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Adaptive Dilated Cascaded Recurrent Neural Network Framework for Energy-Efficient Routing in Wireless Sensor Networks

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Abstract *– Energy-Efficient Routing in Wireless Sensor Networks is crucial for extending network lifetime and guaranteeing dependable communication, especially in large-scale battlefield environments. Wireless Sensor Networks (WSNs) are made up of resource-constrained sensor nodes that communicate thru multi-hop paths and have limited battery capacity. The limited energy of sensor nodes is frequently overlooked by traditional routing protocols. Energy histograms are used to create a workable energy-aware routing method in order to overcome this difficulty. Outlier detection and classification are preceded by data preprocessing methods such as data cleaning, shuffling, and normalisation. To get the best chi-squared value, a ADRNN is combined with a chi-squared filter-based feature-selection technique. The best routing paths for effective data transfer are then found using ADRNN. The conveyed information is further analysed thru an Adaptive Dilated Cascaded Recurrent Neural Network (ADRNN) for the purpose of energy-efficient routing, whereas ADRNN fine-tunes the parameters of the ADRNN model. The suggested ADRNN framework achieves a high classification accuracy of 94.08% by successfully integrating intelligent energy-efficient routing, energy-aware routing, and feature selection. The findings show that in energy-constrained wireless sensor network situations, the suggested ADRNN framework can enhance communication effectiveness and offer precise illness diagnosis.*

Keywords— *Wireless Sensor Networks (WSNs), Quality of Service (QoS), Adaptive Dilated Cascaded Recurrent Neural Network (ADRNN).*

I. Introduction

An essential technology, WSNs allow sensors to gather a variety of sensing data from the monitoring area and make smart judgements based on that data. Nodes in a typical WSN work together to detect and process data using self-organising ways; after collecting data, nodes send it to the sink, which is then in charge of integrating, processing, and uploading it to the server. Environmental monitoring, healthcare, and industrial monitoring are just a few of the many areas that make extensive use of WSNs due to their numerous benefits, such as low power consumption, high dependability, and easy deployments [1]. It is usual practice for WSN nodes to be placed in specific areas in order to gather data and send it to either a central hub or other nodes in the network. The collected data can then be analysed to draw meaningful conclusions, allowing for better-informed

decision-making. A wide range of applications can benefit from WSNs due to their unique characteristics, such as their ability to self-organise, scale, and operate in tough or distant environments. While a single mobile sink has been employed to shorten the distance between sensor nodes and the sink, its inadequacy in covering the full network area can result in data transmission problems, ultimately reducing the network's lifetime [2]. Nevertheless, in order to conquer the present obstacles encountered by WSNs, it is imperative to establish several mobile sinks that feature limitless power, communication and energy capacities. A dependable and efficient routing protocol will take into account the following: network topology, data transmission mode, data aggregation, energy usage, and service quality. Therefore, power saving sensor nodes is the primary objective of WSN routing protocols. This ensures that the network is operational for a longer period of time and that nodes can maintain connectivity [3]. Furthermore, WSN routing algorithms must detect and remove redundant information because nearby sensor nodes could generate comparable sensing data. While IP-based organization is not explicitly used and sensor nodes are limited in processing and storage capabilities, most data flow in WSNs is channelled to a single sink [4]. However, problems such as these are not considered by routing methods designed for wired networks. Their main focus instead is on ensuring a high QoS. Therefore, they are not fit for use in WSNs. As a result, they are deemed inappropriate for WSN. It follows an outline of the rest of the paper: The second section provides a summary of the literature on energy-efficient routing in wireless sensor networks. The ADRNN model-based energy-efficient routing is introduced in Section III. The methodology and outcomes of the experiment are detailed in Section IV. Section V concluded the paper.

