and words cause changes that have an impact on the degree of behaviour. A process of accumulation, deepening, and expansion of consequences occurs. The following research work which are carried forward to our research in the narrow way. The literature with their applications and pitfalls are given in the following Table 1 as shown. To overcome the discussed pitfalls in this research article proposed the ICAMA method in section 2.

Table 1. Review Literature of Existing Aggregation Methods

Methodology	Contribution	Result
Cognitive Computing Model [21]	Cognitive decision algorithm based on deep confidence network and linear perceptron	The related technologies of task scheduling and resource allocation are studied, but the problems related to security mechanism are not considered.
Neural Network Embedding (NNE) [22]	Simplification Process Using A Two-Step Analysis Of Topological Patterns Of Function	Relationships with NNE features that were not found to be significantly related to the commonly used network metrics
Cognitive Network Science [23]	Operationalized as structural changes in cognitive systems on different timescales and resolutions	The cognitive science community has developed a suite of experimental tasks that can provide crucial evidence that constrains and informs network models of cognition.
SDN, the controller is responsible for controlling the logic of the entire network [24]	Strategies for detection and mitigation of cyberattacks by enhancing SDN	SDN's architecture, besides those found in conventional networks and those produced by human error
Cluster-based data aggregation algorithms [25]	Optimal cluster-based data aggregation (OCDA) technique	All cluster members send its sensed data during its allotted time slot where CH eliminates the duplicates

2 Methodology

The proposed methodology is an enhanced clustering and data accretion approach, shown in Figure 1. The clusters are created by determining the correlation of data from the sensor nodes on form the CIC-IDS 2019 Dataset. Following node deployment, the data similarity of adjacent sensor nodes can be assessed in terms of correlation value.

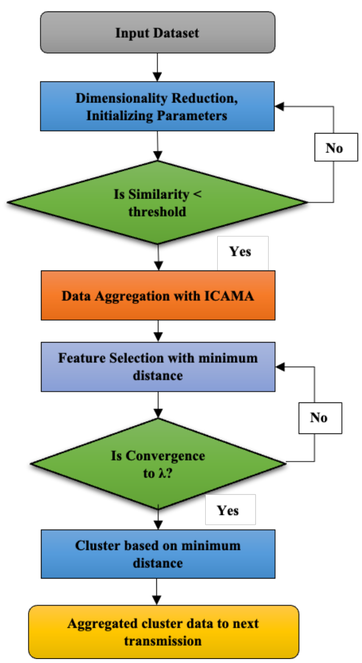

Fig 1. The Process flow of the proposed ICAMA method

Assuming that the cluster heads are determined, the transmission radii of each of their neighbors are estimated. Each cluster's average correlation value can be determined after gathering creation with its neighboring nodes. The correlation measure of a cluster should be set at a reasonable threshold value exceeds measured correlation value of a cluster, then the cluster is designated as having higher similarity. Because aggregation procedures like OCDA, NNE, and ocSVM data transmissions and cluster formation with higher similarity data aggregation requirements can reduce computation and energy consumption.

The clusters are identified as dissimilar and data aggregation is not required for them if the correlation metric is below the threshold. Disparate data clusters deliver data to the cluster head before sending to the descend. In the cluster-based data aggregation approach, ICAMA is used.

The suggested architecture makes use of a tree topology, where each node stands in for a network. As we go through the hierarchy, the level of complexity increases, indicating different levels of classification fine-tuning (see Figure 2). These levels range from broad models to specialized models. By permitting any type of tree-structured reliance within a cluster, a rich but manageable model for intra-cluster dependence can be produced.

Let $x_1 \ldots\ldots\ldots x_m$ a probability distribution p(x) is said to factorize in the non-spanning undirected tree T as well as clusters of nodes that stand in for intermediate transitional categories when x_m denotes m random variables. And a probability distribution p(x) is said to factorize in T if and only if it can be expressed as $p(x) \propto \Pi_{(u,v)\in T}\, \varphi_{uv}\left(x_u, y_v\right)$ where φ_{uv}

is the clustering technique that allows input examples to belong to multiple groups, and φ_{uv} is the potential function for the k linked components of T.

