E-ISSN 2581 – 7957
P-ISSN 2277 – 3916
CVR Journal of Science and Technology, Volume 25, December 2023
DOI: 10.32377/cvrjst2513

Effective Event Exposure Classifier (E3C) in Wireless Sensor Network through SVM

G. Malleswari[1], A. Srinivasa Reddy[2]
[1]Asst. Professor, CVR College of Engineering/CSE Department, Hyderabad, India
Email: gkmalleswari@gmail.com
[2]Asst. Professor, CVR College of Engineering/ET Department, Hyderabad, India
Email: srinivas.asr@gmail.com

Abstract: **A Wireless Sensor Network (WSN) is composed of distributed nodes designed for environmental monitoring and event detection. To optimize energy usage during correlated data gathering, the Correlated Data Gathering (CDG) scheme utilizes the Adaptive Routing algorithm. While this approach effectively conserves energy, it introduces a significant energy-delay tradeoff when securing data within the sensor network. In response to this challenge, the E3C-SVM system leverages Support Vector Machine (SVM) classification with minimal energy consumption to assess event significance. E3C-SVM also employs the Doppler Effect method for efficient sensing data event recovery, particularly in identifying periodic events caused by moving objects. By reducing classification time, E3C-SVM mitigates the energy-delay tradeoff. Furthermore, E3C-SVM incorporates a mechanism for generating event-specific keys, reducing energy consumption during key generation, and enhancing security when broadcasting notifications to sensor nodes. This feature elevates the security level of object collection. Experimental evaluations primarily assess classifier performance, security levels, and energy consumption rates.**

Index Terms: **Correlated Data Gathering, Wireless Sensor Network, Support Vector Machine, Classification time, Adaptive Routing.**

I. INTRODUCTION

Due to the different positions of items in Wireless Sensor Networks (WSNs), the presence of several sensor nodes frequently results in significant correlations. Occasionally, transmitting data from all these sensors to the destination can result in heightened network traffic and congestion. This practice not only increases network congestion but also leads to congestion at the destination nodes, subsequently elevating the overall energy consumption of the network. To tackle these challenges, several researchers have proposed object classification techniques that leverage data aggregation within WSNs to alleviate network traffic. A multi-hop data aggregation strategy has been introduced to enhance energy efficiency and reduce energy consumption throughout the entire network. This strategy primarily focuses on optimizing data aggregation times. To facilitate this, researchers have introduced an integrated algorithm called the Adaptive and Distributed Routing Algorithm, operating within a game theoretic framework to enable efficient data gathering. However, despite achieving a reduction in energy consumption across the network, it's important to note that the energy-delay tradeoff remains a concern when it comes to securing data within the sensor network.

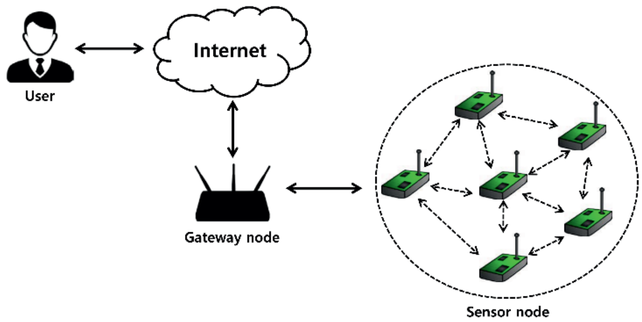

Figure 1. WSN architecture

WSNs encompass networks comprising diminutive, independent sensor nodes endowed with wireless communication capabilities. These nodes are engineered to amass and dispatch data originating from their immediate surroundings. Below, you will find some vital characteristics and constituents of wireless sensor networks:

Sensor Nodes: Sensor nodes serve as the fundamental building blocks within WSNs. They typically take the form of small, cost-effective devices equipped with sensors designed to gauge diverse physical parameters, including temperature, humidity, light, sound, or motion. These nodes often grapple with limited processing capabilities, memory, and energy reservoirs.

Wireless Communication: Sensor nodes engage in wireless communication, both amongst themselves and with a central base station or sink node, using various wireless communication protocols such as Zigbee, Bluetooth, Wi-Fi, or tailor-made protocols. Communication in WSNs can take on the form of single-hop (direct communication with the sink node) or multi-hop (data relayed through intermediary nodes).

