SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I5P102

Volume 12 Issue 5, 13-22, May 2025

Original Article

Energy-Efficient Cluster-based Routing in Multimedia assisted Wireless Sensor Networks Using Resilient Honey Badger Optimization Algorithm

Sowmiya Sree C[1] M. Sangeetha [2], T. Niranjan Babu [3], Naveen P [4], P. Sangeetha[5], Mohanaprakash T A[6]

[1]*Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, India.*
[2]*Department of Computer Science and Engineering, St.Joseph's Institute of Technology, OMR, Chennai, India.*
[3]*Department of Computer Science and Engineering (Cyber Security), Madanapalle Institute of Technology & Science, Andhra Pradesh, India.*
[4]*Department of Computational Intelligence, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamilnadu, India.*
[5]*Department of Physics, Panimalar Engineering College, Chennai, India.*
[6]*Department of CSE, SOET, CMR University, Bengaluru, India,*

[6]*Corresponding Author : tamohanaprakash@gmail.com*

Received: 26 February 2025 Revised: 02 April 2025 Accepted: 16 April 2025 Published: 31 May 2025

Abstract *- Clustering and routing are effective solutions for addressing the potential design difficulty of energy efficiency in multimedia-assisted Wireless Sensor Networks (WSNs). However, imbalances in the distribution of chosen Cluster Head (CH) nodes and difficult data transmission routes might lead to unequal energy exhaustion in the network. This work focuses on Energy-Efficient Cluster-based Routing Protocols using the Resilient Honey Badger Optimization Algorithm (EECR-RHBOA) for Cluster Head (CH) selection in WSN. Inspired by honey badger foraging behaviour, the RHBOA algorithm incorporates resilience and adaptation into cluster formation and routing selections to guarantee optimum network energy usage. RHBOA selects the best cluster head among all the sensors regarding distance to the residual energy, Base Stations (BS), distance to neighbours, node degree, and centrality. The two main steps of the suggested EECR protocol are cluster formation and data transmission. The RHBOA algorithm arranges sensor nodes into clusters during the cluster formation phase. The method then examines a fitness function considering residual energy, node centrality, and intra-cluster communication cost to choose cluster heads. Extended network lifespan is achieved by reaching balanced energy consumption among multiple nodes. The RHBOA algorithm minimizes energy dissipation during data transmission by optimizing multi-hop routing processes from CHs to BS. These approaches avoid nodes with low energy and help alleviate network congestion. The numerical outcomes show the suggested EECR-RHBOA technique to achieve a lower packet ratio of 0.05, throughput of 104Kbps, packet delivery ratio of 96.2% and coverage rate of 94.8% compared to other methods.*

Keywords *- Multimedia assisted Wireless Sensor Networks, Resillent Honey Badger Optimization Algorithm, Data Transmission, Energy Efficiency, Routing Protocols, Cluster Head Selection.*

1. Introduction

Multimedia assisted Wireless Sensor Networks (WSNs) are a new paradigm in computing and networking used in many fields, including the military, healthcare, weather prediction, surveillance, environmental management, and more [1]. The widespread adoption of WSNs directly results from network technology's continuous development and advancement. The Internet of Things (IoT) is one of the newest ideas that have entered WSN [2]. WSNs are structured networks that use many inexpensive, autonomous devices known as sensors to gather data about their surroundings [3]. A mobile sink node receives data collected from the environment and either stores it locally or sends it to other networks for processing or other uses [4]. While multimedia-assisted Wireless Sensor Networks (WSNs) provide several advantages, accessible deployment, self-organization, and data transfer pose certain difficulties [5].

The metaheuristic algorithm is considered a possible remedy to this problem with the coverage of WSN nodes [6]. Metaheuristic algorithms are recommended for WSN coverage optimization because they identify near-optimal solutions rapidly and with little computer resources [7]. Metaheuristic algorithms provide approximation optimization strategies to address optimization problems in high dimensions. Nodes in a heterogeneous network have different characteristics, whereas nodes in a homogeneous network have identical energy, physical, and software properties [8].

Establishing a heterogeneous network is more effective for distributing the network's load and energy equally, providing distinct features to each node, and varying the quantities of energy used by each node [9]. Clustering is a method by which network sensors are grouped based on specified characteristics [10]. Each group is called a cluster, and each cluster has an assigned leader responsible for the other cluster members, gathers data from them, and sends it to a fixed or mobile sink node [11]. Base Stations (BS) may be an MS that doubles as one or a separate device with more advanced capabilities [12]. Figure 1 shows a high-level architecture of WSN.

Clustering is a powerful tool for ensuring WSNs maintain a balanced energy consumption [13]. Since each node in a cluster gets information from the physical region, CH lowers energy consumption by prohibiting them from communicating data. At the same time, CH transmits all the data it collects to BS via adjacent CH or a single hop [14]. The communication capabilities of each node in a homogeneous WSN are identical [15]. For large-scale WSNs, the energy-efficient option is not to transmit information directly from the CH to the sink, as sensors have energy-limitation balancing issues.