II. RELATED WORKS

A wide range of fields are currently relying on WSNs, such as smart farming, healthcare, industrial automation, environmental monitoring, and even military surveillance [5]. The sensor nodes in these networks work together to collect data from the environment and send it to a central location, all while keeping their energy consumption to a minimum. The performance and lifetime of WSNs are directly affected by issues such limited battery power, changing topology, and security concerns, despite the fact that these networks have wide-ranging applications [6]. To enhance the efficiency of data transmission in IoT-based wireless sensor networks, they employed a state-of-the-art energy optimisation technique. This methodology's primary goal was to improve data transmission energy efficiency by means of adaptive duty cycle and transmission power modulation [7]. The goal of the task was to find the perfect spot where network performance and energy efficiency met. They brought a PSO-based sleep scheduling and innovative clustering approach to the WSN community. By efficiently forming clusters and dynamically allocating sleep and wake-up durations for sensor nodes, the method aimed to improve energy efficiency. In order to improve clustering for WSNs, the authors suggested using several mobile sinks. To maximise data collecting and overcome energy hole problems, their system employs an algorithm based on ant colony optimisation for routing. When compared to other algorithms like as LEACH, GA, and PSO, the simulation results demonstrate that it is more successful, with longer network lifetime, less data loss, and balanced energy usage. There is hope for improving WSN performance and efficiency with the improved clustering approach using numerous mobile sinks[8]. Despite these improvements, current approaches frequently have serious flaws. Although clustering methods

can save transmission costs, they can cause energy consumption to be unequal and necessitate regular re-clustering because of the large demand on cluster-heads [9]. Changes in traffic, energy distribution, or node failures cannot be adequately addressed by static and heuristic methods. Although long-term energy equilibrium and complete network robustness are important, certain RL-based methods put an emphasis on immediate optimisation at the expense of these factors [10]. Additionally, adaptive routing decisions are not often guided by methods that make use of global knowledge or predictive procedures [11]. Their proposed ADRNN method for energy-efficient transmission in WBANs combines supervised and reinforcement learning techniques. The FNN is used to make transmission decisions based on packet error probability, and a DRL model is used to optimise transmission parameters like power levels and block length [12]. Clusters of one or more sensor nodes, headed by a cluster head, are becoming more common in WSNs as a means of improving energy consumption. More power is given to the cluster leaders than to the common nodes. Each cluster's nodes are responsible for gathering raw data from the network's sensor nodes and transmitting that data to the BS for processing [13]. This way, it may minimise the processing power required by each sensor node [14]. Hierarchical Routing Protocols are the name given to this clustering algorithm. Using SVM, it offers a hierarchical routing protocol in this study. This section provides a brief overview of the paper's key points:

- Our goal is to develop an innovative algorithm called ADRNN that can find the best possible solution or values.
- Using the dilated and cascaded RNN approach and properly set parameters, create a novel ADRNN model for Energy-Efficient Routing in Wireless Sensor Networks identification.
- The goal is to evaluate the Energy-Efficient Routing model and the routing that has been put into place by taking into account the current algorithms and classifiers.

III. METHODLOGY

A wireless sensor network is a collection of tiny, power-strapped devices. The small sensor nodes are typically unreachable once installed, making it impractical to replace the energy source. Therefore, improving the network's energy efficiency is a critical design challenge for extending the network's life. The effective lifetime of a network with a restricted energy supply can be improved with a number of proposed protocols at the network layer.

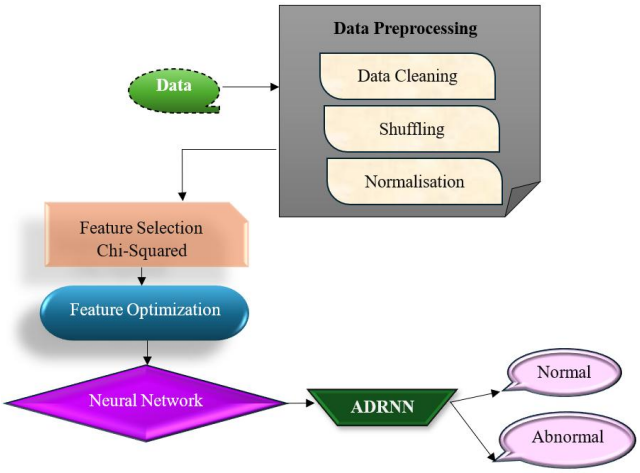


Fig. 1. Overview Of The Research Workflow

The suggested ADRNN architecture for Energy-Efficient is illustrated in Fig. 1. Energy efficiency is a key component of the ADRNN system that has been developed. The first step is to pre-process the data that has been collected from the network[15]. It is a data preprocessing method that uses data cleaning, shuffling, and normalisation. A popular feature selection method is chi-squared. Uses ADRNN model for energy efficiency. The process then moves on to model classification.

