Neural Network aided Optimal Routing with Node Classification for Adhoc Wireless Network

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Abstract

Optimal routing grabs researchers' interest across the globe, as it is the QoS's vital phenomenon for the wireless networks. The nodes in Wireless networks such as Mobile Adhoc NETwork (MANET), Delay Tolerant Network (DTN), and Bluetooth move freely, and these nodes communicate wirelessly. Consequently, the routes used for transmitting data are unstable in such networks due to the nodes' mobility. To cope this, this paper proposes an Optimal Routing with Node Prediction (ORNC) algorithm which uses a neural network for the prediction, facilitated by real-time metrics. The models are trained using node features like available internal storage, IP address, battery power utilization, range of node, etc. This classification is followed by the application of an optimal routing algorithm for network types MANET or DTN. The performance of the proposed algorithm is compared against machine learning algorithms like K-nearest neighbor (KNN), support vector machine (SVM), and multinomial logistic regression (MLR). Simulation results reveal the enhanced performance of the proposed algorithm by predicting the type of the node with an accuracy of 95.21%, followed by KNN with an accuracy of 93.61%.

Keywords 1

Wireless network, machine learning; optimized routing, neural networks, k-nearest neighbor, multinomial logistic regression, support vector machine.

1. Introduction

Routing plays a vital role, especially in wireless networks that establish the essential communi- cation among internetwork nodes. It also administers an addressing structure for identifying each device uniquely, and organizes individual device into a hierarchical network structure. Due to the various essential functions that it performs, it is of great interest to modern-day researchers to find ways to optimize it. Due to the characteristics of wireless communication, there are various challenges to routing in wireless networks. Some of them are bandwidth constraints, the dynamic topology of the network, limited storage capacity, and little processing memory. Moreover, most of the devices are battery-operated. Battery technology is falling behind microprocessor technology. Nowadays, the lifetime of the Li-ion battery sustains hardly for two to three hours. This battery limitation leads to the idea of effective energy optimization. As the source and destination nodes belong to different networks, packets cannot be transmitted directly from source to destination. To facilitate this transmission, intermediate nodes are used to relay the packet from the source to the destination. The choice of these intermediate nodes affects the time taken, the distance traveled, and the efficiency of packet delivery. Therefore, the selection of these nodes is vital for the successful and on-time delivery of data. However, the selection of non-optimal nodes in routing results in sub-optimal routing.

Among many types of wireless networks, the three networks, such as DTN, MANET, and Bluetooth, are considered in this paper. Bluetooth is the technology that enables the exchange of data between devices within a

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short range of each other. It is based on close proximity between the sender and receiver nodes. Hence, the message can be transferred directly from the sender to the receiver without the need for intermediate nodes. In contrast, in MANET and DTN, intermediate nodes are used to route data because the source and destination nodes may be far apart. Bluetooth uses ultra-high frequency waves to share data amongst fixed and mobile devices over short ranges. This is often used for the construction of Personal Area Networks (PAN). It is associated with low power consumption as it uses low energy. It is incredibly robust, cheap, and energy-efficient. It is also able to take care of data and voice transmissions in tandem.

MANET is a wirelessly connected, self-configured, and self-healing network of mobile nodes [12]. It continuously self-organizes itself and doesn't possess an infrastructure connected via physical wires. This network is decentralized and does not rely on any previously existing infrastructure. As it has frequent disassociation of nodes, dynamic topological structures, shared bandwidth, and a decentralized network, routing is more challenging operation. Moreover, it suffers physically due to its reliance on CPU capacity, battery and memory power, and channel width. If the node belongs to MANET, the collocation algorithm is used to check whether the source and destination nodes are in the same network. If they do, the probability of the message being delivered successfully increases, and no relay nodes are required. If they belong to different networks, the next best hop is chosen based on factors such as battery and internal storage. The previous history of successful transmissions using the particular intermediate nodes is also considered while choosing it as the next hop.

Delay Tolerant Networks (DTN) [11], is a technique in which it attempts to tackle the issue of continuous network connections, which is prevalent in heterogeneous networks. These are commonly seen in forest regions. DTNs have one-way links which join a few nodes to each other. It uses the store and forward functionality to transmit messages from one node to another. The DTN suite comprises network management, routing, and quality-of-service capabilities. If the network type is found to be DTN, the next hop is chosen using the same approach as described for a node of network type MANET.