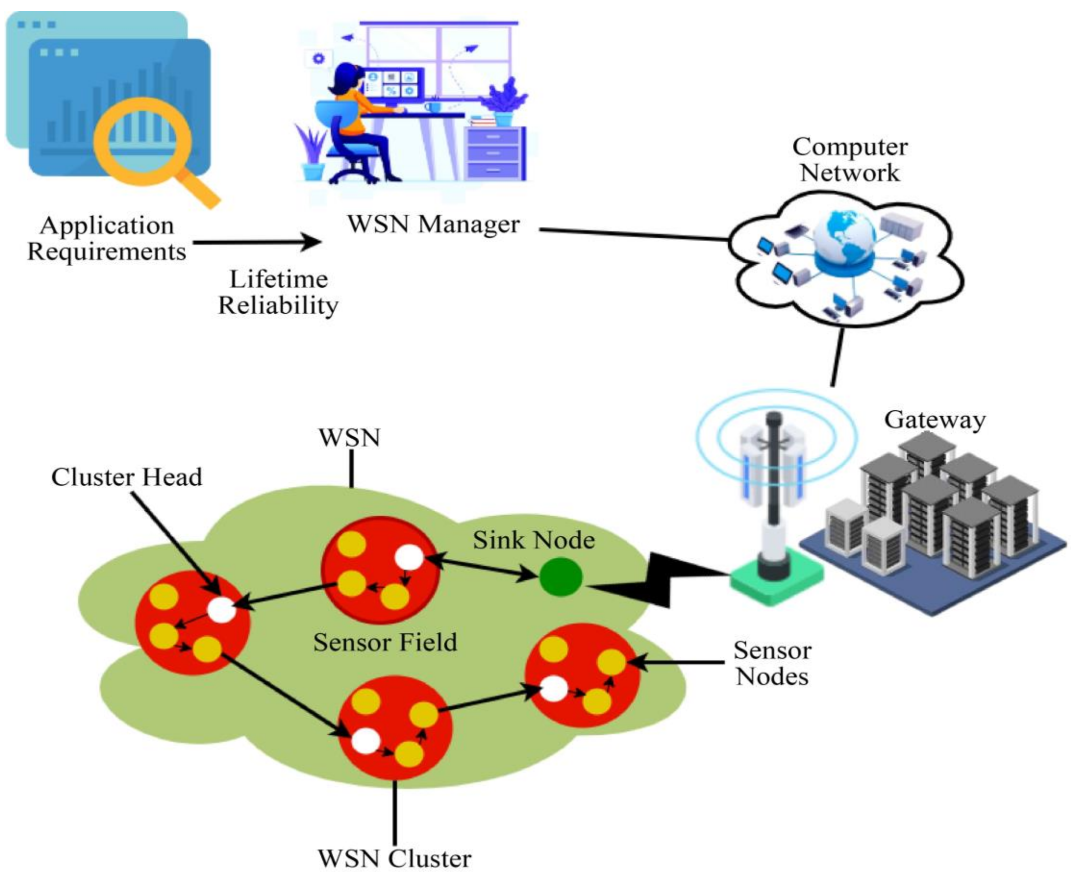

Fig. 1 Architecture of WSN

Consequently, data transfer across clusters and delivery of collected data from CH to sink need a multi-hop routing protocol. It is a nondeterministic Polynomial Time (NP), and it is hard to determine the shortest energy-balanced route for these goals. Numerous researchers have carefully considered routing and clustering issues in this study. A newly created metaheuristic algorithm, the Honeybadger Algorithm (HBA), primarily mimics the dynamic search behaviour of honeybadgers when they mine and hunt for honey. The proposed technique has the same flaw as previous metaheuristic approaches: it cannot provide optimal outcomes in all instances. Consequently, the suggested approach provides satisfactory and rapid convergence ideal outcomes. HBA has a lot of potential future uses due to its simple form, few parameters, and ease of implementation. The paper's novelty: The Resilient Honey Badger Optimization Algorithm (RHBOA) is proposed as a revolutionary approach to WSN energy efficiency. A novel cluster head selection approach by the RHBOA harnesses honey badger feeding behaviour to promote WSN robustness and adaptation. RHBOA chooses a cluster head based on the network's total number of nodes, residual energy, distance to neighbours, degree of connectivity, centrality, and base station distance. Increased energy consumption enhances low-power performance and network lifetime using this multi-criteria strategy.

1.1. The Major Contribution of this Article

- The design of the proposed EECR-RHBOA is to efficiently group WSN nodes into clusters and arrange routes based on energy efficiency.
- The proposed RHBOA protocol optimizes energy utilization using node centrality and residual energy to extend network life, and the protocol controls energy use and dissipation.
- The numerical results have been implemented, and the recommended EECR-RHBOA decreases energy consumption while improving delay, packet loss rate, packet delivery rate, and throughput.
- The remainder of the section is as follows: section 2 examines the literature review, section 3 discusses the suggested methodology, section 4 designates the results and discussion, and section 5 concludes the research article.

2. Related Work

Efficient, balanced clustering reduces power consumption for WSN by Energy-Efficient Lifetime-aware Cluster-based Routing (EELCR) using the Modified Giant Trevally Optimization (MGTO) method [16]. The ideal node to pick as the Cluster Head (CH) to encompass the lifespan of sensor networks is determined using an Optimal Squirrel Search (OSS) method. Using optimum selective Huffman compression, each CH node can compress clustering information to a maximum compression rate, resolving the region overhead issue in current Huffman compression.

Constrained Minimum Spanning Tree (CMSTR)–based energy-efficient routing protocol [17]. An innovative multichain routing technique is introduced to achieve energy efficiency in intra-cluster communications. To find the starting point for intra-cluster communications, this study proposes a Constrained Minimum Spanning Tree (CMST), which is based on the multichain routing scheme and uses a graph-theoretical analysis model to convert the intra-cluster routing problem into a direct Hamiltonian path issue.

Ant colony optimization for multimedia-assisted wireless sensor networks using the ACO-UCR technique, based on the levy-uneven clustering and routing theory [18]. Clusters are first built by selecting CHs using several factors. Finding the best possible routes between any two nodes in the network is the next step after using the ACO algorithm with levy distribution. Rapidly-Explored Random tree with based Obstacle-Aware Mobile Sink Trajectory (RRTMT) efficiently selects RPs and plans paths for mobile sinks in WSNs that account for barriers [19]. Using a spectral clustering technique, find the best RPs with the smallest hops between them and their offspring. The adaptive route between the RPs considers environmental obstacles using a Quickly-Explored Random Tree (RRT). A passive clustering-based approach called Meta Inspired Hawks Fragment Optimization (MIHFO) [20]. The nodes' remaining energy, distance from neighbours and the base station, degree, and centrality are the criteria for choosing the cluster leader. Efficient packet transmission was achieved in WSNs by implementing the suggested HWAO MIHFO optimization. Heuristic Wing Antfly Optimization (HWAFO) is a method that chooses the best route between the CH and BS by considering node degree, residual energy, and distance.