Data Collection: Sensor nodes operate in a continuous cycle of gathering data from their immediate surroundings, subsequently transmitting it to a central hub or sink node. This collected data encompasses a wide spectrum, ranging from environmental measurements and surveillance data to any pertinent information relevant to the specific application.

Energy Constraints: Arguably one of the most pivotal challenges confronting WSNs pertains to energy efficiency. Sensor nodes are typically reliant on battery power and possess only finite energy reservoirs. Striking a balance between maximizing the network's operational lifespan and ensuring dependable data transmission constitutes a paramount design consideration.

Received on 26-09-2023, Revised on 20-10-2023, Accepted on 03-11-2023.

E-ISSN 2581 – 7957 CVR Journal of Science and Technology, Volume 25, December 2023
P-ISSN 2277 – 3916 DOI: 10.32377/cvrjst2513

Distributed Deployment: Sensor nodes are commonly deployed across an expansive area in a distributed fashion, often in remote or hard-to-access locales. These nodes typically self-organize and must adapt to dynamic changes in network conditions.

Data Processing: Depending on the application, data processing may take place at the sensor nodes themselves, or alternatively, the data can be transmitted to a central base station for processing. The decision hinges on the specific requirements of the application.

WSNs are made up of widely dispersed sensor nodes that oversee gathering and sending environmental data to predetermined locations. This study delved into bandwidth allocation by distributing data slots among multiple users at a significant rate, aiming to ensure Quality of Service (QoS). Furthermore, a mathematical model was developed to evaluate delay metrics for Service Data Units (SDUs) in a multiuser scenario. However, it's crucial to remember that the transmission of the recognition of the effectiveness of this distribution came with a sizable delay. The utilization of wireless sensor networks is experiencing a remarkable surge in applications across various domains, including healthcare, environmental monitoring, and surveillance, among others. While numerous research efforts have introduced data aggregation techniques, these methods often encounter limitations. These constraints were effectively addressed through the inventive design of a base station capable of recovering all aggregated sensing data objects, aptly termed as "recoverable." Although these aggregation techniques successfully reduced transmission overhead, they did so at the cost of a higher energy consumption ratio.

II. Literature Study

Tao Cui et al. [1] investigation “focused on enhancing High-Speed Downlink Packet Access (HSDPA) single-user throughput. In their research, offline and online optimization methods were developed that modified the Channel Quality Indicator (CQI) used by the network to schedule data transmission. By adjusting the CQI in the offline algorithm based on the acknowledgment/negative acknowledgment (ACK/NAK) history, the team was able to reach a particular target block error rate (BLER). They discovered the target BLER that maximizes throughput offline by experimenting with different target BLER values. This technique helps HSDPA allocate resources fairly among many users while simultaneously improving throughput. On the other hand, the online approach does not require a specified goal BLER because it changes the CQI offset using an expected short-term throughput gradient. Additionally, they suggested an adjustable step size device to monitor environmental changes over time. Both algorithms' convergence behavior was examined, and some of the research' conclusions were generalizable to other stochastic optimization methods. Simulations that were used to validate the study's findings also helped to shed light on the ideal BLER target value. When compared to the typical strategy of aiming for a 10% BLER, both the offline and online algorithms showed the potential for up to a 25% improvement in throughput.”

Engin Zeydan et al. [2] investigated that "With the use of energy-efficient data aggregation trees, our study implements multi-hop data aggregation in an effort to reduce the overall energy consumption in wireless sensor networks. We offer an adaptive and distributed routing method designed for the aggregation of correlated data to accomplish this. This algorithm is based on game theory and takes advantage of data correlations between nodes. In this plan, routes are carefully chosen to reduce the network's overall energy consumption. To modify routes in response to local data features, we use the best response dynamics technique. Our routing algorithm's cost function considers a number of variables, such as energy consumption, interference, and in-network data aggregation. Our iterative technique also shows convergence in a finite number of steps, which is significant."