Amongst multiple classification methods, Machine Learning models are applied on node data to classify the types of networks. Machine learning is chosen because of its rapidly increasing popularity as well as its efficacy in classification problems. Node data such as IP address, MAC address, battery, and internal storage is used to classify the network. In [8], an optimal routing algorithm is implemented using three machine learning models, namely, k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Multinomial Logistic Regression (MLR). To achieve better prediction of node type, Neural Networks (NN) is adopted in the proposed algorithm.

The neural network outperformed the other machine learning models because it is has the capability to model and learn complex relationships that may not be identified by many simpler models. The neural network is built on top of logistic regression, so theoretically, it will always perform better than it. The same results were seen in this paper too. This is because a neural network can draw difficult relations between non-linear and complex data points.

Neural networks are computing systems with interconnected nodes where each connection has a weight. These are based on the neurons in the human brain. They have been proven useful to find patterns and correlate non-linear and complex data. Moreover, Neural networks utilize spatial data that other algorithms do not in order to reduce the number of parameters and overall complexity while learning similar information. This gives Neural Networks a higher potential to achieve better accuracy, precision, and recall. Hence, using neural networks for our network type classification yields a higher accuracy as compared to the other three models.

Furthermore, the routing algorithm provided in [8] gives priority to random nodes without giving a chance to other nodes to act as intermediate nodes. Over a period of time, efficient nodes may remain unused while other nodes may be overused and may lose their efficiency as intermediate nodes due to changes in internal state as well as traffic and congestion. To mitigate this problem, the proposed Optimal Routing with Node Classification (ORNC) algorithm learns the current network environment and gives equal opportunity to all capable nodes to act as an intermediate node. Further, the proposed ORNC utilizes a different fitness function to tackle the issue of the trust factor having a higher weightage than the node's internal state with an increase in time. This ensures the successful delivery of a message in disaster-prone areas, which is specifically required to carry out rescue and relief operations. In such cases, the message must be delivered successfully without much delay.

The rest of the paper discusses the literature survey in section 2, the proposed Optimal Routing with Node Classification (ORNC) algorithm in section 3, and the results and simulation in section 4. The conclusion is presented in section 5.

2. Literature Study

Taking inspiration from the human brain, the intention that a machine can imitate humans has been seizing by many researchers and visionaries alike. This led to the development of machine learning concepts. In the last two decades, processing power and access to data have increased exponentially, which has led to the progress of machine learning algorithms. With this, much research has come up to facilitate the routing process in the wireless network. Some of them are discussed in the following paragraphs.

Russel et al. [1] proposed Wireless Adaptive Routing Protocol (WARP) which is context-aware routing in heterogeneous networks. It defines the cost parameter considering environment noise and router traffic to take intelligent routing decisions. If a node wants to elect an interme- diate node, then it broadcasts a packet and gets the acknowledgment, where it calculates the turnaround time. The node that has lesser turnaround time is chosen to act as the next hop to reach the destination. This protocol avoids the congestion, and achieves a better result in terms of lesser packet drops and maximized throughput, compared with the existing reinforcement learning based routing protocols.

Ghouti et al. [2] focused on the mobility problems in MANET based on the architectures of the extreme learning machine (ELM) and standard multi-layer perceptron (MLP) to predict the next location. The ELM identifies the existing correlation between the coordinates of random nodes in MANET projecting naturalistic and precise envision. The proposed algorithm leads the results of existing mobility prediction algorithms. Also, it achieves a higher accuracy score because it captures the interaction between nodes and mobility patterns more accurately.

An opportunistic network protocol assuring successful packet delivery has been proposed by Sharma et al. [3] The primary aim of this protocol is to improve throughput and reduce packet drops through the application of machine learning approaches like neural networks and decision trees. A machine learning model based on PROPHET routing scheme is used to derive a prediction value with successful delivery ratio, location and power consumption of a node as the parameters. Further, it proposed a new deep learning-based router protocol for priority-based message scheduler. Better results are achieved over the existing protocols via this approach.

