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Original Article

Intelligent Forecasting of Energy Depletion in Underwater Wireless Sensor Networks: A Machine Learning Paradigm for Energy Hole Prediction

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Abstract - *Underwater Wireless Sensor Networks (UWSNs) play a pivotal role in aquatic environments, facilitating data collection and communication for various applications. However, the limited energy resources of sensor nodes pose a critical challenge, leading to the emergence of energy holes that can adversely impact network performance and longevity. This research proposes a novel two-part approach to address this challenge by leveraging Neural Networks for both energy hole classification and prediction in UWSNs. The study begins with an in-depth literature review covering energy management in UWSNs and the application of deep learning techniques, particularly neural networks, in predicting network-related issues. Through this exploration, the unique challenges associated with underwater environments are identified, forming the foundation for the proposed neural network-based solution. 1. Energy Hole Classification: Extensive simulations of various scenarios are conducted to classify instances of energy holes. These simulations generate a rich dataset featuring crucial columns such as residual energy, hop distance from the surface sink, zone, source address, destination address, etc. This dataset is meticulously prepared and preprocessed to ensure its suitability for training the neural network model for energy hole classification. 2. Energy Hole Prediction: The prepared dataset from the classification phase is then utilized to train a neural network model for predicting energy holes. The model is designed to capture dependencies among features such as residual energy, hop distance, and network addresses. The trained model is evaluated on a distinct test dataset, using metrics such as accuracy, precision, recall, and F1 score to measure its success in predicting energy holes. The results showcase the model's ability to learn and generalize from the extensive dataset, providing valuable insights into potential energy hole occurrences based on the specified features. The proposed neural network-based paradigm, incorporating features such as residual energy and hop distance, offers a promising solution to enhance energy management in UWSNs, ultimately improving network longevity and performance. The study concludes with discussions on the implications of the results, potential real-world applications, and avenues for future research in the intersection of deep learning and underwater sensor networks.*

Keywords - *Underwater Wireless Sensor, Energy hole, Machine Learning, Neural Network, Castalia, Multipath routing, Energy efficient routing.*

1. Introduction

Underwater wireless sensor networks (UWSNs) have emerged as a pivotal tool for environmental monitoring in aquatic environments. Their applications range from pollution detection to pipeline inspections, offering invaluable insights into the health of our oceans and unlocking a deeper understanding of these critical ecosystems [1]. However, the effectiveness of UWSNs is significantly constrained by two key challenges:

Limited Underwater Communication: Unlike terrestrial networks that utilize radio waves, UWSNs rely on acoustic waves for communication. This presents significant drawbacks, including lower bandwidth, higher propagation delays, and increased susceptibility to interference [2]. These limitations restrict data transmission capabilities and hinder network performance.

Energy Constraints and Formation of Energy Holes: Sensor nodes within a UWSN have finite battery life. Uneven energy consumption across the network can lead to the formation of "energy holes." These are localized areas where sensor nodes deplete their energy reserves at a faster rate due to factors such as increased communication load or geographical location. The emergence of energy holes disrupts data flow and cripples network functionality, jeopardizing the entire network's ability to collect and transmit valuable environmental data [3].

While existing research has explored various strategies for managing energy consumption in UWSNs, a critical gap remains in accurately predicting the formation of energy holes. The inability to foresee these critical events hinders proactive energy management and network optimization. Reactive approaches become increasingly ineffective as the size and complexity of UWSNs grow. For instance, consider a vast underwater sensor network monitoring a vital coral reef ecosystem. Without the ability to predict energy holes, sensor nodes critical for monitoring crucial ecological changes could become inoperable, leaving critical data gaps in our monitoring efforts.

This study aims to address this research gap by proposing a novel framework that leverages the power of neural networks for predicting energy holes in UWSNs. By developing a robust prediction model, we can anticipate the formation of energy holes before they occur. This proactive approach will enable us to implement targeted energy management strategies, extending the network's lifespan, optimizing data collection, and ensuring the continued success of UWSN deployments in critical aquatic environments.