The EECR-RHBOA protocol improves WSN CH selection and routing. RHBOA is used. The RHBOA uses multi-criteria optimization instead of single-factor optimization or less flexible algorithms to achieve network-wide energy equity. This method incorporates communication costs, node centrality, and residual energy. This makes the network more resilient to node failures. The protocol surpasses previous approaches for optimizing WSN energy use and data delivery by reducing energy dissipation during multi-hop data transfer.

3. Proposed Methodology

Energy-Efficient Cluster-based Routing Protocols using the Resilient Honey Badger Optimization Algorithm (EECR-RHBOA) - Multimedia assisted Wireless Sensor Networks (WSNs) often contain several sensor nodes working together to monitor a certain region, including forest fire detection, among other functions. However, WSNs have certain limitations that drive several researchers, mostly stemming from their restricted communication, computations, and energy resources. More specifically, the limitation associated with the energy is seen as a basic issue. It is vital to control energy use effectively to extend the network's lifetime. Typically, sensor nodes are motorized entirely by batteries. Many sensor network applications deploy nodes in challenging conditions, making recharge or replacing their batteries impractical. The sensor nodes' batteries solely determine the network's aggregate lifespan. To tackle this problem, significant efforts have been made to use low-power radio communication gear and energy-aware Media Access Control (MAC) protocol to minimize energy consumption. Energy-efficient clustering and routing models are often regarded as the most promising areas of focused research for WSNs. The sensor nodes in cluster-based WSNs are arranged in separate clusters. A master node, or CH, oversees all clusters. Cluster nodes in this setup communicate with their respective CHs directly. The latter gathers information from the nodes in its cluster and transmits it to the sink either straightly or via other CHs. There are many benefits to clustering a WSN. (1) Eliminating unnecessary data guarantees data aggregation at the CH level, reducing energy usage. Since only specialized nodes, like CHs, are required to keep track of the local route configuration of other CHs and, therefore, need little routing data, (2) routing may be readily handled. In addition, the network's scalability will be greatly enhanced. (3) It also helps to save bandwidth by preventing sensor nodes from communicating with one other and instead having them communicate with their own CH. Nevertheless, with the clustering approach, a CH takes on significant work by collecting data from other CHs and cluster members, then aggregating and transmitting that data to the sink. Typically, CHs are selected from among regular sensor nodes, which makes matters worse as nodes under heavy load might rapidly die from their excessive energy usage.