Ghaffari et al. [4] utilized nearest neighbor and stable link to reduce the packet transmitting time. A reinforcement algorithm is used for choosing the best among the neighbor nodes. It predicts nature of the relationship of chosen node with the target node. This algorithm uses the Q-learning approach which checks homogeneity between the actions. In comparison to the existing protocol, it achieves better results in term of average end-to-end delay and the packet delivery ratio.

The limitations of the existing deep learning-based algorithms is eradicated by the Value Iteration Architecture-based routing algorithm that has been proposed n Mao B et al. [5]. Here, the next best node for routing a packet is predicted by analyzing the edge routers' traffic patterns through supervised deep belief architecture. Routing tables are constructed using supervised deep learning integrated with the programmable routers that use Graphics Processing Units and Central Processing Units. This paper achieves better results in terms of delay, throughput, and signaling overhead.

Delay and the power-based protocol was introduced by Rath et al. [6] which improves the quality of service for MANETs by capitalizing on the load-balanced routing strategies in AODV networks. An imbalance in the energy level of a network is caused by conventional algorithms as they do not take into account the energy in nodes while selecting a routing path. As a result, lesser energy nodes drain off consequently making an open or broken route which ultimately results in failure of delivering messages. The neighboring node's power and delays is taken into consideration while selecting a load balanced path. The simulation results in [9] reveals a much better performance in comparison to the existing AODV protocol.

The main goal of Roy et al. [7] is the detection of dumb nodes that can sense their surround- ings but cannot transmit the data to neighboring nodes due to damaging environmental effects in a wireless sensor network (WSN). Due to the presence of such nodes, the network is unable to provide the expected services. The dynamic nature of these nodes prevents the existing schemes from the detection of other misbehaviors. The proposed scheme uses a cumulative sum test, which helps in detecting the dumb behavior. The simulation results show that there is 56% degradation in detection percentage with the increment in the detection threshold, whereas energy consumption and the message overhead increase by 40% with the increment in the detection threshold.

The Major researchers did not apply the Machine learning algorithms in the networking domain to the features of a node or network in order to classify a network type. As machine learning is rising and its impact can be seen in almost every field, it is imperative to see if machine learning can be utilized to improve network classification and routing of packets to intermediate nodes.

The ORuML [8] attempts to achieve this by using various machine learning techniques such as KNN, SVM and MLR to perform network type classification using a dataset of node features as input.

The ORuML [8] uses the machine learning techniques mentioned above to classify the net- work type. Using predefined rules, each node is assigned a class label denoting how well it can perform as an intermediate node. This label is decided on the basis of internal storage and battery percentage. In case the network type is Bluetooth, no routing algorithm is used. If the network type is MANET or DTN, the source and destination nodes are checked for collocation. If the nodes are collocated, direct routing is done. If the nodes are not collocated, the intermediate node with the best class label and the highest trust factor is chosen as the next hop. In case of a successful transmission, the trust factor of that node is incremented.

The accuracy achieved by the three machine learning techniques mentioned above can be improved by tuning the hyperparameters. Moreover, the accuracy achieved can be further improved by using a Neural Network learning technique for classification. The ORuML paper [8] assigns static class labels to nodes during network type classification and does not revise these during subsequent transmissions. This can cause a problem because the class label of a node may change due to use with time. We aim to eradicate this problem by assigning class labels to only the viable intermediate nodes dynamically during each transmission.

This paper aims to improve the accuracy of the network type classification in two ways. First, by increasing the accuracy of the machine learning techniques used in the base paper, and second, by introducing other machine learning techniques that perform better than the aforementioned ones. The new technique introduced was neural networks which gave an accuracy of 95.21%. Furthermore, the routing algorithm is optimized by considering both the present state and past performance while choosing an intermediate node as the best hop. The next best hop is chosen by examining the fitness value associated with it. A higher fitness value represents a node's greater fitness to act as an intermediate node. The node with the highest fitness function is chosen as the next hop. This method prevents the nodes that have failed to deliver packets in the past despite having all the favorable features to be selected as the next best hop. This method hence eradicates the problem of choosing a node for rout- ing just because it belongs to a class with more favorable characteristics. To better evaluate the efficiency of the classification, we have added another performance metric, namely, precision.