A. *Dataset Description*

This file contains a dataset that mimics the behaviour of nodes in a WSN setting. Attributes pertaining to energy consumption, authentication performance, communication latency, node responsibilities, and security status are included in each row, which represents a single node. The dataset is created to facilitate studies and experiments that center on safe, energy-aware network operations in wireless systems with limited resources[16]. To aid in the evaluation or training of models that identify nodes performing efficiently and securely within the network, a labelled target column labelled secure and efficient is supplied.

B. *Data Preprocessing*

The classification accuracy is enhanced by applying multiple preprocessing approaches prior to outlier detection.

1) Data Cleaning

Numerous records are contained inside each dataset. It is necessary to check the dataset for blank or undefinable records prior to training the model. The goal of cleaning up these datasets was to convert all undefined records into empty re-records[17]. This technique involved converting undefined values to empty records and then removing them from the databases.

2) Shuffling

Dataset tuples are shuffled using this method. It needed shuffled data to make the model work better and to test better. All of the data was shuffled randomly using the shuffling method.

3) Normalisation

Scaling numerical values between common scale ranges and eliminating abnormalities from the dataset are both part of the normalisation process. To ensure that the input data remains organised within certain ranges during the normalisation process a linear normalization method is employed. The suggested ADRNN model makes advantage of Min-Max normalisation, one of the best-known and most-used data preparation methods. Equation (1) shows the technique that linearly alters the variables max and min, where v is the sum of all observed values of v and min and max are the minimum and maximum values of v respectively.

$$V_{new} = \frac{V - \min(V)}{\max(V) - \min(V)} \quad (1)$$

The new value from the normalised results is represented by V_{new}, whereas the old value is shown by V. $\max(V)$ represents the highest value in the dataset and $\min(V)$ shows the lowest value.

Feature Selection

A popular feature selection technique, the chi-squared test is based on filters. The feature selection method is advantageous since it minimises the burden on the network. In statistics, the independence of two events can be tested using a chi-squared test. Observed count OC and anticipated count EC are the two variables that are attributed to the data. The discordance between the predicted and actual counts of EC and OC is quantified by chi-squared test[18]. In order to find the most important features in the sensor data for anomaly detection, the chi-squared test is used to locate the high-level feature. The chi-squared test is a data dimensionality reducer that improves network efficiency by selecting an array of novel features.

$$Q_{k.a} = \Sigma \frac{OC_k - EC_k}{EC_k} \quad (2)$$

The degree of freedom (c), observed count (OC) and expected count (EC) are all variables in Equation (2). A link exists between a feature (the responder) and a feature (the prediction) in the dependent category. Using a chi-squared test on the response, our feature selection method seeks out characteristics with a high dependence value. These features are then used to train the ADRNN model.

Model Training

Recurrent Neural Network

RNN takes a static characteristic as input and generates a prediction sequence using several time series. The RNN algorithm is trained using the values of the time series that have already been observed. The result is then attained with the aid of the trained model. In RNN, the input is the output from the present state in the past. The implementation of the hidden layer notion by RNN aids in issue solving. Remembering the previous informational sequence is the main aspect of this buried layer. One component of RNN that aids in remembering past data is the memory element. Output, hidden, and input parameters are all set to the same value. For RNN parameters, this works to reduce complexity. Data storage is made easier by the RNN's feedback connection. Each node in the neural network is given a weight in order to improve performance. The linear combination went through a nonlinear function and generated an ordinary node.