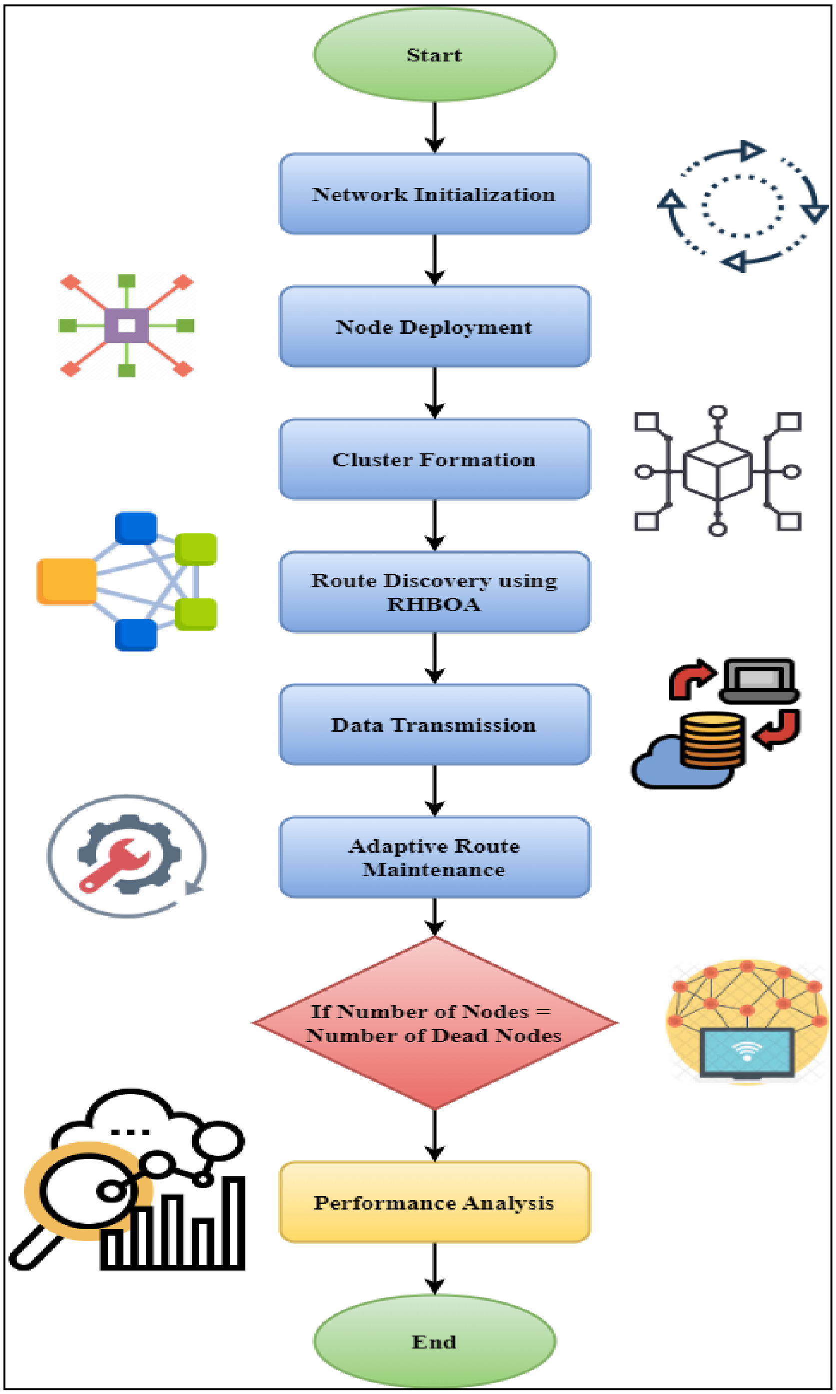

Fig. 2 Proposed EECR-RHBOA model

Figure 2 shows the proposed EECR-RHBOA model. Sensor nodes are arbitrarily distributed around the network area, and essential features like energy levels, locations, and transmission ranges are established during the initialization step of the network. The next step, Cluster Head Selection, involves ranking all nodes according to predetermined criteria, such as their remaining energy, distance from other nodes, and network connection. Next, we mimic the honey badger's resource-seeking behaviour by using the Honey Badger Optimization Algorithm to choose the best nodes and serve as cluster heads. Nodes are grouped around CHs in the Cluster Formation stage to build the network effectively. The assignment of nodes to cluster heads is based on signal strength or other parameters.

The algorithm determines the most energy-efficient and dependable routes for data transmission during the Route Discovery (Optimization Phase) by considering variables including node energy levels, distance between nodes, and overall network characteristics. This adaptive routing has two benefits: reduced power usage and improved load balancing. Nodes deliver data to cluster heads, which aggregate it to remove duplication and transmit it to the BS via the best path during data transmission and aggregation. The Energy Monitoring and Adaptive Maintenance phase constantly monitors the network's energy levels and general state to ensure the protocol is functional. The protocol re-clusters the network or re-routes the data pathways dynamically in the event of major changes like energy depletion or node failures. After the network stabilizes, the procedure terminates; if not, it starts again with selecting the cluster heads to ensure optimum performance. The key performance measures include energy efficiency, latency, packet delivery ratio, network lifetime, and throughput.

Given a specified sensing radius, the optimal placement of deployed nodes is the WSN node coverage optimization issue. When placed in the designated deployment region, each sensor can only detect objects inside its detecting radius. If the network is to function properly, all nodes must be located within a certain sensing radius to communicate with one another. Its sensing radius is just right for solving the problem of item detection within it in certain optimization domains. Approximately M sensor nodes are arbitrarily placed in the 2D monitoring zone where the WSN is supposed to be set up. For simple calculations, we split the rectangular area of the deployment network into grids of uniform area, with the monitoring node n serving as the centre of each grid. The ideal number of sensors to cover the whole monitoring region with no unnecessary redundancy. It is common practice to use two models to calculate the coverage of the sensor node. One is the binary model, and the other is the probabilistic perception model. In the binary models, the Euclidean distance amongst sensor nodes m_j and the tracking points q is $d_j = q\,(y_j - y)^3 + (x_j - x)^2$, where (y_j, x_j) is the coordinators of the sensor nodes m_j. (y, x) symbolizes the coordinators of tracking points q, and d_j is the distance amongst m_j and q. The likelihood that the sensor nodes m_j covers tracking points q is q_{cover} described as:

$$q_{cover} = \begin{cases} 1, & if\ d_j < R_s \\ 0, & otherwise \end{cases} \tag{1}$$

Assuming there are no environmental interferences or attenuations of wireless signals, the binary model fails to consider the WSN's complexity while operating in a wireless environment. However, in real-world settings for wireless transmission, there is interference from both nodes and other noise sources. Meanwhile, the wireless signal's power deteriorates as the receiver's and transmitter's distance rises. The exploration phase focuses on the global search for optimal routing paths by simulating the random movements of honey badgers. The distance amongst the current honey badger (sensor nodes) and the best-known food source (optimal path) is calculated as:

$$D_j(t) = \left\| Y_j(t) - Y_{best}\,(t) \right\| \tag{2}$$

As shown in Equation (2), where $D_j(t)$ signifies the Euclidean distance of the jth node at iteration t, $Y_j(t)$ represents the current position, and $Y_{best}\,(t)$ indicates the position of the best solution found. Initiation and communication between WSN nodes constitute the fundamental step. After that, the HBAC method was used to group the nodes in the network and choose the CHs. This method avoids local optimum solutions and quickly transmits the searching space, balancing the exploration and exploitation phases. Furthermore, the HBA has successfully resolved complex searching space empirical issues. The following are key points from the RHBA procedure:

A honeyguide bird leads an exploratory honey badger to a beehive, where it is predicted to:

$$y_{new} = y_{prey} + F \times r_1 \times \beta \times c_i \tag{3}$$

As shown in Equation (3), whereas y_{new} refers to the new place of Honey Badger y_{prey} signifies the optimum prey places, F represents the flag, which endorses exploration, c_i signifies the distance between the prey and $i\ th$ badger and r_1 describes the arbitrary values between zero and one. Besides, β is validates the arbitrary control variables, which decreases the diversity of the population and is calculated as:

$$\beta = 2 \times \exp\left(\frac{-t}{Max\ Jt}\right) \tag{4}$$

While exploiting its prey, a honey badger will dig with a cardioid-shaped motion and be roughly:

$$y_{new} = y_{prey} + F \times \alpha \times J_i \times y_{prey} + F \times r_2 \times \beta \times c_i \times |\cos(2\pi r_3) \times [1 - \cos(2\pi r_4)] \quad (5)$$

In Equation (5), where J_i refers to the intensity factor dependent upon the distance between all two neighbouring searching agents and the distance between the honey and prey badger. In addition, r_2; r_3 and r_4 are arbitrary variables from zero to one. Figure 3 shows the operations of the routing protocol. Multiple rounds make up the network lifespan in the suggested protocol. The two stages of protocol functioning are the setup and steady-state phases. The Base Station (BS) collects data such as nodes' locations and energy levels during setup. Then, it selects CHs using the suggested RHBOA algorithm and a dual-hop path connecting the CHs to the BS. Nodes transmit data gathered to CHs during the steady state phase. To transmit data to the BS, CHs either work together or use another CH. This protocol only runs the setup step if the existing CHs are about to die, which improves energy efficiency. This reduces the power needed to build clusters by exchanging control packets. According to this, every CH's residual energy must be more than the sum of all nodes' energies. This restriction is implemented to prevent solutions where CH are low-energy nodes. The function of each node in the network allows one to determine when it will die. Because of their negligible relative importance to communication energy, sensing and processing energy use was omitted from this investigation. The sink node may cover the deployed area since it has infinite energy, computing power, and buffer capacity.