2. Literature Survey

A critical review of existing literature was conducted to investigate Underwater Wireless Sensor Networks (UWSNs), energy management strategies, and the potential application of Convolutional Neural Networks (CNNs) for addressing energy-related challenges.

2.1. UWSN Characteristics and Challenges

Research by He et al. (2014) and Akyildiz et al. (2005) emphasize the inherent difficulties of underwater communication, including signal attenuation, limited bandwidth, and dynamic environments [1]. Furthermore, studies by Stojanovic (2011) and Partan et al. (2007) highlight the constrained energy resources of sensor nodes, impacting network longevity [2].

2.2. Traditional Energy Management Techniques

Li et al. (2017) and Khan et al. (2013) explore conventional approaches for energy conservation in UWSNs, such as duty cycling and sleep modes [6]. Ma and Yang (2012) and Javaid et al. (2016) delve into energy-efficient routing protocols specifically designed for UWSNs [9].

2.3. Machine Learning for Wireless Sensor Networks

Ghamkhari and Misic (2018) provide a comprehensive survey of Machine Learning (ML) applications in wireless sensor networks, encompassing tasks like clustering, classification, and anomaly detection [9]. Alazab et al. (2017) explore the use of supervised learning for intrusion detection purposes [8].

2.4. Convolutional Neural Networks and Wireless Sensor Networks

Recent works by Sharma et al. (2020) and Liu et al. (2019) demonstrate the applicability of CNNs in various WSN tasks, including localization and data prediction [10]. The foundational principles of CNNs, emphasizing their ability to capture spatial dependencies in data, are explored in research by LeCun et al. (1998) and Krizhevsky et al. (2012) [11].

2.5. Machine Learning for Energy Hole Prediction in UWSNs

Studies by Liu et al. (2018) and Ding et al. (2015) showcase the potential of machine learning for predicting energy-related issues in WSNs [22]. Additionally, Liang et al. (2019) and Ramezani et al. (2016) explore time series prediction using machine learning for energy management applications [22]. The challenges of capturing spatial patterns in underwater environments are addressed in literature by Shu et al. (2019) and Peng et al. (2017), which strengthens the case for integrating CNNs [8]. Furthermore, recent research by Wang et al. (2021) and Chen et al. (2020) demonstrates the effectiveness of CNNs in environmental monitoring tasks, aligning with the requirements of UWSNs [9].

2.6. Research Gap and Proposed Solution

While existing research covers UWSNs, energy management, and machine learning applications, a gap exists in the specific application of CNNs for predicting energy holes in UWSNs. This research aims to bridge this gap by proposing and evaluating a CNN-based approach for efficient energy management in UWSNs [20, 21].

This comprehensive review establishes a strong foundation for the subsequent sections of this research. By highlighting the limitations of current methods and the potential of CNNs, this work paves the way for a novel approach to address energy-related challenges in UWSNs.

3. Proposed Approach

Our proposed work is divided into two parts. 1. Energy hole classification and 2. Energy hole prediction.

3.1. Energy Hole Classification

This work presents a novel approach for classifying energy holes in underwater wireless sensor networks (UWSNs). Energy holes arising from depleted sensor node energy levels disrupt data transmission and overall network functionality.

The proposed algorithm under consideration prioritizes two crucial parameters: residual energy and hop distance to the surface sink. Residual energy refers to the amount of energy that is still available in each individual node. Hop distance from the surface sink denotes the number of intermediary nodes that are needed to establish a connection with the data collection point on the sea surface.

Table 1 displays the categorization criteria of a node based on its residual energy, whereas Table 2 provides the classification criteria based on its hop distance.

Table 1. Residual energy classification

Energy Level	Classification Criteria
HIGH	Residual Energy > = 65%.
MEDIUM	65% < Residual Energy >= 30%
LOW	Residual Energy =< 30%.