Liang Liu et al. [3] introduced “a fresh method of looking at the coverage issue that centers on target localization in wireless camera sensor networks. They first introduced a special localization-focused sensing model that makes use of camera sensors' capacity for perspective projection. The authors developed a brand-new idea known as "Localization-oriented coverage" (abbreviated as L-coverage) on the foundation of this innovative sensing paradigm. Bayesian estimating theory was employed in the creation of this idea. Additionally, they carried out a thorough research to comprehend the connection between camera sensor density and the likelihood of reaching L-coverage in scenarios of random deployment, where camera sensors are dispersed according to a 2-dimensional Poisson process. The authors set density requirements to get a desired level of L-coverage probability based on their findings regarding the relationship between camera sensor density and L-coverage probability. Detailed simulations were run to validate and rate the efficacy of their proposed models and strategies.”

A.S. Reddy et al. [4] stated that “A Wireless Sensor Network (WSN) is made up of sensor nodes that are responsible for tracking and gathering information about the physical environment and storing it in one place. WSN technology serves as the foundation for emerging network paradigms such as the Internet of Things, Sensor Control Networks, Ubiquitous Sensor Networks, and Machine-Oriented Communications. It is essential to develop an energy-efficient routing protocol in order to carry out the sensing, communication, and processing functions within a WSN. A protocol of this kind is essential for controlling network energy consumption, reducing traffic, and lowering overhead during data transmission phases. Clustering is a crucial strategy for attaining energy balance between the sensor nodes. We use bio-inspired methods, notably the Firefly and Spider Optimization algorithms, to create an ensemble method in our suggested strategy. By routinely recycling data from the source node to the sink, this cutting-edge protocol assists in preventing the development of redundant routing messages, which can cause significant energy waste. The best route path can be chosen more easily thanks to this routing technology. In order to determine the ideal cluster heads in each iteration, our proposed algorithm takes into account a number of factors, including node residual energy, inter-cluster distances to the sink, and cluster overlaps. Furthermore, the parameters of the suggested solution can be dynamically changed when clustering in order to meet the unique needs of the network and achieve optimal performance."

III. Support Vector Machine

A supervised machine learning approach called Support Vector Machine (SVM) is used for classification and regression. SVMs are notably acclaimed for their prowess in tackling classification tasks, excelling at discerning an optimal decision boundary to segregate data points into distinct classes. The foundation of SVMs hinges on the notion of pinpointing a hyperplane, a flat affine subspace, that achieves the most effective separation of data points across classes. Central to this concept is the maximization of the margin, representing the minimum distance between the hyperplane and its closest data points, known as support vectors. Typically, the margin is denoted as "2/||w||," where "w" signifies the weight vector associated with the hyperplane. An inherent strength of SVMs lies in their capacity to address datasets that are not linearly separable. This capability is realized through the application of kernel functions, which implicitly project the original feature space into a higher-dimensional realm where data points become linearly separable. Various kernel functions serve distinct purposes:

Linear Kernel: Suited for data that can be readily separated by straight lines.

Polynomial Kernel: Ideal for data separable by polynomial curves or surfaces.

RBF Kernel: Effective in handling intricate, non-linearly separable data.

Sigmoid Kernel: Often employed in neural network applications.

In essence, SVMs, bolstered by their kernel functions, provide a versatile and robust tool for a wide spectrum of classification tasks, accommodating both linear and non-linear data separation challenges.

