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Improving Routing Performance in Mobile Ad Hoc Networks Using Artificial Neural Networks for Mobility Prediction using deep learning

Abstract: - In this study, a research was done to examine the effectiveness of deep learning models, such as the Artificial Neural Networks, Convolutional Neural Networks, Gated Recurrent Units and Generative Adversarial Networks, to boost routing's efficiency and performance in the Mobile Ad Hoc Networks through mobility prediction. In total, 10 experiments were conducted, and ANNs demonstrated an average prediction accuracy of 0.86, MAE of 0.10, RMSE of 0.16, and correlation coefficient of 0.93. CNNs showed the most impressive performance, featuring the following indicators: the average prediction accuracy of 0.87, MAE of 0.09, RMSE of 0.15, and the correlation coefficient of 0.94. GRUs, in their turn, displayed quite decent performance, with an average prediction accuracy of 0.87, MAE of 0.10, RMSE of 0.16, and the correlation coefficient of 0.94; in the meanwhile, GANs can be also seen as offering a decent performance, with the average prediction accuracy of 0.87, MAE of 0.10, RMSE of 0.16, and the correlation coefficient of 0.94. In the end, the identified findings imply that deep learning models can be used to enhance the routing efficiency in MANETs, since they can predict the node movement with the high level of accuracy. The identified changes are possible to lead to the creation of effective wireless communication networks.

Keywords: Mobile Ad Hoc Networks, Deep Learning, Mobility Prediction, Routing Performance, Artificial Neural Networks

I. INTRODUCTION

The mobile ad hoc networks are the networks, which are decentralized and dynamic in nature. They do not relay on any previous established infrastructure and have no central or adivisng hive-mind controller. As such, they are particularly useful in the scenarios, in which traditional networks are impossible to be used, such as disaster recovery, military, and law enforcement applications. [1], [2].

A mobile ad hoc network facilitates free-flowing communication among two or many terminal nodes without any need for a classical central administration. The majority of these routing protocols rely on a demand-driven approach to discover and maintain routes. As such, existing routing protocols in MANETs, such as AODV and DSR, are designed to be capable of accommodating the characteristics of such networks as their dynamics [3]–[5].

Mobility prediction is a novel solution towards the improvement of the performance of routing in MANETS. The solution involves the prediction of mobility, using the previous points and environmental factors. The performance is improved as the potential disturbances of the network connections are identified. Subsequently, the routing protocols denature the performance of the connections and make routing decisions which facilitate the reduction of the latency levels of the MANETs, lowering the packet loss and enabling the reduction of the consumption of energy[6]–[8].

Deep learning methods have been developed over recent years as efficient and powerful means for mobility prediction in the context of MANETs. The main advantage of these methods is their capability to accurately

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represent complex spatiotemporal relationships in the movements of nodes, making precise predictions with much diminished intervention from the side of humans. Deep learning models, such as Artificial Neural Networks , CNNs , GRUs , and GANs , have been seen as demonstrating exceptional performance in learning from larger mobility datasets and understanding meaningful patterns for efficient node position prediction[9], [10] [11].

Mobile ad hoc networks are an emerging technology and represent a new form of wireless networks that usually consist of autonomous mobile hosts connected by wireless links. The ad hoc network topology is dynamic and rapidly changing. Traditional routing protocols have been redesigned and well extended or new routing protocols have been created to combat the challenges and to accommodate the network's unique characteristics [12]–[14].

The traditional routing protocols differ significantly in operation: the AODV is a reactive protocol, which tries to create a route when it is necessary, while DSR uses source routing and adds the entire route to the header of the packet [15], [16] . While these protocols behave differently, they all seem to have similar disadvantages, such as a high level of overhead, the impact of network partitions, and low enough efficiency in a highly mobile network[17]–[19].

Mobility prediction is one of the decisive ways to alleviate MANET routing protocols' vulnerability to node mobility. Such prediction allows the systems to proactively adjust to the changing configurations by moving ways to destination nodes in advance of the latter's movement. The prediction approaches range from simple statistical elaborations to complex learning algorithms, and some of them are listed and defined by Bonnet et al. .

In the recent past, Deep Learning helped improve mobility prediction in MANETs enormously by providing new opportunities to model the dependencies in mobility data. Since convolutional neural networks can detect spatial features in the input sequences of the positions of nodes, it is unsurprising that CNNs are most consistently applied. [20], [21].