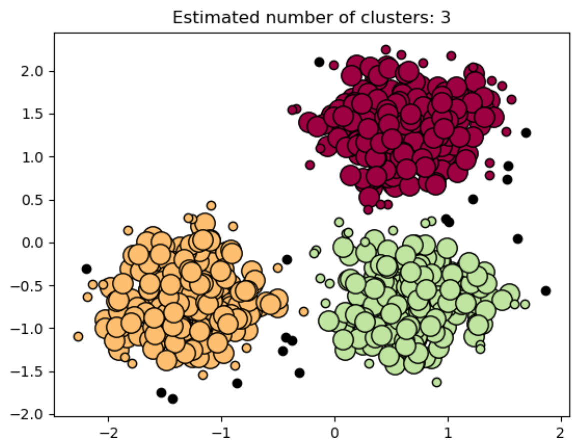

Fig 2. Detected Interaction of Overlapped Clusters (Estimated number of clusters n=3)

In Figure 2 indicates one of the problems for the duration of thresholding areas at the map cannot be assigned with actuality to one of the agencies, because the membership is shipped among two or more groups for pattern popularity primarily based on the minimization of the goal feature as,

$$d_m = \sum_{i=1}^{N} \sum_{j=1}^{c} U_{ij}^{m} \left\|x_i - c_j\right\|^2 \tag{1}$$

Here, U_{ij} is the club level of x_i to the cluster j, x_i is the i^{th} example of the styles have to be grouped, c_j is the center of the cluster of j, and sophistication feature $||*||$ expresses the similarity among the located facts and a cluster middle. A vector area is converted into a vector subspace with jointly independent signals using ICA. According to statistics, a combined probability distribution of the unbiased signals is the sum of the random distributions for each of the vector. Dimensionality deduction is used to procedure the enterprise control performance evaluation index statistics obtains the internal houses and legal guidelines of the facts and improves the ability of the clustering effects.

For a given target T and a goal distribution p(x), for all distributions $q \in |T|$ have $T_i(x) = I\left(x_1, x_2, \ldots\ldots x_n\right) - \sum_{(u,v)\in T} I\left(x_u, x_v\right)$ is the minimum possible lack of facts whilst encoding the distribution p(x) with a distribution that factorizes in T. The proposed method is providing the better results on the detection rate, classification and energy consumption rate, all the three-evaluation metrics to perform the network fabrication functionalities. The performance examination of proposed algorithm carried out the strategy is made as far as three boundaries of metrics as the energy utilization, accumulation proportion, and computational intricacy. While applying this procedure progress participation level components are those don't have an identity for any of the clusters previously formed.

2.1 Proposed ICAMA Algorithm for Network Functionality Fabrication

Input: dataset $\{x\}=\{x^1,x^2,\ldots..x^N\}$, for all n, x^n U

1. Initialization: T= , w as rand(x)

2. For i=0 to n-1
3. Find best tree T with i edges, for W
4. While is decreasing
5. If and
6. Find
7. else
8. Compute the typical similarity degree of the collection
9. If the ratio of resemblance < tmin
10. Mark low similarity cluster {c, c≠0}
11. else
12. Update the cluster member to the total set {U}
13. End While
14. End For

Output: Transmission matrix W = Wi, forest T =* T_i

The standard for the enrollment of a model to a cluster depends on a limit (λ). This interaction addresses each level a fine-tuning phase of the characterization is perfect for naming calculation to keep an underlying rationality of the characters. A dad hub should contain the tags of every one of its relatives linked to the leave nodes, so every descendant hub addresses a specialization of the dad hub of sort or the ideal change is found by limiting a differentiation capability in view of shared data, straightforwardly expands the difference capability utilized for traditional ICA.

2.2 Evaluation Process

Utilizing base energy to gather all the data and being aware of information flow within the organization are both necessary for the distribution of organizational usefulness manufacture. The acquisition of the circulation is mostly accomplished using two ways. The first strategy involves the hub processing and selecting pertinent information, then delivering the refined information to the channel and finally to the destination. The second method of information transmission is collecting all sensor hubs submit their unprocessed data to the cluster head before being sent to the target.