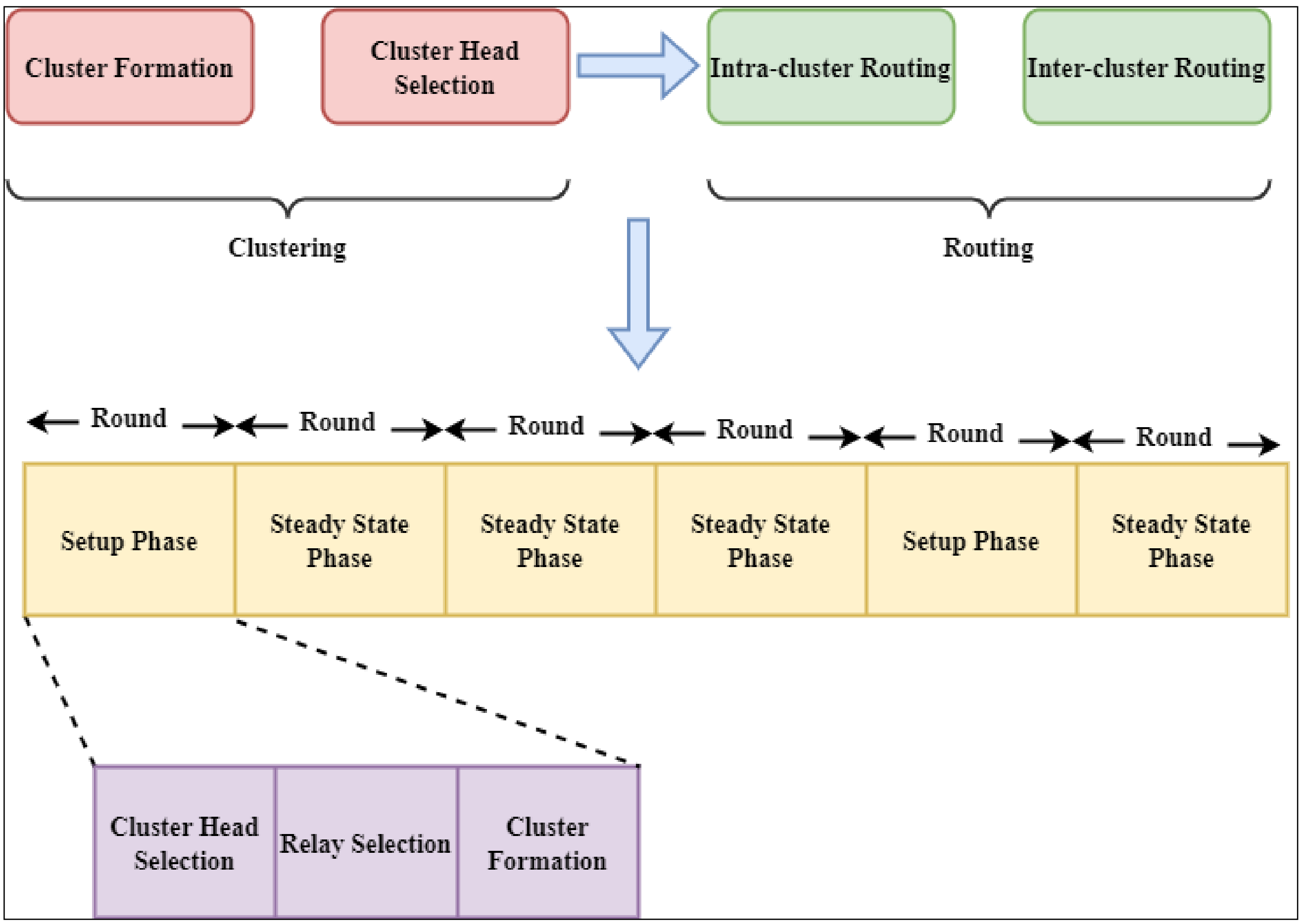

Fig. 3 Operations of the routing protocol

The RHBOA Objective Function (OF) aims to assign the nodes at a negligible cost as CH and fitness parameters are identified. The Residual Energy (RE) is fitness parameters, F_R. The amount of the rate of RE of nodes j is connected to E_{rj} and the total energy of the network E_t. Estimating the RE of every node for each iteration can be essential. Therefore, a balanced energy reduction can be achieved through the network.

$$F_R = \sum_{j=1}^{m} \frac{E_{rj}}{E_t} \quad (6)$$

In Equation (6), where m represents the total amount of nodes. A node having a lower F_R increases likelihood of choosing as a CH: Alternative of the fitness parameters is the average energy F_A of nodes. This parameter signifies that nodes with greater primary energy are extremely likely to choose CH. Famg can be assessed in the subsequent Equation and regularized within the range of [1,0]. Now E_j signify the RE of nodes j:

$$F_A = \frac{1}{m}\sum_{j=1}^{m} E_j \tag{7}$$

Additional fitness parameters are the distance (F_d) of nodes in mobile sink nodes. The node closer to the mobile sink node consumes less energy when transmitting data. Therefore, taking this variable as a basis to estimate further accurate objective functions can be essential. F_d can be shown as follows.

$$F_d = \sum_{j=1}^{m} \frac{d(m_j \ to \ mobile \ sink \ node)}{d(m \ avg_j \ to \ mobile \ sink \ node)} \tag{8}$$