This paper implements deep learning techniques such as CNNs for routing in wireless networks like Bluetooth. MANET and DTN. The proposed work is different from the ones mentioned above as it involves the use of neural networks to classify the nodes. The neural network has two hidden layers. The input to the neural network includes features of the node such as RAM, battery, CPU, range, etc. The proposed algorithm is then applied to the nodes to classify them into MANET, DTN, and Bluetooth.

3. Proposed Optimal Routing with Node Classification (ORNC) Algorithm

The proposed ORNC algorithm uses a neural network to classify the network type among the Bluetooth or

MANET or Delay Tolerant Network (DTN). This is done with the aid of run time metrics such as network class, IP Address, range, and more. Due to the faster and more accurate classification by the proposed ORNC algorithm, a routing decision can be taken with lesser time thus leading to faster transmission to achieve enhanced network performance.

In the proposed ORNC algorithm, the dataset considered is cleaned, where unnecessary features from the dataset are removed, after which the algorithm classifies the type of node using ML methods. Based on the network type, the ORNC algorithm decides whether the packet needs routing or not. If the network node is found as the Bluetooth, then no routing is needed as the distance between the nodes is very less, and the packets are routed directly to the destination node by the source node. If the node is classified as the MANET or DTN node, then the routing is needed as the distance between the source and destination nodes is large. When the distance is more, it chooses to route the packet by selecting the next efficient intermediate node to the destination. The entire design of the algorithm is shown in fig. 1.

- **Dataset:** The dataset is like a database that contains features for a particular topic. If a dataset is a tabular set, then columns are considered as features and rows as records. This paper consists of a dataset that is collected via crowdsourcing using google forms. The dataset used contains characteristic features of a network node is collected from individuals by a Google Form. The parameters included in the dataset are RAM, internal storage, CPU, Battery, MAC Address, IP address, network id, network class, and range of the mobile wireless device. This dataset contained some irrelevant data, and hence cleaning was done to get an appropriate dataset. However, all this information for a node is not necessary to assess the type of network. So, the dataset is cleaned, and the unwanted features are removed before classifying the network type. Our dataset contains nodes that belong to Bluetooth, MANET or DTN alone. Apart from the listed network type nodes, any other node is found, then it throws an error message 'The node does notbelong to any of the classification types in the dataset'.

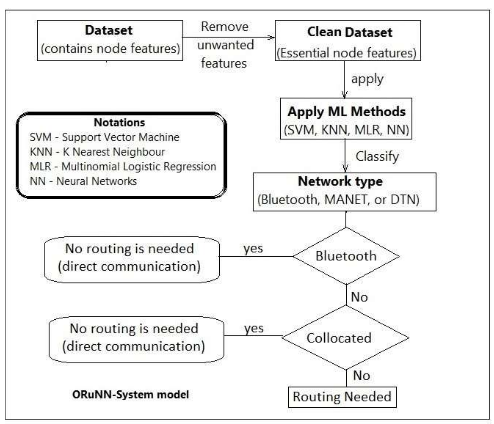

Figure 1: ORNC System model

- **Dataset Cleaning:** It is the process of removing features that are not helpful for the classification from the dataset. In the given dataset, features such as IP address, MAC address, node number, and node id are unhelpful in classifying the network type. So, these features are removed prior to the classification. The other features are crucial to classifying the network type and hence are retained.

- **Classification of the network node:** The proposed ORNC algorithm applies various Machine Learning (ML) methods such as support vector machine (SVM), K nearest neighbor (KNN), multinomial logistic regression (MLR), and neural networks (NN). All these machine learning approaches can classify the network node type satisfactorily. If a network node is classified as a Bluetooth network node, then the routing algorithm is notapplied as explained above. The packets can be directly routed from source to destination. Else the proposed ORNC checks whether the source and destination nodes are collocated or not using the collocation algorithm.

3.1. Collocation Algorithm

The collocation algorithm is applied to nodes belonging to the other two network types – MANET and DTN. The algorithm checks whether the source and destination nodes belong to the same network or not. This algorithm can be implemented using the network graph in fig.2. Suppose the source is node 4, and the destination is node 6. Since both the nodes belong to network A, the message can be transmitted directly to the destination without the use of any routing algorithm.