The energy consumption to transfer the aggregated data to the target channel or node calculated using the T_E as shown

$$T_E(a,n) = \begin{cases} l \times E_{f,} \times a^2 + U \text{ if } a < a_0 \\ E[s(t)].\Gamma(h)e^{-iw} \end{cases} \tag{2}$$

Where $E_{\mathrm{fs}} \times a^2$ is the energy utilization by the speaker inside the transmission of information over the organization region. The information collection utilizing the proposed calculation utilizes the m layered information to n layered for changing the space from a m-aspect to novel interstellar with the factors λ characterize the configuration of the information comprising the profoundly critical data from the sensor's hubs. Notices lattice, here x should be focused and implies the factors have mean worth as nothing. Focusing is determined as deducting its mean from noticed cluster centroid.

$$X_c = X - E\{X\} \tag{3}$$

Next process is transformed such that they have the variance and Covariance matrix of centered data is calculated with Eigen value and also decay of performance on covariance is calculated by $z = U^{-1/2}\square T_E \times X_c$. The aggregation on the given weightage to the transmission over the designated path estimation is given by

$$w_{tp} = E\left\{zb\left(T_w w_j b\right) - E\left(za\left(T_w w_i a\right\}\right.\right. \tag{4}$$

The calculation intricacy of the ICAMA is determined in view of the arrangements of irregular conveyances contain such dispersion produce the examples of parts as in the past. However the information is created from causal autoregressive models, with arbitrary coefficients. Computational intricacy of the proposed strategy is assessed and plotted against number of hubs.

2.3 Performance Analysis

The experimental setup for this study uses an i5, a 1TB hard drive, and 8 GB of RAM. Energy use, aggregation ratio, and computing complexity are evaluated between the conventional ICA and the suggested techniques.

2.4 Data Cleaning

The common knowledge of all the data utilized in this research came from actual medical records, particularly data gathered from various infirmaries and remedial service providers the numerous ”bad data” items like clashing letters, blank fields, and strange inputs must be present. Prior to entering the model, strictly control these noises. Although the technical substance of the data cleansing step is not very high, knowing and analyzing the company and using common sense in judgement plays a crucial function. Understanding the pertinent medical knowledge has taken up a significant amount of time during the research procedure for this work.

2.5 Data Preprocessing

After data integration and cleaning, correctness is ensured and a real and useful dataset is obtained. However, the portion of the data is primarily in the format of the data source, is very different from the format required by the model.

2.6 Performance Metrics

The performance of the proposed ICAMA evaluation is concentrates for the fabrication process on the functionalities are tested against the existing methods with the different aspects of the metrics for network analysis. Metrics are having the ability withstand on the detection, classification of attacks and apply the reformation process over the network functions.

To determine the accuracy level the detection and classification and aggregate weightages are used. The detection rate uses the true and false positive rates as to get the network functionality misuses and fault identification by using the formula

$$Detection\ Rate\ (DR) = \frac{TP}{TP+FN} \times 100 \tag{5}$$

The Classification of the true fabrication need detection is based on the total number of positive and negative detection rates mentioned by the following formula

$$Classification\ Rate\,(CR) = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \tag{6}$$

Data aggregation using the transmission and weightage based on the destination consumed energy observation rate and the detection rate, which is identified by

$$Weighted\ Aggrigation\ Rate\,(WAR) = \frac{DR}{(T_E+W_T)} \times 100 \tag{7}$$

Evaluation of this work carried on a hybrid of state-of-the-art practices with the synthetic attack nature like Brute Force, Heart bleed, Web, Infiltration, Botnet, PortScan, DDoS are the Seven types listed in Table 2. Selection of cluster classes done by Euclidean distance scores in the CIC-IDS 2019 dataset performance based on a multi-objective optimization problem improve prevalence of all attack labels significantly reducing the class imbalance rate.

Table 2. Labelling Attacks based on the attack nature and prevalence (%) of instances on CIC-IDS 2019 Dataset

S. No	Labels	Number of Instances	% of Prevalence with majority classes	% of Prevalence with the total instances
1	Normal	2359087	100	83.34
2	Broute Force	13835	0.59	0.48
3	Botnet	1966	0.083	0.06
4	Infiltration	36	0.001	0.001
5	Port Scan	158930	6.74	5.61
6	Web	2180	0.092	0.07
7	DDoS	294506	12.49	10.4
8	Heart bleed	11	0.000005	0.00039

3 Results and Discussion

The complete set of the features based on nature of attack classes selects only three cluster classification of intrusion to predict the accuracy level. The proposed method investigates the clusters with the performance metrics given in the equations 5 to 7, Comparing with the existing methods which are discussed in the review literature.