Layers, connections between nodes, operation mode and architecture are all parts of the neural network. Layers denote the presence of nodes on the same level of a hierarchical structure. Constant weight allocation forms the linkages. Equation (3) is used to equalise the hidden state of RNN.

$$q_r = e(q_{r-1}, l_r) \qquad (3)$$

In this case, e denotes the nonlinear mapping, q_r stands for the hidden state, l_r for the current input and q_{r-1} for the hidden state that came before it. Additionally, the concealed state stores the sequence's long-term data. Equation (4) provides the framework for the RNN model.

$$q_r = tanq(v_{kk} q_{r-1}, v_{lk} l_r + a_k) \qquad (4)$$

In this context, v_{kk} denotes the weight of the recurrent neurone, $tanq$ denotes the activation function, v_{lk} denotes the input neurone and r stands for the time. The output is evaluated using Equation (5) and the longer sequence has several states.

$$w_r = v_{kw} q_r \qquad (5)$$

Depending on the neuronal values and weights, the outcomes are computed for all values of the preceding layers.

Dilated Cascaded Recurrent Neural Network

A cell-independent multilayer variation connected by the dilated recurrent skip connection, DC-RNN aids in efficient computing problem solving[19]. The DRNN enables the single-layer skip connection to shorten the sequence. Equation (6) represents the information flow that is linked between the layers with defined timesteps through the dilated skip connection.

$$g_r^p = f\left(w_r^p, g_{r-y^p}^p\right) \qquad (6)$$

Layer w_r^p is the RNN operation layer and g_r^p is the cell at layer n with time r. The skip length is denoted by y^p . The dilations grow exponentially along the piled recurrent levels. Consequently, Equation (7) represents the dilation.

$$= N^{r-1} \frac{y^r}{} \quad (7)$$

The first layer of DRNN is fed by the medical information F_b^z. It makes it easier to train by reducing the number of parameters. The second layer of DRNN learned complimentary information by feeding the output from the first layer. In order to obtain the categorised result, the third layer of the DRNN receives the output from the second layer. A direct connection exists between the output layer and the third layer of DRNN. Therefore, it outperforms the first layer of DRNN in terms of optimisation. The third and final layer produces the Energy-Efficient categorised outcome F_{bb}^a . The proposed ADRNN's structural view is established in Fig. 2.

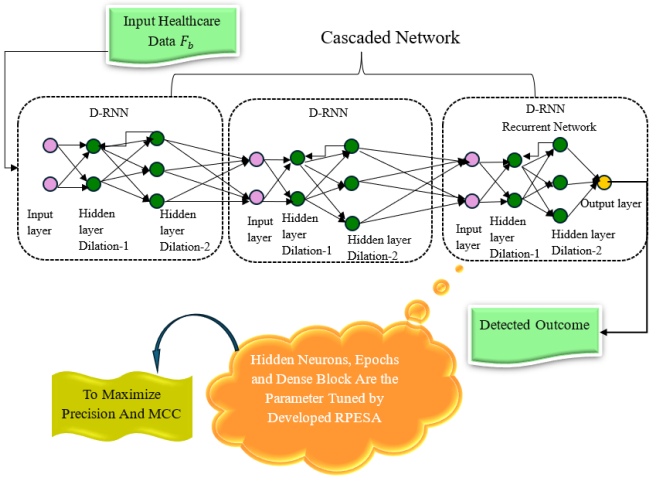


Fig. 2. Structural View Of Implemented ADRNN

DC-RNN is distinct from classical RNN in that it uses many networks rather than just one for classification. Deep energy-efficient routing is utilised by the DC-RNN with the adoption of a cascaded network. Nevertheless, the second and third-layer DRNN are impacted by the first-layer DRNN's performance. The parameter optimised by the developed ADRNN and the objective function of the suggested ADRNN technique, which increases the ability and constructs the relation between the DRNN layers and the output layer.

IV. RESULT AND DISCUSSION

The very low energy usage of individual sensor nodes is a major barrier to the widespread use of WSNs. Consequently, creating more energy-efficient routing protocols is a major area of interest in WSN research. Despite their diminutive stature, sensor nodes pack a powerful punch in terms of sensing, processing and communication, and technical advancements in recent years have made their mass manufacture possible at a reasonable cost. WSNs connect geographically dispersed sensor nodes wirelessly.