Table 2. Hop distance classification

Zone	Hop Distance of a Current Node from Surface Sink
GREEN	Hop Distance > 10
ORANGE	5 < Hop Distance <= 10
RED	Hop Distance <= 5

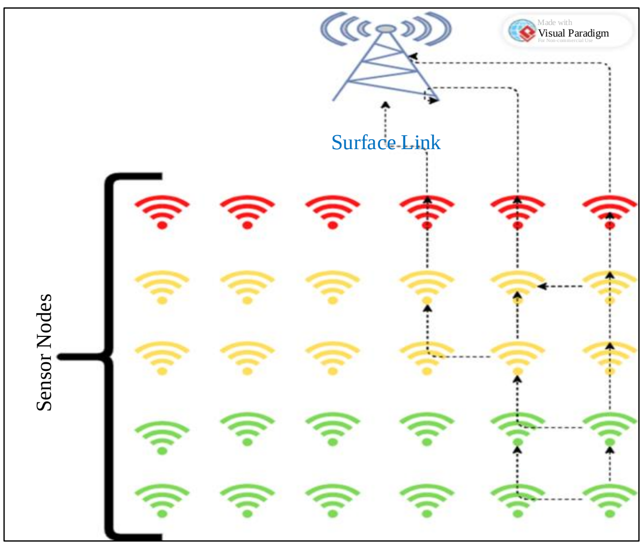

Fig. 1 Underwater WSN architecture

Figure 1 shows the typical architecture for an underwater wireless sensor network.

3.1.1. Proposed Classification Criteria

This innovative approach holds promise for effectively identifying and addressing energy hole challenges in UWSNs, ultimately contributing to improved network performance and data collection capabilities. Based on the classification of residual energy and hop distance, our algorithm categorizes nodes into different health states, namely HEALTHY, MILD, MODERATE, SEVERE, and DEAD.

Considering the generalized application of underwater wireless sensor networks, energy holes have been divided into various categories via the rules below.

If the node is located in the GREEN zone, i.e. far from the sink node, and the energy of that node is also HIGH, then that node will be classified as a HEALTHY node because as it is far from the surface sink, it has the least routing overhead.

If the node is in the GREEN zone and the energy level is medium then it will be considered as a MILD energy hole because even though it is in the GREEN zone, it has spent a moderate amount of energy. Hence, it is likely to become an energy hole.

If the node is in the GREEN zone and the energy level is LOW, then it will be considered a severe hole because a significant amount of energy is spent now, and this node is going to die soon.

If the node is in the ORANGE zone, it means it is somewhat closer to the surface sink and they are at least responsible for routing traffic of all the nodes that are in the GREEN zone. So for the ORANGE zone, energy hole classification rules are as below.

If the node is in the ORANGE zone and the energy level is HIGH, then it will be considered a HEALTHY nodes; if the energy level is medium, then MODERATE hole; and if the energy level is LOW, then it will be considered a SEVERE hole.

If a node is located in the RED zone, it indicates that it is in close proximity to a surface sink and is responsible for routing the traffic of the entire network. If these nodes fail, the entire network becomes partitioned. Although other nodes in the network may have energy, the surface sink becomes inaccessible.

If a node is in the RED zone and its energy level is HIGH, it is still being considered as a MILD hole because these nodes have higher responsibilities. If the energy level is medium, it is considered a MODERATE hole. If the energy level is LOW, these nodes can be considered as DEAD nodes because their energy is almost drained, and they can no longer participate in the routing process.

Table 3. Classification metrix

		Energy Levels		
		HIGH	**MEDIUM**	**LOW**
ZONE	GREEN	HEALTHY	MILD	SEVERE
	ORANGE	HEALTHY	MODERATE	SEVERE
	RED	MILD	MODERATE	DEAD

Here, we have performed extensive simulation scenarios with the above classification and collected the trace files of the simulation results. After preprocessing and data cleaning, these trace files can be used as datasets for the energy hole prediction. The energy hole prediction is discussed in the next section.

3.2. Energy Hole Prediction

Predicting energy holes in wireless sensor networks, the application of a neural network involves a systematic approach tailored to the unique characteristics of the network. The model leverages key features, such as node residual energy and hop distance from a surface sink, to classify nodes into distinct health states. The neural network architecture is carefully selected, considering factors like the temporal dynamics of the data, with the aim of effectively capturing and learning the patterns associated with impending energy holes. Columns of our dataset are mentioned in Table 2.