Table 3. Labelling Attacks based on the attack nature and prevalence (%) of instances on CIC-IDS 2019 Dataset

Methods	Attack Classes	Detection Rate (DR)	Classification Rate (CR)	Weightage Aggregation Rate (WAR)
K-Means [2]	3	75.34	84.24	83.56
DBSCAN [5]	5,7	83.15	89.00	90.31
GSVM [6]	5	79.76	90.45	92.22
SOM [8]	5	75.00	78.73	93.51
PCA [11]	3, 5	85.69	94.88	93.11
ocSVM [15]	3, 5	80.23	92.57	90.55
ICA [20]	3, 5, 7	90.78	95.57	96.42
Proposed Method	5, 7, 14	92.52	96.77	98.63

From Table 3, K-Means process the three different cluster classes to find the accuracy level to 83.56%, the energy consumption rate is low to compute the cluster set. But the Algorithm improves the classification to 84.24% comparing the other network functionality to fabricate the attacking nodes. DBSCAN method improves the performance comparing with the attack classes to find the density factor than the cluster centroids and obtain the accuracy 90.31%. Genetic SVM and SOM methods obtain the equal number of clusters but deviates from of accuracy to 1.71%. PCA deals with two different cluster sets and finds the dimensionality reduction improves the detection and classification rate comparatively increase the weighted aggregation rate. The SOM picks one class for intrusion and anomaly identification for the attack types but new types are ignored to care. ICA applies multiple classes of attack categories but in case of damaged network functionalities identified, the method ignored the path and process to next node.

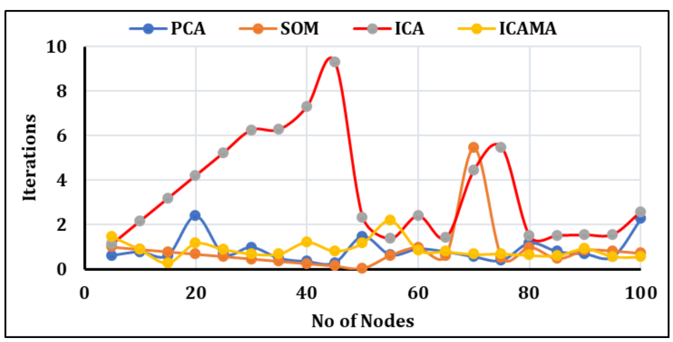

Fig 3. The Computational Complexity of the ICAMA Compared with the Conventional Methods (Number of iterations against the number of nodes)

Due to the constraint the detection and classification of edge cutting are improved to better weighted aggregation rate (96.42%) than the listed existing methods. Based on the experimental processing the proposed method finds the fabrication limitations to take care and modified to improve the detection, classification ratio. ICAMA uses the three components like energy utilization, accumulation proportion, and computational intricacy for preforming better (98.63%) of WAR value then the existing list of methods. Using the independents components as variables were grouped into distinct clusters can be observed that the clusters presented very distinct expression patterns as in Figure 3.

In the Figure 4, the ICAMA has the very low computational complexity compare to the traditional algorithms. The Energy consumption of the total transmission over the target with the proposed method has shown.

The Energy Consumption of the proposed system to transmit a single byte against the network traffic to the target node ignores the false positive rate, number of rounds to calculate the optimum path and transmission is given in the Figure 5.

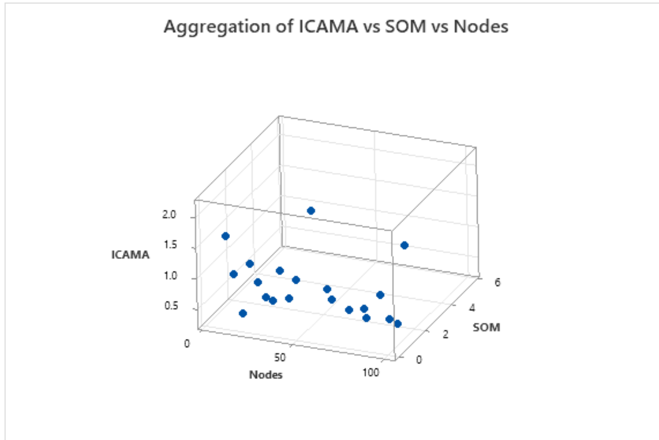

Fig 4. Aggregation of proposed ICAMA based on Number of Nodes vs SOM based on Number of Nodes