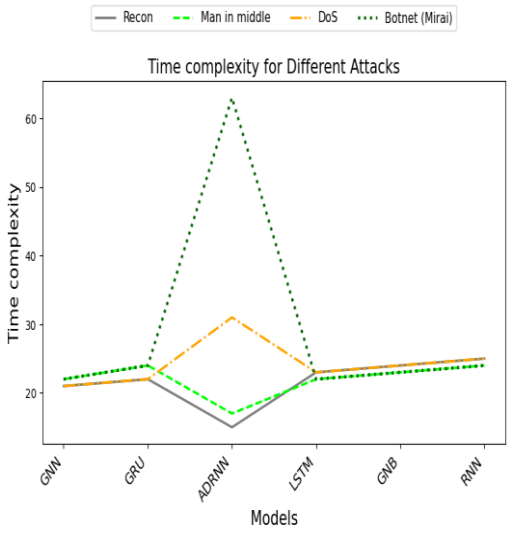


Fig. 3. Time complexity for Different Attacks

Fig. 3 displays the model's computational complexity as a function. The results show that the least time complexity for the ADRNN model was 15.9%, while the others, including GNN, GRU, LSTM, GNB and RNN, were 22, 24, 26, 21 and 23 percent, respectively. Therefore, the effectiveness of the proposed ADRNN model was demonstrated.

TABLE I. ATTACK TYPE STATISTICS OF PROPOSED MODEL

Attack Type	Training Time [min]	Execution Time [min]
Recon	30.3	15.9
Man in Middle	11.2	17.1
DoS	15.7	31.1
Botnet (Mirai)	49	63.9

Table 1 shows that the ADRNN model was trained with the dataset and then used to assess the attacks. The table displays the training and execution times of each attack according to its attributes based on these statistics.

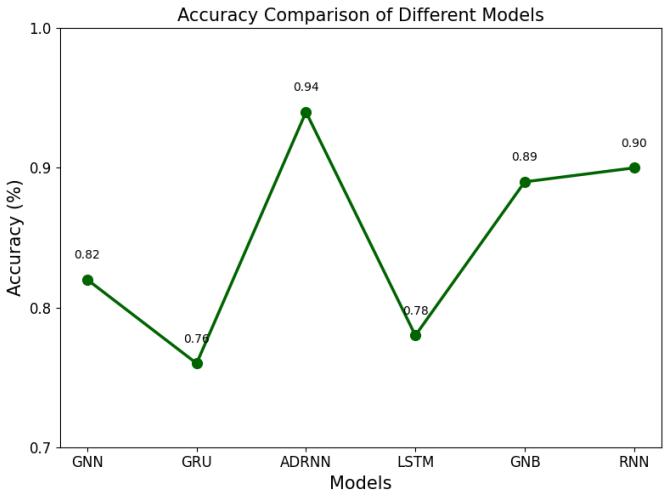


Fig. 4. Accuracy Comparison of Different Models

The proposed ADRNN classifier efficiently detects network outliers. Accuracy and other performance indicators are used to assess the suggested ADRNN classifier. Among the performance techniques are RNN, LSTM, GNB, ADRNN, GRU and GNN. The suggested ADRNN method's performance analysis is very clear. The suggested ADRNN model and current methods are compared in terms of accuracy in Fig.4. Our proposed ADRNN model achieves impressive results with an accuracy rating of 94.08%.

TABLE II. PERFORMANCE EVALUATION

Model	Accuracy	Precision	Recall	F1-Score
GNN	82.36	80.28	78.49	82.62
GRU	76.47	74.59	72.36	76.83
ADRNN	94.08	92.43	90.63	94.92
LSTM	78.34	76.28	74.52	78.74
GNB	89.18	87.61	85.93	89.69
RNN	90.21	88.86	86.74	90.86

Table 2 presents the performance evaluation of six deep learning models (RNN, BiLSTM, GA-BindRN, GRU, CNN and LSTM) utilising Accuracy, Precision, Recall and F1-Score measures. GA-BindRN has the greatest performance overall among all models with 97.37% Accuracy, 95.28% Precision, 93.59% Recall and 97.98% F1-Score. Whereas GRU and BiLSTM have relatively lower performance. The table shows that GA-BindRN achieves better performance than the other models.