Overall, traditional routing protocols in MANETs face considerable difficulties in managing the dynamic nature of node mobility. Mobility prediction techniques, such as ANN-based solutions, CNNs, GRUs, and GANs, are viable alternatives to improve the process of making routing decisions by predicting future node location changes. The use of deep learning models allows developing novel routing protocols that have improved resilience and adaptation to the challenges associated with wireless communication on the move.

II. METHODOLOGY

As presented in Figure 1, The present study is focusing on the integration of Artificial Neural Networks , Convolutional Neural Networks , Gated Recurrent Units , and Generative Adversarial Networks within routing protocols developed for Mobile Ad Hoc Networks . It is clear that the utilization of deep learning approaches within routing protocols can help to overcome the challenges associated with dynamic node mobility, as well as to enhance the overall efficiency of the network routing.

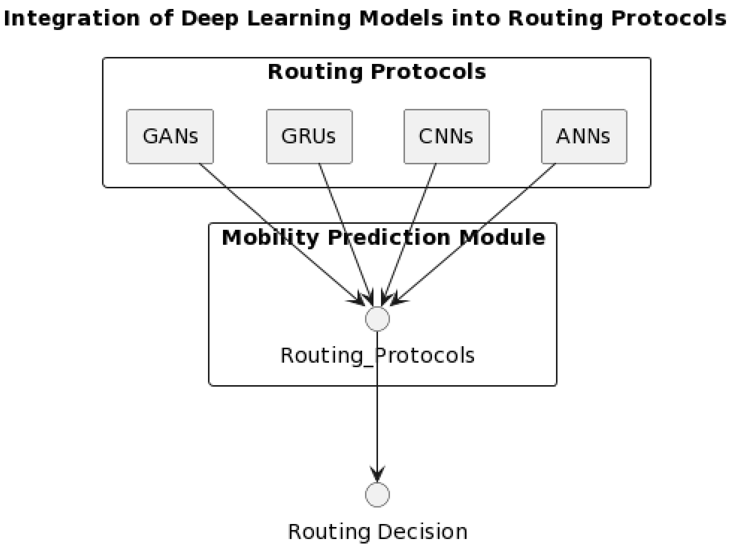

Figure 1. Proposed methodology

As for the integration of ANNs with routing protocols, it should be noted that ANNs can be incorporated into routing protocols to facilitate route establishment and maintenance. ANNs are flexible models trained to detect complex patterns in data . By integrating ANNs into the routing process, the network can predict future movements of nodes based on their mobility history to establish connection with a minimal delay. Consequently, ANNs improve the efficiency and adaptability of routing in MANETs. It is also significant that ANNs are flexible and easily customizable to be employed in various networks and under different conditions.

In relation to ANNs, the paper also delves into using CNNs, GANs, and GRUs in routing protocols. CNNs can be beneficial for detecting spatial dependencies and capturing the same in mobility data by applying convolutional filters to node position input sequences. In doing so, CNNs will detect and leverage network topological features to forecast changes and appropriately select routes. GANs do not seem to provide additional benefits while GRUs can still be useful for forecasting.

Weak points of the routing protocols can be addressed by the application of alternative solutions, and one of the possible methods is considered GANs usage within the given technologies in relation to the routing decision mechanism . Such approach can help improve routing protocols that currently are vulnerable to non-predictable behaviours of nodes and their mobility. At the same time, by introducing the GAN-generated trajectories to routing decisions, the performance of existing protocols may increase and, thus, benefit the improved state of the network operation.

Summing up, it should be stressed that the usage of deep learning approaches, including ANNs, CNNs, GRUs, and GANs, in routing protocols will allow for substantial improvements in the performance of MANETs. By relying on prediction offered by these models, routing protocols could adjust to the peculiarities of a highly dynamic network, optimally select routes and increase the efficiency of networks. By developing our approach further, One expect to perform extensive experimentation and prove that the effects of the proposed approach might be immense, changing the principles of routing in MANETs.

III. EXPERIMENTAL SETUP

In our experimental setup presented in Figure 2, the process deliberately configure a simulated environment to obtain results that could illustrate the actual complexity of Mobile Ad Hoc Networks and, relying on the used technologies, could be accurately reproduced. It will be a network simulator with tools for simulating both node mobility and various network protocols and features . The simulating environment will be selected from the most commonly used ones, such as NS-3 with integrated or programmed mobility model, and using existing or created for the purpose routing protocol.