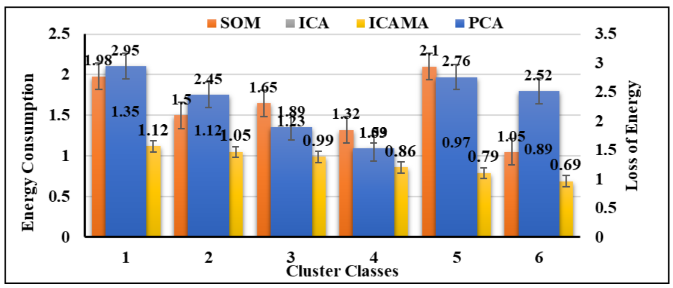

Fig 5. Energy consumption of the proposed method against the conventional process of the existing methods (loss of Energy representation in error bars (%) against the cluster classes)

4 Conclusion

The use of data association and data accretion with Independent Cluster based Medicaid Intellectual Data Aggregation (ICAMA) is proposed as part of a similarity-based clustering technique. The proposed approach is put into exercise to evaluated using factors like accretion ratio, computational intricacy, and energy feasting to get the outcome of the demonstrates that compared with cluster based aggregation, ICAMA using a method has a marginally superior aggregation ratio technique uses less energy 36.6%, 26.2%, and 4.60 and requires minimum computational resources than the conventional methods PCA, SOM and ICA. By offering security services like identification, integrity, and secrecy, the future course can be changed. Homomorphic encryption enables for ICAMA data aggregation and offers complete data confidentiality.

References

1) Abbas A, Khan MA, Latif S, Ajaz MM, Shah AA, Ahmad J. A New Ensemble-Based Intrusion Detection System for Internet of Things. *Arabian Journal for Science and Engineering*. 2022;47(2):1805–1819. Available from: https://doi.org/10.1007/s13369-021-06086-5.
2) Li Q, Zhu L, Li B, Luo J, Liu D, Chen M. Small target detection algorithm based on YOLOv4. *2022 International Seminar on Computer Science and Engineering Technology (SCSET)*. 2022;p. 76. Available from: https://doi:10.1109/SCSET55041.2022.00026.
3) Portela FG, Mendoza FA, Benavides LC. Evaluation of the performance of supervised and unsupervised Machine learning techniques for intrusion detection. *2019 IEEE International Conference on Applied Science and Advanced Technology (iCASAT)*. 2019;p. 1–8. Available from: https://doi:10.1109/iCASAT48251.2019.9069538.
4) Hu T, Wang H, Yin W. Multi-label news classification algorithm based on deep two-way classifier chain. *Journal of Zhejiang University: Engineering Edition*. 2019;53(11).
5) Dash L, Pattanayak BK, Mishra SK, Sahoo KS, Jhanjhi NZ, Baz M, et al. A Data Aggregation Approach Exploiting Spatial and Temporal Correlation among Sensor Data in Wireless Sensor Networks. *Electronics*. 2022;11(7):989. Available from: https://doi.org/10.3390/electronics11070989.
6) Kongar E, Adebayo O. Impact of Social Media Marketing on Business Performance: A Hybrid Performance Measurement Approach Using Data Analytics and Machine Learning. *IEEE Engineering Management Review*. 2021;49(1):133–147. Available from: https://doi:10.1109/EMR.2021.3055036.
7) Wu Z, Chu W. Sampling Strategy Analysis of Machine Learning Models for Energy Consumption Prediction. *IEEE 9th International Conference on Smart Energy Grid Engineering (SEGE)*. 2021;95349:87–87. Available from: https://doi:10.1109/SEGE52446.2021.9534987.