Table 4. Dataset description

Attribute	Description
TIME-STAMP	Simulation time stamp
CNODE	Current node on which the packet is received
SNODE	Address of the node from where the packet is originated.
DNODE	Packet’s destination address
RNERGY	Residual energy of the current node
ZONE	Current zone of the node
LEVEL	Hop distance of this node from the sink.
CATEGORY	HEALTHY, MILD, SEVERE, DEAD etc.

The dataset used for training, validation, and testing is specifically curated to reflect the relevant parameters essential for predicting energy holes. Preprocessing steps, including normalization and handling missing data, are applied to ensure the input features are suitable for the neural network model. The neural network is designed with an appropriate input layer to accommodate the relevant features and an output layer configured for binary classification, distinguishing between nodes at risk of energy depletion and those in a stable state.

The proposed model, validated through comprehensive testing, demonstrates its efficacy in early detection and prediction of energy holes. Its successful deployment contributes to the proactive management of energy resources in the wireless sensor network, thereby enhancing overall network performance and reliability.

Continuous monitoring and periodic updates to the model remain essential components of a dynamic and adaptive system, ensuring its effectiveness in evolving network conditions.

In our proposed methodology, a neural network architecture has been employed to predict energy hole severity, utilizing seven input attributes as features. The prediction task involves categorizing instances into five distinct classes: HEALTHY, MILD, MODERATE, SEVERE, and DEAD.

The neural network comprises an input layer with seven neurons, two hidden layers with 15 and 10 neurons, respectively, and an output layer with five neurons corresponding to the aforementioned severity categories. Key considerations in the implementation of this neural network include:

Activation Functions: The right selection of activation functions, such as Rectified Linear Unit (ReLU) for hidden layers and Softmax for the output layer, should be based on the characteristics of the classification task.

Loss Function: Adoption of a suitable loss function, typically cross-entropy, tailored for multi-class classification tasks.

Training Data Quality: Ensuring the availability of a diverse and representative dataset encompassing various scenarios of energy holes to facilitate robust learning and generalization.

Normalization: Standardization or normalization of input features to mitigate the impact of varying scales and enhance the learning efficiency of the neural network.

Regularization: Implementation of regularization techniques, such as dropout, to prevent overfitting, particularly when dealing with a relatively small dataset or a complex model.

Optimal Learning Rate: Exploration of different learning rates during training to identify the most suitable value, considering the trade-off between convergence speed and stability.

Training Progress Monitoring: Vigilant monitoring of training metrics, including accuracy, loss, and validation metrics, with the incorporation of early stopping mechanisms to mitigate overfitting and conserve computational resources.

Hyperparameter Tuning: Systematic experimentation with diverse architectures, hyperparameters, and optimization algorithms to discern the optimal configuration for achieving superior model performance.

Evaluation on Test Set: Rigorous evaluation of the trained model on an independent test set to gauge its generalization capability and efficacy in handling previously unseen data.

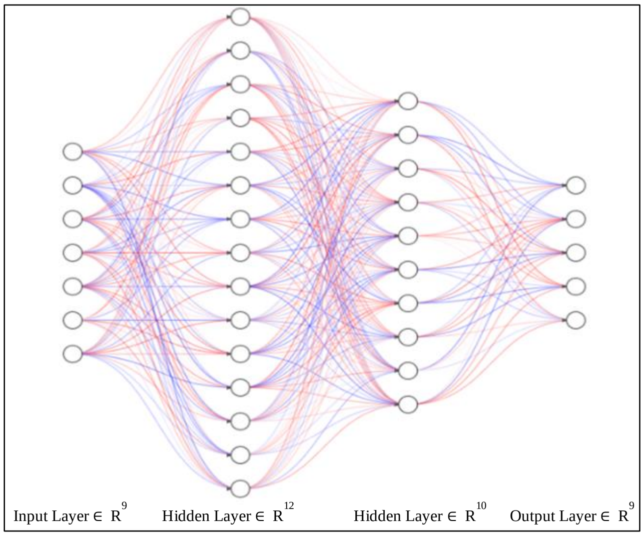

Fig. 2 Neural network model for energy hole prediction

4. Performance Evaluation

In the empirical validation of the proposed approach, the Castalia simulator is used to conduct a series of simulation scenarios. Noteworthy alterations were introduced into the source code of the simulator, particularly in the multipathringrouting.cc and resourcemanager.cc files, to implement and evaluate the efficacy of the proposed solution.