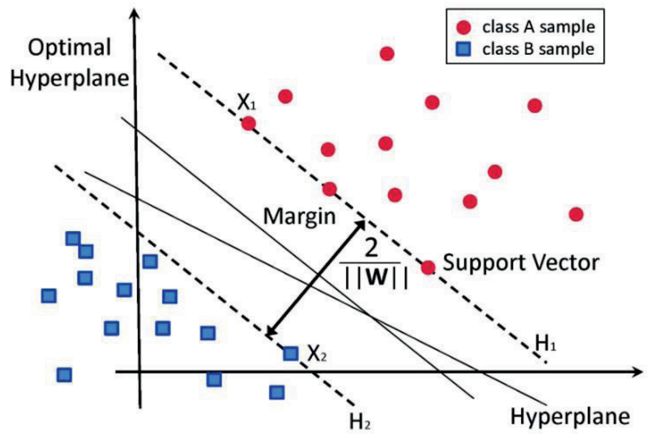

Figure 2. SVM overview

IV. Proposed Methodology

In this specific context, we present a specialized solution known as the Predetermined Event Weight-Based Support Vector Machine, or E3C-SVM, designed for enhancing the efficiency and security of data collection in wireless sensor networks. The core principle underlying our proposed system is the E3C-SVM's capacity to assign event weights in advance within the wireless sensor network, enabling highly efficient node classification with minimal energy consumption. E3C-SVM identifies objects by grouping events differently and establishing decision boundaries to classify events within the sensor network. Our E3C-SVM approach identifies events in the sensor network by maximizing the margin length of hyperplanes, as illustrated in Figure 3. For example, in situations where sensor network nodes are dispersed across a region, monitoring vehicle activities becomes crucial. This system tracks vehicle activities in the designated area while also collecting and categorizing events from various users. E3C-SVM categorizes events related to vehicles based on attributes such as size, shape, and load, all while consuming an exceedingly small amount of energy. Considering that vehicle movements are dynamic within the network, the events in the wireless sensor network also evolve over time.

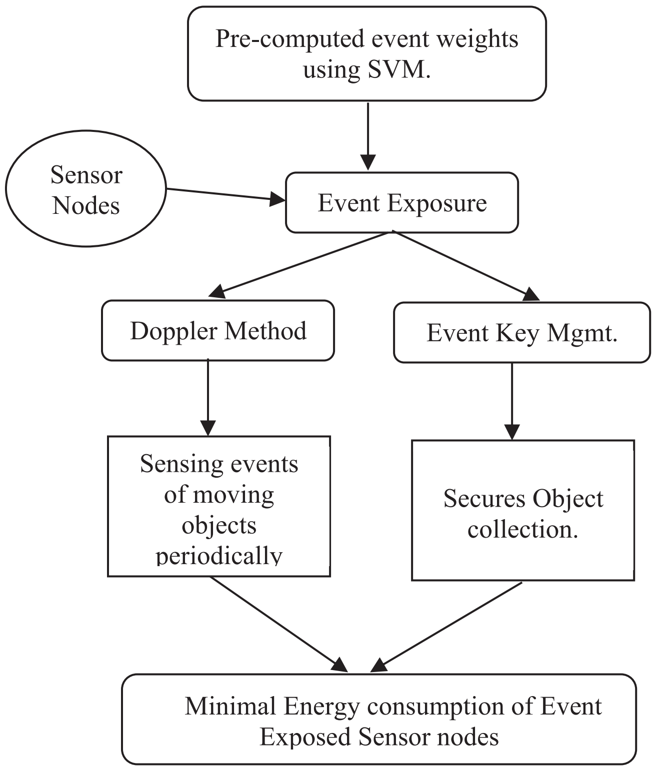

Figure 3. Proposed methodology

Vehicle events are classified by attributes such as shape, load, and size through the utilization of an SVM, where the optimal hyperplane value is chosen to maximize the margin length. Additionally, we introduce the Doppler Effect technique, which can be applied for identifying periodic events across a broad spectrum of frequency ranges. This approach is employed to detect events with diverse frequency characteristics as they propagate from the source object node to the target node. The integration of the Doppler Effect method within E3C-SVM offers efficient event detection with minimal processing time. Despite an increase in frequency values compared to previous iterations, this method minimizes processing time while accurately pinpointing nodes. Additionally, it facilitates the categorization and grouping of similar events, resulting in reduced energy consumption. E3C-SVM employs security measures through event section key management, ensuring the establishment of sensor node keys for safeguarding collected objects with minimal energy consumption. It excels at event detection within sensor networks and effectively utilizes an SVM classifier with predetermined weights, accommodating networks of varying sensor node sizes. These predetermined weights significantly contribute to the precise classification of objects within the sensor network. The system proficiently identifies periodic events through the Doppler Effect method, followed by secure collection and grouping of the detected objects via the event section key management system. The primary goal of E3C-SVM is to both protect and optimize energy utilization within the sensor network during event exposure.

A. Doppler Effect

Within Wireless Sensor Networks (WSNs), the Doppler Effect refers to the change in signal frequency received by a sensor node, resulting from the relative motion between the sensor node and the source of the signal. This concept bears a resemblance to the well-known Doppler Effect encountered in the field of physics, which is observable in occurrences involving sound waves or electromagnetic waves, including light. Although sensor nodes within WSNs are generally static or have limited mobility, there are situations in which the Doppler Effect becomes a pertinent factor to consider.