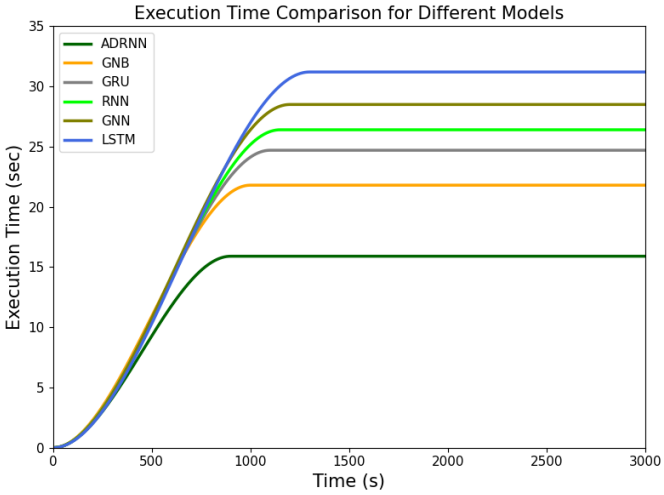


Fig. 5. Execution Time Comparison for Different Models

The Fig.5 compares the execution time of five models ADRNN, GNB, GRU, RNN, GNN and LSTM. For LSTM, the execution time is the longest about 31 seconds, while for ADRNN the execution time is the shortest about 16 seconds. Overall, the results show that ADRNN is the most efficient model in terms of execution time.

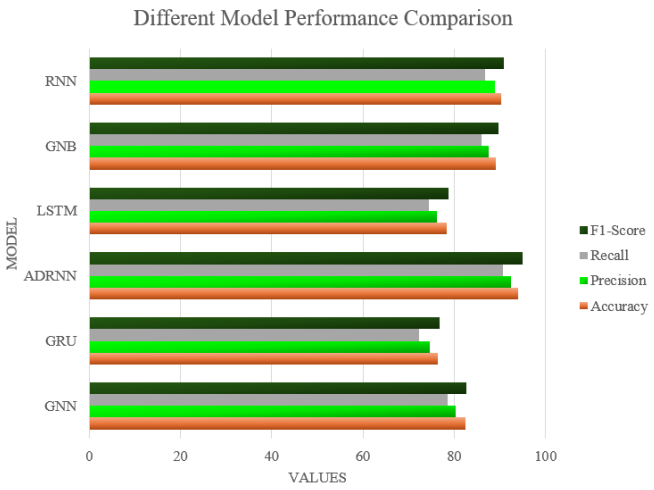


Fig. 6. Different Model Performance Comparison

The empirical results are derived by comparing several models based on their correctness. The effectiveness can be determined using a variety of Energy-Efficient assessment measures, as indicated in Fig. 6. According to the results, RNN achieved 90.21%, GNB achieved 89.18%, GNN achieved 82.36%, LSTM achieved 78.34%, GRU achieved 76.47% and the proposed ADRNN model achieved 94.08%. While recording all positive cases, recall and F1 score metrics give insights on precision and recall.

V. CONCLUSION

As low-power communication and signal processing technologies have advanced, WSNs have attracted a lot of attention and the IoT has made it possible for a variety of devices to communicate via networks. The growing number of connected devices creates a significant amount of traffic, necessitating intelligent data processing and effective communication. In this regard, lowering energy consumption and enhancing network performance require Energy-Efficient Routing in Wireless Sensor Networks. Preprocessing methods like as data cleaning, data shuffling, and normalisation are used before to outlier detection in order to improve classification accuracy. The ADRNN then uses a chi-squared filter-based feature-selection technique to determine the ideal chi-squared value. ADRNN is then used to identify the best routing path for data transfer based on the chosen value. An ADRNN is used for energy-efficient routing once the data have been sent over the best possible path. The RPESA algorithm further refines the parameters of the ADRNN model to enhance its diagnostic efficacy. The suggested ADRNN framework achieves a high classification accuracy of 94.08% by effectively integrating deep learning-based energy-efficient routing, feature selection, and energy-efficient routing. The outcomes show how well the suggested RPESA-optimized ADRNN method is for accurate energy-efficient routing in WSN-IoT settings.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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