8) Ali I, Khan E, Sabir S. Privacy-preserving data aggregation in resource-constrained sensor nodes in Internet of Things: A review. *Future Computing and Informatics Journal*. 2018;3(1):41–50. Available from: https://doi.org/10.1016/j.fcij.2017.11.004.
9) Yadav S, Yadav RS. Redundancy Elimination During Data Aggregation in Wireless Sensor Networks for IoT Systems. *Lecture Notes in Electrical Engineering*. 2019;p. 195–205. Available from: https://doi.org/10.1007/978-981-13-2685-1_20.
10) Forbush KT, Siew CSQ, Vitevitch MS. Application of network analysis to identify interactive systems of eating disorder psychopathology. *Psychological Medicine*. 2016;46(12):2667. Available from: https://doi.org/10.1017/S003329171600012X.
11) Migenda N, Möller R, Schenck W. Adaptive dimensionality reduction for neural network-based online principal component analysis. *PLOS ONE*. 2021;16(3):e0248896. Available from: https://doi:10.1371/journal.pone.0248896.
12) Zhang W, He Q, Chen W. Target tracking algorithm combined part-based and redetection for UAV. *J Wireless Com Network*. 2020;2020. Available from: https://doi.org/10.1186/s13638-020-01696-3.
13) Ruiz M, Mujica LE, Sierra J, Pozo F, Rodellar J. Multiway principal component analysis contributions for structural damage localization. *Structural Health Monitoring*. 2018;17(5):1151–1165. Available from: https://doi:10.1177/1475921717737971.
14) Khoa TV, Saputra YM, Hoang DT, Trung NL, Nguyen D, Ha NV, et al. Collaborative Learning Model for Cyberattack Detection Systems in IoT Industry 4.0. *2020 IEEE Wireless Communications and Networking Conference (WCNC)*. 2020;p. 1–6. Available from: https://doi:10.1109/WCNC45663.2020.9120761.
15) Wang Z, Cha YJ. Unsupervised deep learning approach using a deep auto-encoder with a one-class support vector machine to detect damage. *Structural Health Monitoring*. 2021;20(1):406–425. Available from: https://doi:10.1177/1475921720934051.
16) Zhao F, Zeng Z, Liu H, Lan R, Fan J. Semisupervised Approach to Surrogate-Assisted Multiobjective Kernel Intuitionistic Fuzzy Clustering Algorithm for Color Image Segmentation. *IEEE Transactions on Fuzzy Systems*. 2020;28(6):1023. Available from: https://doi:10.1109/TFUZZ.2020.2973121.
17) Fallahpour A, Nayeri S, Sheikhalishahi M, Wong KY, Tian G, Fathollahi-Fard AM. A hyper-hybrid fuzzy decision-making framework for the sustainable-resilient supplier selection problem: a case study of Malaysian Palm oil industry. *Environmental Science and Pollution Research*. 2021. Available from: https://doi.org/10.1007/s11356-021-12491-y.
18) Hedar ARR, Abdulaziz SN, Mabrouk E, El-Sayed GA. Wireless Sensor Networks Fault-Tolerance Based on Graph Domination with Parallel Scatter Search. *Sensors*. 2020;20(12):3509. Available from: https://doi.org/10.3390/s20123509.
19) Cherif IL, Kortebi A. On using eXtreme Gradient Boosting (XGBoost) Machine Learning algorithm for Home Network Traffic Classification. *Wireless Days (WD)*. 2019;p. 1–6. Available from: https://doi:10.1109/WD.2019.8734193.
20) Larriva-Novo XA, Vega-Barbas M, Villagra VA, Rodrigo MS. Evaluation of Cybersecurity Data Set Characteristics for Their Applicability to Neural Networks Algorithms Detecting Cybersecurity Anomalies. *IEEE Access*. 2020;8:9005–9014. Available from: https://doi:10.1109/ACCESS.2019.2963407.
21) Jin H. Data processing model and performance analysis of cognitive computing based on machine learning in Internet environment. *Soft Computing*. 2019;23(19):9141–9151. Available from: https://doi.org/10.1007/s00500-018-03722-5.
22) Shirakami A, Hase T, Yamaguchi Y, Shimono M. Cold Spring Harbor Laboratory. 2021. Available from: https://doi.org/10.1101/2021.10.19.464982.
23) Siew CSQ, Wulff DU, Beckage NM, Kenett YN, Meštrović A. Cognitive Network Science: A Review of Research on Cognition through the Lens of Network Representations, Processes, and Dynamics. *Complexity*. 2019;2019:1–24. Available from: https://doi:10.1155/2020/1574796.
24) Valdovinos IA, Pérez-Díaz JA, Choo KKRKR, Botero JF. Emerging DDoS attack detection and mitigation strategies in software-defined networks: Taxonomy, challenges and future directions. *Journal of Network and Computer Applications*. 2021;187:103093. Available from: https://doi:10.1016/j.jnca.2021.103093.
25) Ranjani S, Y N, Ananth AG, Reddy LS. Optimal Cluster-Based Data Aggregation in WSN for Healthcare Application. *Adv Dyn Syst Appl*. 2021;16(2):683–701.