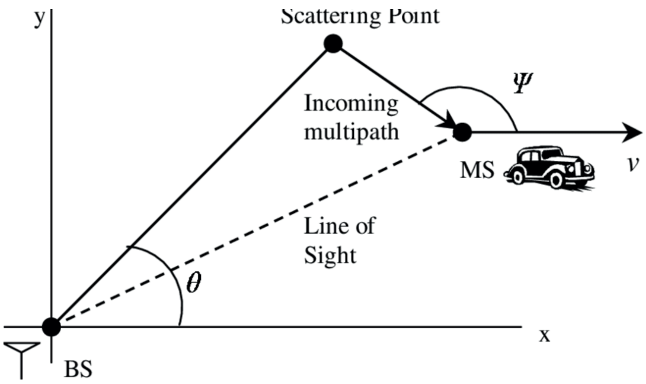

Figure 4. Illustration of Doppler effect

Relative Motion: Whenever a sensor node experiences motion, like a moving vehicle with embedded sensors, or when the signal source is in motion, the relative movement between the node and the source induces a change in the received signal's frequency.

Frequency Shift: If the signal source is approaching the sensor node, the received signal exhibits a higher frequency compared to the source's original signal. This occurrence is termed a positive Doppler shift or a blue shift. Conversely, when the source moves away from the sensor node, the received signal features a lower frequency, denoted as a negative Doppler shift or a red shift.

Communication Reliability: Frequency shifts can influence the reliability of communication among sensor nodes. Significant shifts may result in signal degradation or data loss.

Localization: In WSNs, the Doppler Effect finds application in localization. By analyzing the frequency shift in signals received from various sensor nodes, it becomes feasible to estimate node positions and relative motion.

Energy Efficiency: Understanding the Doppler Effect aids in optimizing energy usage within WSNs. For instance, sensor nodes can adapt their transmission power or duty cycle based on their relative motion, conserving energy.

Adaptive Modulation and Coding: Employing adaptive modulation and coding schemes that adjust signal parameters according to estimated Doppler shifts.

Frequent Updates: Ensuring regular updates of location information to accommodate changes in node positions.

Antenna Diversity: Utilizing multiple antennas or antenna arrays to mitigate fading resulting from Doppler shifts.

B. Pre-computed Event Weight-SVM

Let's examine an object denoted as P, $P = \{x_i, y_i\}$. This object employs the Support Vector Machine (SVM) to determine the optimal hyperplane value, using a weight vector 'w' that has been predetermined. The 'i' value in the E3C-SVM is calculated starting from the hyperplane:

$$\min(w) = \frac{1}{2}|w|^2 + E * \sum_{i=1}^{n}(x_i\,, y_i) \tag{1}$$

The pre-computed weight vector 'w' is applied to the objects x_i and y_i correspondingly. 'E' represents the energy consumption rate within the context of E3C-SVM. The indeterminate vector within the Support Vector Machine is characterized as follows:

$$y_i * (w * x_i + u) \tag{2}$$

The number of vectors used for object classification is dependent on obtaining maximum marginal length, and the sensor network reflects the Lagrange multipliers ρ_i used to find the best hyperplane value. The E3C-SVM judgment function for classifying objects is written as,

$$Fun_{Decision} = CL\{\sum_{i=1}^{n}(\rho_i . x_i . y_i), (x_i, u)\} \tag{3}$$

Objects detected as events are categorized through the decision classifier, and 'CL' is employed to denote their classification. The classification procedure makes use of the optimal hyperplane in conjunction with Lagrange multipliers, treating undetermined vector points distinctly within the sensor network. In the E3C-SVM system, the hyperplane value is harnessed, and the Doppler Effect method is employed through a sequence of incremental steps to discern events within the sensor network. To adapt to the diverse frequency ranges present in the sensor network, the Doppler Effect approach in E3C-SVM contributes to a reduction in energy consumption rates.