The source and destination nodes are said to be collocated if and only if these two nodes belong to the same network. If the nodes belong to the same network, they can communicate with each other directly, and the transmission of packets between these nodes does not need any intermediate node. The network node type classification and identification of collocated nodes reduces heavy traffic in the inter-network, as the packet transmission does not involve any complex and lengthy procedure. If the node is not part of the Bluetooth network and the source and destination nodes are not collocated, the proposed ORNC performs the optimal routing of the packets.

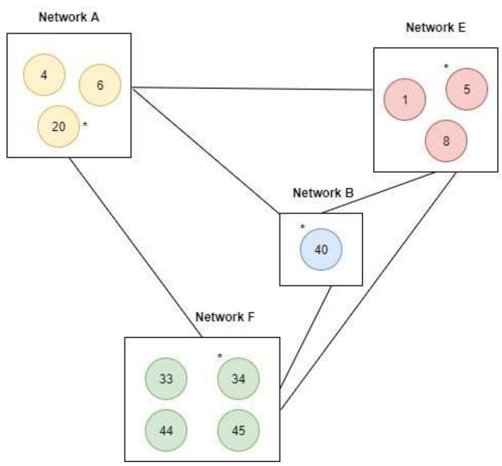

Figure 2: Proposed ORNC System model

3.2. Optimal Routing Algorithm

The optimal routing is applied when the source and destination nodes belong to different networks. In such a case, the proposed ORNC algorithm calculates a fitness function (FF) to determine whether the next node is to be chosen as an intermediate node or not. This fitness function is calculated based on the trust factor (FT) and node classification type. The proposed ORNC divides the routing process into three phases. These are Node classification, calculating the trust factor, and calculating fitness function. These three phases are described below.

3.2.1. Node Classification

Initially, the proposed ORNC senses the current battery utilization (βC) and internal storage (ΨInt) of all the neighbor nodes. Based on these values, a network node is classified into four categories. The classification is made into class-A, class-B, class-C, and class-D. The classification criterion is shown in the table. 1.

The values in table 1 are truth values, and these are assigned based on the classification criterion, as shown below. This classification is based on the current battery utilization and the internal storage of the next node. Here the values are mentioned in percentages. This classification clearly shows that a node belonging to class-A and class-B should be preferred for transmitting the packets. In rare cases, the class-C nodes can be used, while the class D network nodesshould be avoided as much as possible in the next node selection.

Table 1: Truth table for the categorization of nodes

β_C	Ψ_{Int}	Class
1	1	Class A
1	0	Class B
0	1	Class C
0	0	Class D

Table 2: Node classification

S. No Math value	β_C	Truth value-β_C	Ψ_{Int}	Truth value-Ψ_{Int}	Type
01	>=80%	1	>=60%	Class A	1.00
02	>=80%	1	<=60%	Class B	0.75
03	<=80%	0	>=60%	Class C	0.50
04	<=80%	0	<=60%	Class D	0.25

Classification is logically defined using equations 1,2, and 3 given below. Equation 1 defines class A node, equation 2 determines the class B& C, and equation 3 belongs to class D. Here,ˆrepresents logical AND, and v represents logical OR. All these values are stored in the parameter called node class truth value represented with NT.

$$N_T = (\beta_C \wedge \psi_{Int}) \wedge (\beta_C \vee \psi_{Int}) = 1 \quad (1)$$

$$N_T = (\beta_C \wedge \psi_{Int}) \vee (\beta_C \vee \psi_{Int}) = 1 \quad (2)$$

$$N_T = (\beta_C \wedge \psi_{Int}) \vee (\beta_C \vee \psi_{Int}) = 0 \quad (3)$$

3.2.2. Trust Factor Calculation

The second phase of the optimal routing is to calculate the trust factor (FT). This trust factor estimates the past efficiency of a next node to be selected as the best next neighbor node. Initially, the trust factor of all the nodes participating in the network is initialized to 1. Later, in each successful transmission through that node, the trust factor is incremented by one, and this is shown in equation 4. In case a packet drop occurs by selecting a particular next node, then its trust factor is decremented by 1, this scenario is shown in equation 5. This trust factor parameter strengthens the calculation of fitness function.