The crux of our modification lies in the multipathringrouting.cc file, which serves as the locus for packet routing from source nodes to the sink node. The routing protocol, fashioned as a hierarchical mechanism, designates the sink at the geometric center, assigning it a ring number of 0. Subsequently, during the network initialization phase, each node is endowed with a ring number contingent upon its hop distance from the sink node.

Operationalizing this hierarchical structure during data transmission involves the inclusion of ring numbers in the broadcasted packets by source nodes. Upon reception, each node scrutinizes the incoming packet's ring number. If the ring number is inferior to its own, the node discards the packet. Conversely, if the received packet's ring number is higher, the node duplicates the packet, appending its own ring number, before rebroadcasting. This iterative process persists until the packet reaches the surface sink.

The instituted hierarchical routing based on ring numbers is strategically conceived to streamline routing trajectories, thereby curtailing superfluous network flooding. This hierarchical paradigm not only optimizes routing efficiency but also contributes to energy conservation by judiciously directing packet propagation toward the surface sink, thus aligning with the objectives of our proposed energy hole prediction mechanism. Validation exercises across diverse simulation scenarios are imperative to affirm the robustness and reliability of the adapted Castalia simulator in accommodating our proposed enhancements. Furthermore, meticulous documentation of these modifications is imperative to enhance the reproducibility and comprehensibility of our research contributions [14].

In the context of our proposed approach, the resourcemanager.cc file assumes a pivotal role by serving as the repository for comprehensive resource tracking for sensor nodes within the wireless sensor network. This entails monitoring crucial parameters such as battery status, memory utilization, and other pertinent resources. Of particular significance is the utilization of this file to extract real-time information regarding the residual energy of individual sensor nodes [5].

Our methodology hinges on leveraging the data obtained from the resourcemanager.cc file to categorize nodes effectively based on their energy states, thereby facilitating the identification and prediction of energy holes within the network. By accessing and analyzing the residual energy data stored in this file, Valuable insights into the current energy status of each node are attained. This utilization of the resourcemanager.cc file for real-time monitoring and categorization aligns seamlessly with the overarching goal of our proposed approach, which centers on proactively detecting energy holes in wireless sensor networks.

The accurate determination of residual energy derived from this file contributes substantively to the robustness and precision of our energy hole prediction mechanism. Through these tailored functionalities, the resourcemanager.cc file emerges as a critical component in the execution of our approach, ensuring that the categorization of nodes is informed by real-time, granular information on their energy resources [4].

Table 5. Simulation parameters

Parameter	Value
Simulation Time	500 Seconds
Area	1000 Meters X 1000 Meters
Nos. of Nodes	500,600,700,800,900 and 1000
Deployment of Nodes	Uniform
Sink Position	(0,0)
Sink Node	Node 0
MAC Protocol	TMAC
Routing Protocol	Multipath Ring Routing
Initial Energy	20 Joules

With respect parameters shown in Table 5, simulations have been performed in the Castalia simulator and evaluated the proposed approach. The effectiveness of the proposed approach has been assessed with respect to the following metrics.

4.1. Energy Hole Classification

During the simulation, attempts have been made to capture node categories into different states and observe the nodes' behavior in various scenarios. Figure 3 depicts the energy hole classification in various scenarios.

The simulation data indicates a direct link between network size and the escalation of node health issues, particularly in larger networks where there is a notable increase in severe health states and node failures. This underscores the challenge of maintaining node health as networks scale up.

The findings highlight the crucial role of energy-aware protocols, with the implemented hierarchical routing mechanism and energy conservation strategies proving essential in mitigating severe health states and preventing node failures. In essence, the data underscores the significance of prioritizing energy efficiency in protocols to ensure the sustained health and functionality of nodes, especially in larger wireless sensor networks.