In which $d(m \ avg_j \ to \ mobile \ sink \ node)$ and $d(m_j \ to \ mobile \ sink \ node)$ indicates the mean and Euclidean distance of nodes j to mobile sink nodes, respectively. The following parameter is the number of neighbours near nodes from clusters. The data transmission issue becomes more severe as the number of nodes in the cluster rises. The number of neighbours close to the node should be considered when choosing the CH. The fitness variables F_n express the number of neighbours of a node.

$$F_n = \frac{\sum_{j=1}^{m_{cl}} d(j,i)}{m_{cl}} \tag{9}$$

As inferred from Equation (7), whereas $d(j,i)$ represents the distance amongst nodes j and i, and m_{cl} specifies the number of nodes in clusters. Finally, the objective functions and the fitness parameters are estimated using the subsequent equations.

$$F_o = \varphi * F_R + \delta * F_A + \gamma * F_d + \theta * F_n \tag{10}$$

Now f; c; d and g weight coefficients are multiplied by the fitness parameters, and the sum is $(\varphi + \delta + \gamma + \theta = 1)$.

To calculate the cost function for a route from the cluster-head node y to the sink s, this study defines the following equation:

$$Cost(y,s) = \sum_{j,i \in \{y,V,s\}} cost_{ji} \tag{11}$$

As inferred from Equation (11), where V is a set of intermediate nodes from cluster head y to sink s. RHBO dynamically adjusts the routing paths in WSNs to achieve optimal performance, ensuring robust data transmission with minimal energy expenditure. The algorithm's ability to balance exploration and exploitation phases enables it to adapt to varying network conditions, such as node mobility, energy depletion, and changing topologies, making it well-suited for real-time applications in WSNs.

$$Pr = \frac{tp}{tp+fp} \tag{12}$$

Recall: Recall or sensitivity assesses how well the model identifies all actual malignant cases, reducing false negatives. A high recall ensures that most cancerous cases are detected, which is crucial for medical applications.

$$Re = \frac{tp}{tp+fn} \tag{13}$$

F1-Score: The F1-score combines both precision and recall into a single metric, balancing the trade-off between these two, especially when dealing with imbalanced classes where false positives and false negatives might be equally critical.

$$F = 2 \times \frac{Pr \times Re}{Pr+Re} \tag{14}$$

4. Results and Discussions

This study's subject is the efficient cluster-based routing protocols for WSN that employ the Resilient Honey Badger Optimization Algorithm (EECR-RHBOA) for cluster head selection. The RHBOA algorithm gets its information from honey badger foraging behaviour to ensure the most efficient use of network energy.

It applies resilience and adaptability to cluster formation and routing options. Based on factors such as proximity to the base station, remaining energy, distance to neighbours, node degree, and centrality, RHBOA chooses the optimal cluster head from among all the sensors.

Cluster creation and data transmission are the two primary stages of the proposed EECR protocol. Through the cluster creation phase, the RHBOA algorithm organizes sensor nodes into clusters. Next, to choose cluster leaders, the technique uses a fitness function considering the cost of intra-cluster communication, node centrality, and residual energy.

This study uses the public Kaggle dataset for the WSN clustering and routing energy optimization [21]. Table 1 shows the experimental setup.

Table 1. Experimental setup

Parameter	Description
Area of Deployment	50m x 50m, 100m x 100m, 150m x 150m
Number of Iterations	200, 500, 1000,
Sensing Radius	10m
Communication Radius	20m
Number of sensor Nodes	10, 50, 100, 150, 200

Coverage Optimization Ratio (%)

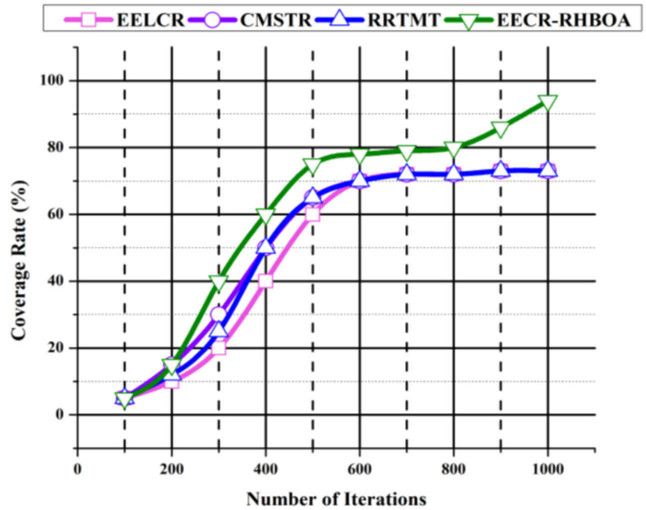

Fig. 4 Coverage rate (%)

$$Coverage\ Rate = \frac{\sum_{i=1}^{m} Q(t,S_i)}{Z.K} \quad (15)$$

Figure 4 and Equation (15) show the coverage rate (%). TheWSN coverage rate of nodes is denoted as $Coverage\ Rate$, and the likelihood of the target points reaching the 2D network deployed area is denoted as $Q(t,S_i)$ and area of region $Z.K$.

There is a mapping between the coverage distribution and solution Y of the RHBOA optimization, and every badger in the model stands for coverage distributions. By translating it with $E(Y)$ the WSN objective function, node coverage optimization is represented in equation. Deploying nodes to optimal locations solves the coverage optimization issue.

The honey badger group's various movement patterns toward food or a particular spot are abstracted as the location-seeking process of the node. The objective of WSN coverage optimization using the RHBOA approach is to optimize coverage of the target tracking region by deploying an appropriate number of sensor nodes in the most opportune spots.

The objective function is established by finding the optimal coverage rate of the likelihood of the 2D WSN tracking region placed on the network's surface.

4.1. Packet Delivery Ratio (%)

The Packet Delivery Ratio (PDR), a critical network protocol effectiveness and dependability metric, is especially relevant in WSNs.