$$F_{T(node-i)} = F_{T(node-i)} + 1 \quad (4)$$

$$F_{T(node-i)} = F_{T(node-i)} - 1 \quad (5)$$

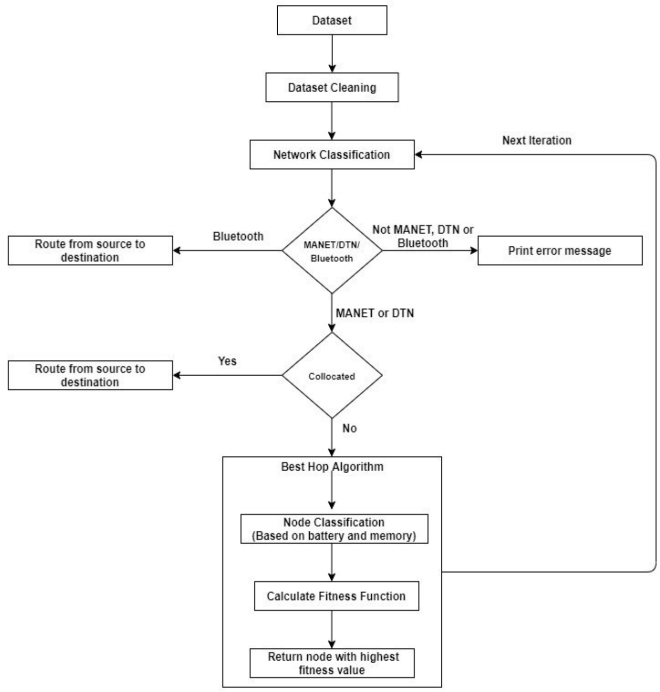

Figure 3: Proposed ORNC algorithm flowchart

3.2.3. Fitness Function Calculation

The third phase calculates the fitness function, where it utilizes the results yielded in phase 1 and phase 2 of the optimal routing algorithm. Equation 6 includes the parameters FT node-j and NTj, where FT node-j is the trust factor of node-j, NTj is the network node class's mathematical value as shown in Table 2, and j indicates the viable node. The fitness formula is given in equation 6.

$$F_{\pi_{node-i}} = F_{T(node-i)} * N_{Ti}) \,/\, \Sigma F_{T(node-j)} * N_{Tj}) \tag{6}$$

The behavior of the node is determined from its fitness function value. The values of fitness function are in the range 0 to 1. The fitness value is determined for each viable node. A higher fitness value represents a node's greater fitness to act as an intermediate node. The node with the highest fitness function is chosen as the next hop. The complete working of the proposed ORNC is depicted in Fig. 3.

The best path is selected based on the classes of each of the nodes. The classes range from 1 to 4, where class 1 refers to the most stable node, while class 4 is the least. This determines the fitness of the nodes. Another aspect taken into consideration to ensure that our algorithm is robust is the trust factor. The trust factor is a measure of the reliability of the path between two nodes. For every successful transmission, the trust factor is incremented.

On the other hand, a failure in the transmission is penalized by decrementing the trust factor of all the participating edges. These two factors are taken into consideration to determine the optimal route between the source node and the destination node. The more precious steps in the proposed ORNC algorithm are given in Algorithm 1 and 2.

3.2.4. Proposed ORNC Algorithm

Algorithm-1: ORNC

Input: Dataset, T – Graph, s-source node, d-destination node, F_T – trust factor.
Output: The next best_hop

Method:

Begin
Step 1: Dataset cleaning
Step 2: Classify network node type using Machine learning techniques
Step 3: if (node == Bluetooth)
Source and destination are nearby, establish direct connectionelse if
(node == MANET || node == DTN)
if(T (s,d) == 1) // Represent these are in the same network footprintcollocated = 1
Source and destination are in the same network, establish connectionelse //
routing is needed
go to Best hop Algorithmreturn best
hop
end if
throw The node does not belong to the classification types in the dataset
end if
End

3.2.5. Best-hop Selection Algorithm

Algorithm-2: Best-hop Selection

Inputs: $\beta^{n}{}_{C}$ – Current battery utilization, IS_N - Internal Storage of nodes, L_N – neighbor list, N_C - node class of all neighboring nodes, N – node, T_F [N] – Trust factor of a node (initialize to 1) Initialize max_value=0, F_T [N]=1.