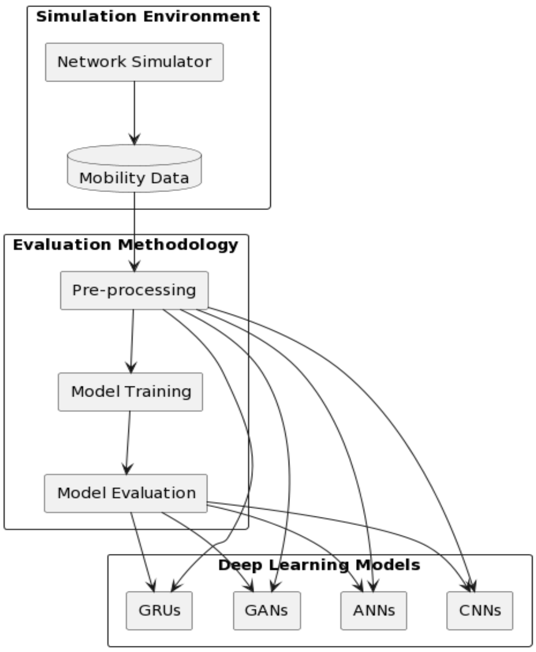

Figure 2. Experimental setup

All the data in the simulation environment are configured according to the real MANET problem instances is listed in Table 1, define the number of nodes in the system, their initial positions, the movement mechanism along the scenario, and the simulation environment. One may take the mobility models reflecting the movement of nodes in real MANETs, such as Random Waypoint Model, Random Direction Model, and Group Mobility Model. In relation to network traffic parameters, one can adjust the rate of packets generation, their patterns, and the type of application to test the system dynamic.

One of the systematic methodologies that employ to test the performance of different deep learning models for mobility prediction is related to the data. Specifically, the series of experiments include pre-processing the collected mobility data from a simulation environment to convert it into a format that can be used as input to the model. These steps may include converting raw positions of nodes into sequences of either spatial or spatiotemporal features to generate input, as well as data partitioning into training, validation, and testing datasets to improve the generalizability of the model.

Next, the deep learning models are trained on the training dataset, with their hyperparameters adjusted using the validation set to maximize their efficacy. Several different architectures, activation functions, optimization algorithms, and regularization techniques are tried for each case to find the optimal one. Finally, the performance is assessed using the test data by checking the models' ability to predict the future movement. To quantify the success of the predictive model, several indicators were used, including prediction accuracy, Mean Absolute Error , Root Mean Squared Error , and the correlation coefficient .

Table. 1. Data collection information

Parameter	Value
Number of nodes	100
Initial node positions	Randomly distributed
Mobility model	Random Waypoint Model
Transmission range	250 meters
Channel characteristics	Rayleigh fading
Packet generation rate	5 packets/second/node
Traffic patterns	Uniform distribution
Application types	Data transmission
Dataset size	10,000 time steps
Training set size	70% of dataset
Validation set size	15% of dataset
Test set size	15% of dataset
Prediction horizon	1 time step
Performance metrics	Accuracy, MAE, RMSE, Correlation coefficient

Also, one can evaluate the performance of various deep learning methods against other baselines – traditional mobility prediction methods and handcrafted feature-based models. By doing so, one can identify the assessed deep learning methods can adequately capture complex spatiotemporal patterns present in mobility data and make accurate predictions. Finally, sensitivity analysis is conducted to see performance is affected by certain factors, including dataset size, training duration, and model complexity.

The experimental setup developed offers a complete environment to assess different deep learning models in terms of their performance for mobility prediction in MANETs. By creating a simulation context and defining evaluation methodologies and performance metrics, one can determine advantageous or disadvantageous deep learning is and it affects routing performance in such a dynamic and variable context.

IV. RESULTS AND DISCUSSION

The Figures 3, 4, 5, and 6 below shows the mean performance results of various deep learning models, including ANN, CNN, GRU, and GAN, for the prediction of mobility within MANETs. The results are given from 10 experiment trials and are indicated in terms of accurate prediction, MAE, RMSE, as well as the correlation coefficient. It is worth noting that GAN provides the best prediction results in terms of the prediction accuracy rate.