The formula includes subtracting destination packets received from source packets provided. More PDR means greater network performance, which is how well the protocol distributes data.

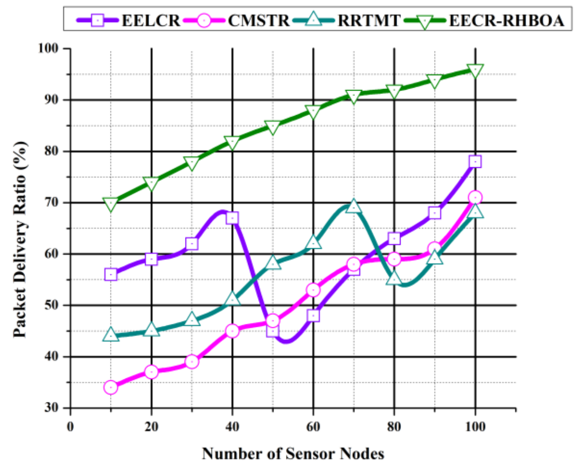

Fig. 5 Packet delivery ratio (%)

$$Packet\ Delivery\ ratio = \frac{total\ packets\ received}{total\ packets\ sent} \quad (16)$$

Figure 5 and Equation (16) deliberates the packet delivery ratio (%). This equation provides a percentage value that quantifies the proportion of successfully delivered packets, which helps to simplify the process of evaluating the effectiveness of different routing protocols based on their respective capabilities. Regarding multimedia-assisted Wireless Sensor Networks (WSNs), a high Packet Delivery Ratio (PDR) is excellent since it implies a reliable connection with little packet loss. These aspects are essential for maintaining data integrity and ensuring the network operates well.

4.2. Throughput Ratio (%)

Throughput is a crucial performance metric for any network since data transmission efficiency is often considered important. In multimedia-assisted Wireless Sensor Networks (WSNs), throughput represents the pace at which information packets are sent over the network channel within a certain time.

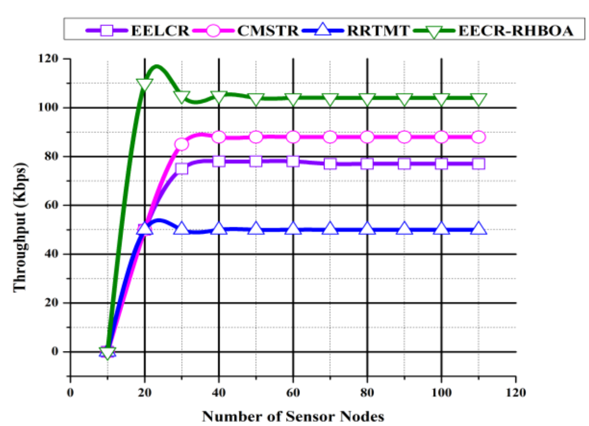

Fig. 6 Throughput (Kbps)

The throughput of a network is a measurement of its capacity to process data; a higher number suggests that the network is generally working better and conveying data more efficiently.

$$Throughput\ Ratio\ (\%) = \frac{Total\ Data\ Received\ (in\ bits)}{Total\ Time\ Taken(in\ seconds)} \quad (17)$$

Figure 6 and Equation (17) express the throughput. In most cases, the successful data transmission rate is determined by this formula, which is often given in bits per second (bps). Regarding data-intensive wireless sensor network applications, high performance depends on a network's capacity to use its resources to transfer data quickly and dependably effectively; a higher throughput ratio indicates this functionality.

4.3. Packet Loss Ratio (%)

Packet loss is a significant statistic in WSNs to evaluate the network's resilience. This illustrates the percentage of data packets that cannot reach their intended destination due to network congestion, signal interference, or node failures. The effects of a network with significant packet loss include inaccurate data and less efficient communication.

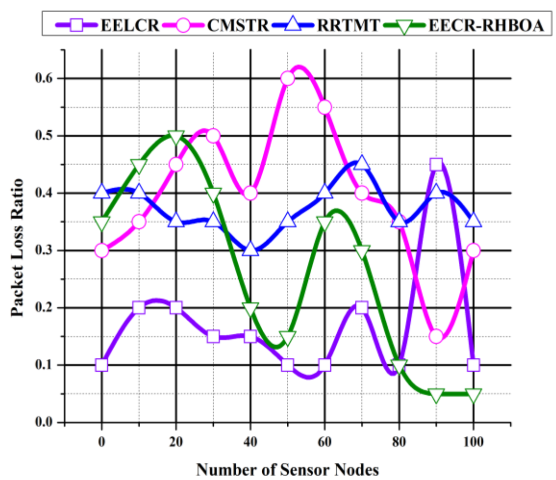

Fig. 7 Packet loss ratio

$$Packet\ Loss = \left(1 - \frac{Total\ Packets\ received}{Total\ Packets\ Sent}\right) \times 100\% \quad (18)$$

Figure 7 and Equation (18) denote the packet loss. This equation provides a clear picture of the network's dependability by assigning a numerical value to the percentage of lost packets compared to the overall number of sent packets. In wireless sensor network applications, where data transmission must be exact and quick, limiting the number of lost packets is of the highest significance for ensuring data integrity and effective communication.

5. Conclusion

An automated breast cancer diagnostics system that leverages deep transfer learning techniques on histopathological images to provide accurate and efficient breast cancer detection. By utilizing the deep transfer learning technique VGG-19 and incorporating Global Average Pooling (GAP) layers, the system reduces computational complexity without compromising accuracy. The evaluation results on the Breast Cancer Histopathological Image (BACH) dataset demonstrate the system's superior performance, achieving an accuracy of 96.7% and an F1-score of 94.3%, surpassing traditional methods. Additionally, the use of GAP layers led to a 35% reduction in training time compared to fully connected layers, proving the efficiency of the proposed system. This study illustrates that deep transfer learning, combined with GAP layers, is a promising approach for automating breast cancer diagnosis, offering both high accuracy and reduced computational overhead. Future improvements include integrating multi-modal data (genomic, radiological) for more personalized predictions, exploring unsupervised learning for better feature extraction, and incorporating explainable AI (XAI) to enhance model transparency.