Outputs: A List of class types of all nodes, The node index with highest fitness value

Begin
sum = 0
for each node i in $\beta^{n}{}_{C}$
if (($\beta^{n}{}_{C} \geq$ 80%) ($\psi_{Int} \geq$ 60%))
class[node] = 'A' and val[node] = 1
else if (($\beta^{n}{}_{C} \geq$ 80%) ($\psi_{Int} \leq$ 60%))
class[node] = 'B' and val[node] = 0.75
else if (($\beta^{n}{}_{C} \leq$ 80%) ($\psi_{Int} \geq$ 60%))
class[node] = 'C' and val[node] = 0.5
else
class[node] = 'D' and val[node] = 0.25
end if
i++
sum+= F_T[node]*val[node] end for

```
node_index = 0
max_value = 0
        for each node i in β^n_C
            fitness (node) = F_T [node] * val[node]/sum
            if (fitness [node] > max_value)
                max_value = fitness (node)
                node_index = i
            end if
            i ++
        end for
return node_index
End
```

4. Simulation and Performance Analysis

The simulation of the proposed ORNC is carried out using python 3.8. The proposed ORNC algorithm is tested with the learning approaches such as neural networks, support vector machine, multinomial logistic regression, and k-nearest neighbor. Out of all these, the best results are given by the neural network approach. The neural network used has an input layer, output layer, and two hidden layers. The input layer consists of 24 neurons, the hidden layers consist of 36 neurons each, and the output layer consists of 3 neurons. The stochastic gradient descent is used with a momentum of 0.5 and a learning rate of 0.007. For the Support Vector Machine, the radial basis function is utilized as a kernel type. The degree of the polynomial kernel function is 3. The regularization parameter is 1.0. In K-Nearest Neighbor, the number of neighbors is set to 5. The weights are 'uniform', and all points in each neighborhood are weighted equally. We have used Manhattan distance to calculate the distance between the neighbors.

4.1. Accuracy and Precision

The performance metrics used to evaluate the proposed algorithm are accuracy, area under the curve (AUC), and Precision [9]. Accuracy refers to the degree of correctness of a measurement or calculation. With respect to this paper, accuracy is the measure of the percentage of times the network is classified accurately as MANET, DTN, or Bluetooth. The highest accuracy is achieved with the Neural Network (NN) model.

Considering each observation is either positive or negative. If the observation is positive and predicted to be positive, the outcome is called true positive (TP). If the observation is negative and predicted to be so, then it is called true negative (TN). If the observation is positive and predicted to be negative, then it is called false negative (FN), and lastly is the observation is negative and predicted to be positive, it is called false positive (FP).

Using these outcomes, the accuracy can be calculated as:

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (7)$$

And the precision is calculated as:

$$Precision = TP/(TP + FP) \quad (8)$$

Figure-4 shows compares the accuracy among the learning approaches compared with the base paper, and it can be concluded from the results that NN has the highest accuracy (95.21%) for classifying the network type.

4.2. Area Under the Curve (AUC)

AUC is Area Under Curve, which is calculated for the ROC curve. The ROC curve is a graph plotted between Sensitivity and False positive rate. AUC measures the entire two-dimensional area underneath the entire ROC curve, [10]. It provides an aggregate measure of performance across all possible classification thresholds. One way of interpreting AUC is the probability that the model ranks a random positive example more highly than a random negative example. The ROC curve is a graph plotted between Sensitivity and False positive rate. Sensitivity is calculated as,

$$Sensitivity\,(recall) = TP/(TP + FN) \tag{9}$$

From the figures Fig 4 to 6, it is inferred that the accuracy and AUC achieved by SVM classifier was 89.89% and 85.98% respectively. KNN has achieved 93.61% of accuracy and 93.94% of AUC. The same measurement is done for MLR and 93.08% of accuracy and 93.32% of AUC have been obtained. Whereas the proposed ORNC algorithm achieves better performance in terms of accuracy and AUC. It gains 95.21% of accuracy and 91.43% of AUC.