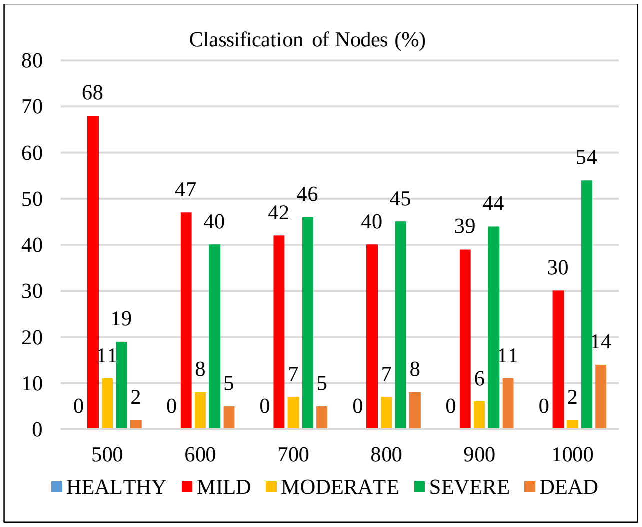

Fig. 3 Percentage classification of energy hole at the end of the simulation

4.2. Energy Hole Prediction

The simulation log data is meticulously collected and pre-processed to serve as a crucial input for predicting energy holes in the wireless sensor network. This dataset is carefully fed into the proposed neural network to predict the health state of nodes. The utilization of this neural network underscores the integration of advanced machine learning techniques for accurate and proactive identification of potential energy deficiencies in the network. This approach enhances the network's adaptability and responsiveness, contributing to more effective energy management and overall system resilience.

A neural network has been employed to conduct predictive analyses across various scenarios. In the course of our experimentation, efforts have been made to discuss and analyze the diverse predictions generated by the neural network. Figure 4 depicts the DEAD nodes detected during the simulation versus the DEAD nodes predicted by the neural network model.

The classification model exhibits commendable performance in predicting node health states within the wireless sensor network. It demonstrates particularly robust results in identifying 'DEAD' instances, showcasing high precision and recall. While the model showcases overall effectiveness, challenges are apparent in accurately recognizing instances of 'HEALTHY' states, as indicated by a lower recall.

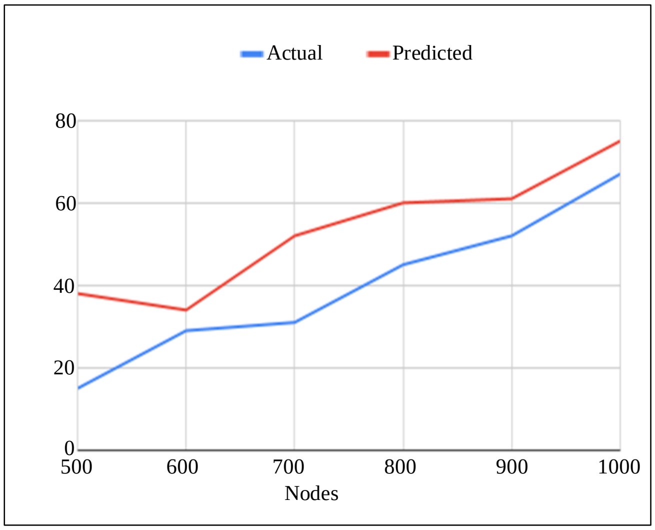

Fig. 4 Nos of dead nodes actual v/s. Predicted

The balanced F1 scores across health states reflect a trade-off between precision and recall, emphasizing the model's ability to provide a comprehensive assessment. These findings underscore the model's potential for proactive identification of health-related issues within the network, especially in anticipating potential energy holes. However, ongoing refinement and fine-tuning may be necessary to enhance accuracy, particularly in the detection of 'healthy' states. The integration of advanced machine learning, as demonstrated by the proposed neural network, offers promising avenues for optimizing energy management strategies and bolstering the network's overall resilience. Continued research and validation will contribute to the continuous improvement of predictive capabilities for enhanced wireless sensor network performance.