For event detection in E3C-SVM, the Doppler Effect technique is used from the source sensor node to the destination sensor node. The frequency 'f', which stands for the velocity of the source sensor node's motion:

CVR Journal of Science and Technology, Volume 25, December 2023
DOI: 10.32377/cvrjst2513

$$Freq\ f = \frac{E + V_t}{E + V_s} * f_0 \qquad (4)$$

In Equation 4, 'E' signifies the energy expenditure related to event detection within the sensor nodes with v_t and v_s the target node velocity 't' and source node velocity 's' for detecting events with the optimal hyperplane value.

V. Result Analysis

The Predetermined Event Weight-Based Support Vector Machine (E3C-SVM), an efficient Event Detection Classifier designed for wireless sensor networks, undergoes experimental assessment using the NS2 simulator. The current Correlated Data Gathering (CDG) and Energy-Efficient and High-Accuracy (EEHA) schemes are compared with E3C-SVM. These simulations employ a network environment comprising 150 sensor nodes. The sensor nodes employ the AODV routing protocol to conduct tests involving randomly moving objects. All nodes' movements occur within a sensor field measuring 750 m × 750 m, with nodes traveling at random speeds of 40 m/s and pausing for an average duration of 0.01 s. Various metrics, including throughput, energy consumption rate, processing time, classifier rate, mean classification time, and other variables, are evaluated in the experimental setup. In the context of E3C-SVM, the classifier rate gauges the speed at which events are classified and captured, with higher rates indicating lower energy consumption. The classifier rate is expressed as a percentage (%). Considering a range of objects, the mean classification time measures the duration required to identify periodic events based on attributes such as shape, size, and load.

TABLE I.
Rate of Classification

Sensor Nodes	Rate of Classification		
	E3C-SVM	CDG	EEHA
20	69	62	57
50	73	65	61
80	76	67	63
120	79	70	66
150	83	74	69

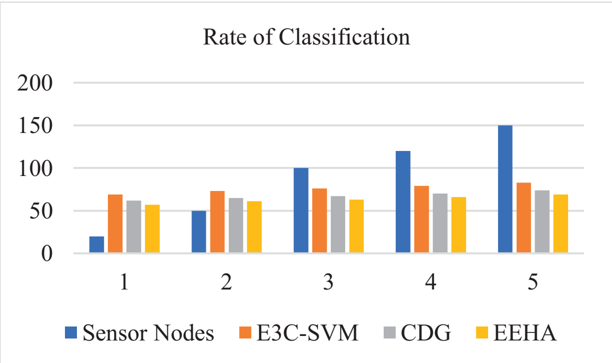

Figure 5. Rate of Classification

TABLE II.
Consumption of Energy

Sensor Nodes	Consumption of Energy		
	E3C-SVM	CDG	EEHA
20	23	28	31
50	30	32	35
80	32	39	42
120	35	46	49
150	39	50	56

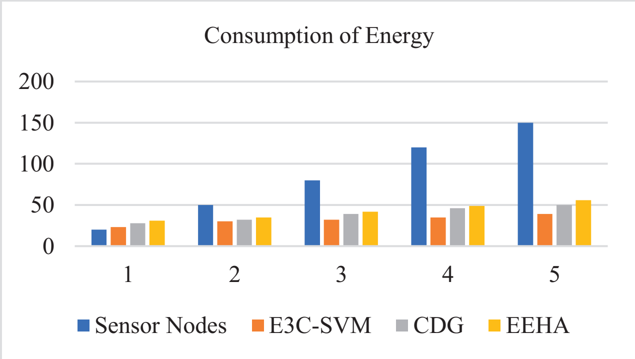

Figure 6. Energy Consumption

VI. Conclusions

Focusing on the detection and categorization of periodic events, the energy-efficient event detection framework offers a comprehensive approach to effectively identify events within a wireless sensor network. This approach reduces energy consumption across diverse sensor nodes by implementing event section key generation techniques, utilizing an SVM classifier. Each sensor node possesses a unique section key, enhancing security through information sharing among sensor nodes. To achieve efficient object classification, this research combines Lagrange classifiers with optimal hyperplanes to propose a decision function classifier. The Doppler Effect method is also employed for swiftly detecting periodic events associated with moving objects, minimizing processing time. By leveraging the Doppler Effect method, the wireless sensor network establishes a theoretical model that enhances classification rates and energy efficiency. Through simulations and real-world applications, it is demonstrated that this energy-efficient approach outperforms state-of-the-art techniques in terms of energy conservation.