Author Contribution

Sowmiya Sree C and M Sangeetha: Conceptualization, methodology design, and supervision of the project.

Mohanaprakash T A: Data analysis, algorithm development, and manuscript writing.

T. Niranjan Babu and Naveen P, Data collection, feature selection, and experimental validation.

P.Sangeetha Literature review, critical revision, and coordination of research activities.

References

[1] Banafsj Khalifa, Zaher Al Aghbari, and Ahmed M. Khedr, "CAPP: Coverage Aware Topology Adaptive Path Planning Algorithm for Data Collection in Multimedia Assisted Wireless Sensor Networks," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 4, pp. 4537-4549, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] C.B. Sivaparthipan, "An Efficient Multi-mobile Agent Based Data Aggregation in Multimedia Assisted Wireless Sensor Networks Based on HSSO Route Planning," *Adhoc & Sensor Wireless Networks*, vol. 57, no. 3-4, pp. 187-207, 2023. [Google Scholar] [Publisher Link]

[3] Peyman Tirandazi, Atefeh Rahiminasab, and Mohammad Javad Ebadi, "An Efficient Coverage and Connectivity Algorithm based on Mobile Robots for Multimedia Assisted Wireless Sensor Networks," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 7, pp. 8291-8313, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Bing Yang et al., "Location and Path Planning for Urban Emergency Rescue by a Hybrid Clustering and Ant Colony Algorithm Approach," *Applied Soft Computing*, vol. 147, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Ahmed M. Khedr, Zaher A.l. Aghbari, and Pravija P.V. Raj, "MSSPP: Modified Sparrow Search Algorithm based Mobile Sink Path Planning for WSNs," *Neural Computing and Applications*, vol. 35, no. 2, pp. 1363-1378, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Anas Abu Taleb, "Using Minimum Connected Dominating Set for Mobile Sink Path Planning in Multimedia Assisted Wireless Sensor Networks," *International Journal of Communication Networks and Information Security*, vol. 15, no. 1, pp. 1-8, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Mallanagouda Biradar, and Basavaraj Mathapathi, "Security and Energy-Aware Clustering-Based Routing in Wireless Sensor Network: A Hybrid Nature-Inspired Algorithm for Optimal Cluster Head Selection," *Journal of Interconnection Networks*, vol. 23, no. 01, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Farzad H. Panahi, Fereidoun H. Panahi, and Tomoaki Ohtsuki, "An Intelligent Path Planning Mechanism for Firefighting in Wireless Sensor and Actor Networks," *IEEE Internet of Things Journal*, vol. 10, no. 11, pp. 9646-9661, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Lun-Ping Hung et al., "Constructing a Search Mechanism for Dementia Patients based on Multi-Hop Transmission Path Planning and Clustering Method," *Mobile Networks and Applications*, vol. 28, no. 1, pp. 313-324, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Ruby Dass et al., "A Cluster-Based Energy-Efficient Secure Optimal Path-Routing Protocol for Wireless Body-Area Sensor Networks," *Sensors*, vol. 23, no. 14, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] D. Hemanand et al., "Analysis of Power Optimization and Enhanced Routing Protocols for Multimedia-Assisted Wireless Sensor Networks," *Measurement: Sensors*, vol. 25, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] T. Shanmugapriya, and K. Kousalya, "Cluster Head Selection and Multipath Routing Based Energy Efficient Wireless Sensor Network," *Intelligent Automation & Soft Computing*, vol. 36, no. 1, pp. 879-894, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Michaelraj Kingston Roberts, and Jayapratha Thangavel, "An Improved Optimal Energy-Aware Data Availability Approach for Secure Clustering and Routing in Multimedia Assisted Wireless Sensor Networks," *Transactions on Emerging Telecommunications Technologies*, vol. 34, no. 3, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Karthik Karmakonda, M. Swamy Das, and Guguloth Ravi, "An Energy-Efficient Learning Automata and Cluster-Based Routing Algorithm for Multimedia-Assisted Wireless Sensor Networks," *Contemporary Mathematics*, pp. 488-504, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Manar Ahmed Hamza et al., "Energy-Efficient Routing Using Novel Optimization with Tabu Techniques for Wireless Sensor Network," *Computer Systems Science & Engineering*, vol. 45, no. 2, pp. 1711-1726, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] N. Nisha Sulthana, and M. Duraipandian, "EELCR: Energy Efficient Lifetime Aware Cluster based Routing Technique for Multimedia Assisted Wireless Sensor Networks using Optimal Clustering and Compression," *Telecommunication Systems*, vol. 85, no. 1, pp. 103-124, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Deyu Lin et al., "CMSTR: A Constrained Minimum Spanning Tree Based Routing Protocol for Multimedia Assisted Wireless Sensor Networks," *Ad Hoc Networks*, vol. 146, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] N. Anil Kumar et al., "Ant Colony Optimization with Levy-Based Unequal Clustering and Routing (ACO-UCR) Technique for Multimedia assisted Wireless Sensor Networks," *Journal of Circuits, Systems and Computers*, vol. 33, no. 3, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Srinivasulu Boyineni, K. Kavitha, and Meruva Sreenivasulu, "Rapidly-Exploring Random Tree-Based Obstacle-Aware Mobile Sink Trajectory for Data Collection in Multimedia Assisted Wireless Sensor Networks," *Journal of Ambient Intelligence and Humanized Computing*, vol. 15, no. 1, pp. 607-621, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] N. Meenakshi et al., "Efficient Communication in Multimedia Assisted Wireless Sensor Networks using Optimized Energy Efficient Engroove Leach Clustering Protocol," *Tsinghua Science and Technology*, vol. 29, no. 4, pp. 985-1001, 2024. [CrossRef] [Google Scholar] [Publisher Link]