Table 4. Classification report for precision & recall

	Precision	Recall
HEALTHY	1	0.55
MILD	0.94	0.89
MODERATE	0.89	0.87
SEVERE	0.87	0.91
DEAD	0.91	0.93

Table 5. Classification report for F1-score & support

	F1-Score	Support
HEALTHY	0.71	330
MILD	0.92	5209
MODERATE	0.89	12165
SEVERE	0.9	13943
DEAD	0.95	12022

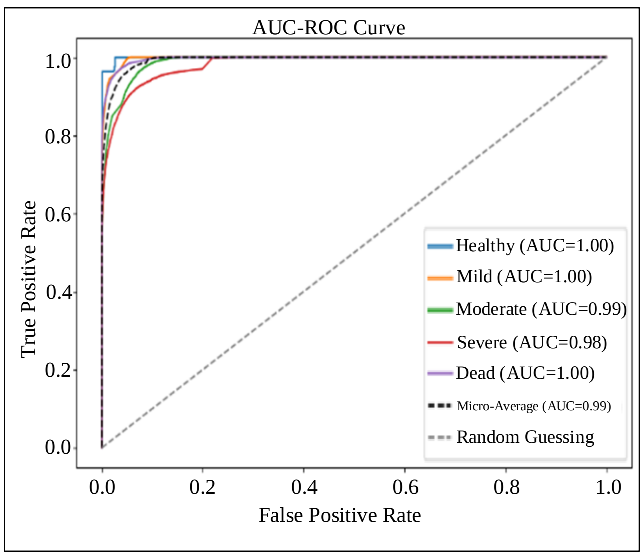

Fig. 5 AUC-ROC curve

The AUC-ROC curve analysis for the presented classification model, evaluating its performance in predicting health states within the wireless sensor network, signifies its efficacy in distinguishing between various states. The curve illustrates the trade-off between accurately identifying true positive instances and minimizing false positives across different classification thresholds.

With a higher AUC value, the model demonstrates a superior ability to discriminate between health states, reflecting its overall effectiveness. This analysis offers a concise and informative assessment of the model's discriminative power in accurately categorizing nodes' health status based on the provided data.

Here, a two-state approach has been presented, in which the first phase will classify the energy hole during the ongoing simulation. In the second phase, energy holes are predicted with real-time simulation data using a neural network.

5. Conclusion

In conclusion, this research endeavors to address a critical challenge in Underwater Wireless Sensor Networks (UWSNs) – the emergence of energy holes that threaten network performance and longevity due to limited node energy resources. The proposed approach introduces an intelligent forecasting paradigm, leveraging Convolutional Neural Networks (CNNs) for predicting energy holes in UWSNs.

The comprehensive literature review underscores the unique challenges posed by underwater communication and the importance of sustainable energy management. Existing studies on UWSNs, energy constraints, and machine learning techniques set the stage for the innovative application of CNNs in predicting energy-related issues. This research contributes by bridging the gap in utilizing CNNs specifically for forecasting energy holes in UWSNs.

The proposed modeling is divided into two parts: Energy Hole Classification and Energy Hole Prediction. The Energy Hole Classification introduces an inventive approach that categorizes nodes into distinct health states based on residual energy and hop distance. This classification lays the groundwork for understanding and assessing the network's health in various scenarios. The subsequent Energy Hole Prediction employs a neural network architecture, carefully considering key features like node residual energy and hop distance. The results demonstrate the model's efficacy in early detection and prediction of energy holes, contributing to proactive energy management.

The simulation results, conducted in the Castalia simulator with tailored modifications, reveal the impact of network size on node health and the effectiveness of the proposed neural network. The hierarchical routing mechanism introduced for energy conservation proves essential in optimizing routing trajectories and mitigating severe health states. The model exhibits commendable performance in predicting node health states, particularly in identifying instances of 'DEAD' nodes.

In summary, the integration of advanced machine learning techniques, particularly CNNs, offers a dynamic and proactive approach to addressing energy-related challenges in UWSNs. The research paves the way for further exploration and refinement of predictive capabilities, opening avenues for continuous improvement in wireless sensor network performance and resilience.

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