References

[1] T. Cui, F. Lu, V. Sethuraman, A. Goteti, S. P. N. Rao and P. Subrahmanya, "Throughput Optimization in High Speed Downlink Packet Access (HSDPA)" in IEEE Transactions on Wireless Communications, vol. 10, no. 2, pp. 474-483, February 2011, doi: 10.1109/TWC.2010.120610.091294.
[2] Engin Zeydan., Didem Kivanc., Cristina Comaniciu., Ufuk Tureli., (2012): "Energy-efficient routing for correlated data in wireless sensor networks" Ad Hoc Networks., Elsevier journal.
[3] Liang Liu, Xi Zhang, and Huadong Ma.(2011):"Localization-Oriented Coverage in Wireless Camera Sensor Networks",

IEEE Transactions on Wireless Communications, Vol. 10, No. 2.

[4] G. Malleswari, "Adaptive Energy Routing Protocol using Spider Optimization in Wireless Sensor Networks," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1-6, doi: 10.1109/ICCCI56745.2023.10128603.

[5] P. C. Reddy and P. C. S. Reddy, "Performance Analysis of Adhoc Network Routing Protocols," 2006 International Symposium on Ad Hoc and Ubiquitous Computing, Mangalore, India, 2006, pp. 186-187, doi: 10.1109/ISAHUC.2006.4290671.

[6] Engin Zeydan., Didem Kivanc., Cristina Comaniciu., Ufuk Tureli., (2012): “Energy-efficient routing for correlated data in wireless sensor networks,” Ad Hoc Networks., Elsevier journal.

[7] Hongjuan Li., Kai Lin, Keqiu Li.(2012): “Energy-efficient and high-accuracy secure data aggregation in wireless sensor networks,” Computer Communications., Elsevier journal.

[8] Qu, Z., Wang, L. (2006). A Spatial Clustering Algorithm Based on SOFM. In: Li, X., Zaïane, O.R., Li, Z. (eds) Advanced Data Mining and Applications. ADMA 2006. Lecture Notes in Computer Science(), vol 4093. Springer, Berlin, Heidelberg.

[9] Kumar Gourav, Dr. Amanpreet Kaur, “A Study of Reinforcement Learning Applications & Its Algorithms:, International Journal of Scientific & Technology Research Volume 9, Issue 03, March 2020.

[10] Reddy, A. Srinivasa. "Effective CNN-MSO method for brain tumor detection and segmentation." Materials Today: Proceedings 57 (2022): 1969-1974.

[11] D. A. Vidhate and P. Kulkarni, Enhanced Cooperative Multi-agent Learning Algorithms using Reinforcement Learning, published in the proceedings of IEEE International Conference on Computing, Analytics and Security Trends, pp 556-561, 2016.

[12] Srinivasa Reddy, A., Chenna Reddy, P. (2020). Enhanced Image Segmentation Using Application of Web Optimization for Brain Tumor Images. Smart Intelligent Computing and Applications . Smart Innovation, Systems and Technologies, vol 159.

[13] J. Hou, Huali, J. Hu, C. Zhao, Y Guo, S. Li, and Q. Pan, A Review of the Applications and Hotspots of Reinforcement Learning, published in the proceedings of IEEE International Conference on Unmanned Systems (ICUS), October, 2017, DOI: 10.1109/ICUS.2017.8278398.

[14] G Malleswari, "Significance of Genetic Algorithms in Image Segmentation", International Journal of Signal Processing, Image Processing and Pattern Recognition,9(4), 177-184.

[15] Srinivasa Reddy, A., Chenna Reddy, P. MRI brain tumor segmentation and prediction using modified region growing and adaptive SVM. Soft Comput 25, 4135–4148 (2021).

[16] A. S. Reddy and G. Malleswari, "Efficient Brain Tumor Segmentation using Kernel Representation," 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2023, pp. 1006-1011.

[17] A. S. Reddy and P. C. Reddy, "Novel Algorithm based on Region Growing Method for Better Image Segmentation," 2018 3rd International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2018, pp. 229-234.

[18] A. S. Reddy, "Performance of VANET over MANET in Mobile Computing Environment," 2022 7th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2022, pp. 659-664.