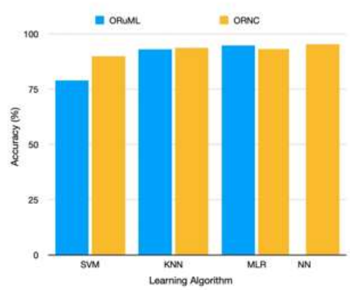

Figure 4: Accuracy

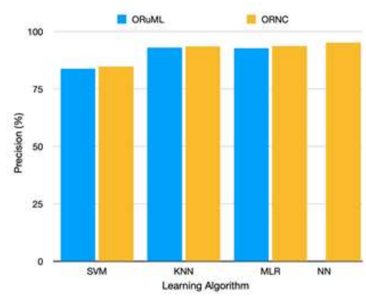

Figure 5: Precision

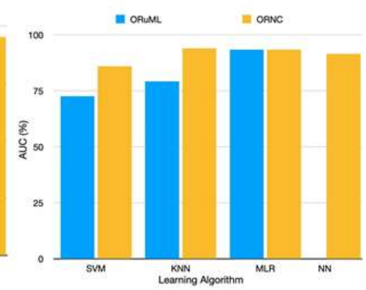

Figure 6: AUC

5. Conclusion

The objective of the proposed ORNC algorithm is, develop an ML-based algorithm to classify networks into MANET, DTN, and Bluetooth, thereby achieving an optimal routing to route the packets from source to destination node. The machine learning techniques KNN, SVM, MLR, and NN, are used for the purpose of classification. This classification helps to determine whether the collocation and hence the optimal routing algorithm is to be applied or not. The node class type and trust factor are then used to calculate its fitness value which determines how fit it is to act as an intermediate node. Out of the four ML techniques used, it is found that the neural network model is superior in classifying the networks as MANET, DTN, or Bluetooth with an accuracy of 95.21%. By using this higher accuracy, the best hop selection can take place with increased efficacy. As a future extension of the research work, these machine learning algorithms can also be used to route messages in an opportunistic network.

6. References

[1] Russell, Brian, Michael L. Littman, and Wade Trappe." Integrating machine learning in ad hoc routing: A wireless adaptive routing protocol." International Journal of Communication Systems 24.7 (2011): 950-966.

[2] Ghouti, Lahouari." Mobility prediction in mobile ad hoc networks using neural learning machines." Simulation Modelling Practice and Theory 66 (2016): 104-121.

[3] Sharma, Deepak K., et al." A machine learning-based protocol for efficient routing in opportunistic networks." IEEE Systems Journal 12.3 (2016): 2207-2213.

[4] Ghaffari, Ali." Real-time routing algorithm for mobile ad hoc networks using reinforcement learning and heuristic algorithms." Wireless Networks 23.3 (2017): 703-714.

[5] Mao, Bomin, et al.” Routing or computing? The paradigm shift towards intelligent computer network packet transmission based on deep learning.” IEEE Transactions on Computers 66.11 (2017): 1946-1960.
[6] Rath, Mamata, et al.” Load balanced routing scheme for MANETs with power and delay optimisation.” International Journal of Communication Networks and Distributed Systems 19.4 (2017): 394-405.
[7] Roy, Arijit, et al.” D3: Distributed approach for the detection of dumb nodes in wireless sensor networks.” International Journal of Communication Systems 30.1 (2017): e2913.
[8] Chaudhary, Sapna, and Rahul Johari.” Oruml: Optimized routing in wireless networks using machine learning.” International Journal of Communication Systems 33.11 (2020): e4394.
[9] Medeiros, Dianne SV, et al.” A survey on data analysis on large-Scale wireless networks: on-line stream processing, trends, and challenges.” Journal of Internet Services and Applications 11.1 (2020): 1-48.
[10] Mongia, Aanchal, et al.” Deep Latent Factor Model for Predicting Drug Target Interactions.” ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019.
[11] Jones, Evan PC, et al.” Practical routing in delay-tolerant networks.” IEEE Transactions on Mobile Computing 6.8 (2007): 943-959.
[12] Bein, Doina.” Self-configuring, self-organizing, and self-healing schemes in mobile ad hoc networks.” Guide to Wireless Ad Hoc Networks. Springer, London, 2009. 27-41.