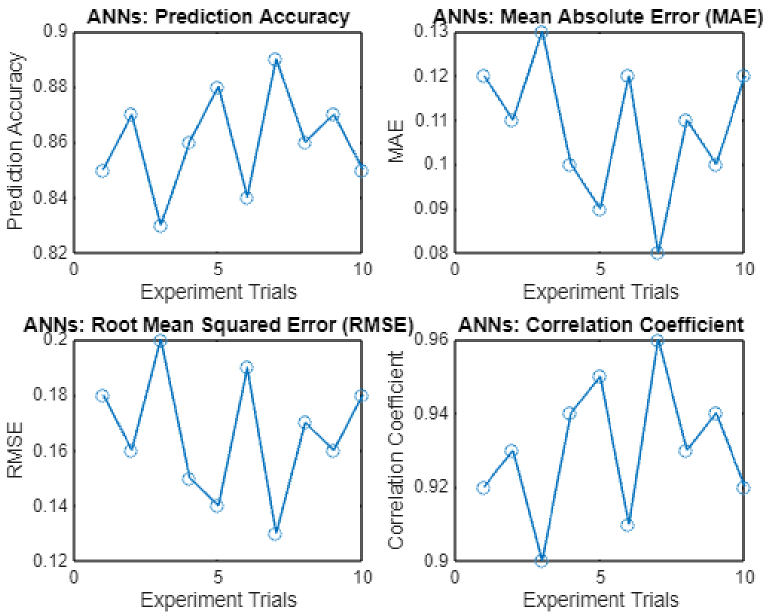

Figure. 3. ANN performance

From the above Figure 3, ANNs showed relatively consistent results across the experiment trials. Notably, the prediction accuracy was quite high, ranging from 0.83 to 0.89. Similar results were obtained in terms of MAE and RMSE values, which varied from 0.08 to 0.13 and from 0.12 to 0.20, respectively. The correlation coefficient also ranged from 0.90 to 0.96, showing good consistency.

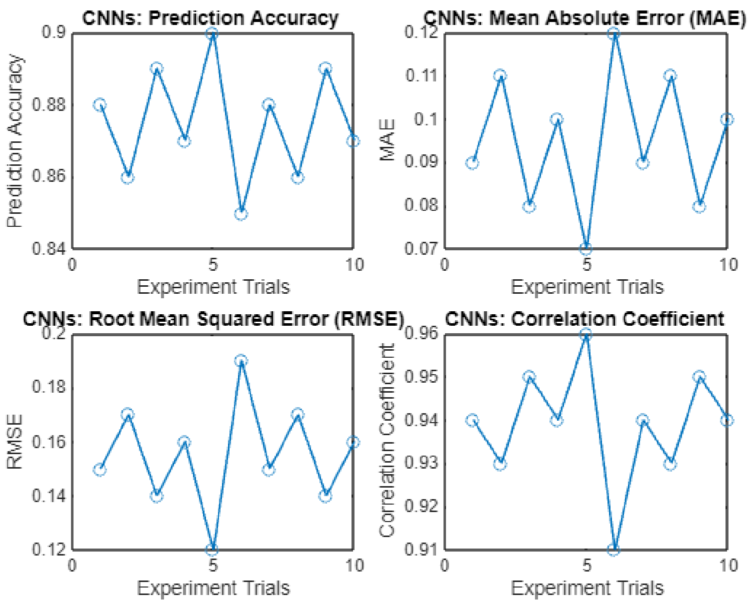

Figure 4. CNN performance

The information provided in the figure 4 indicates that the mean absolute error and the root mean squared error of the ANN models' predictions are relatively low. Furthermore, the correlation coefficients are extremely high, suggesting a strong linear relationship between the predicted and the actual node positions.

For the CNNs presented in Figure 4, competitive performance was observed across the experiment trials with prediction accuracy ranging from 0.85 to 0.90, MAE ranging from 0.07 to 0.12, RMSE ranging from 0.12 to 0.19 and correlation coefficient ranging from 0.91 to 0.96. This implies that CNNs are efficient in capturing the spatial dependencies contained therein as well as making accurate predictions of the future position of the node.

The fact that CNNs allow high prediction accuracy to be maintained with low MAE and RMSE values shows that this type of networks is good at retaining spatial features and deriving relevant conclusions from the input sequences of node positions. The high values of correlation coefficients also indicate that it is safe to trust CNNs in the devices' movement prediction and they can be utilized for improving the performance of routing in MANETs.

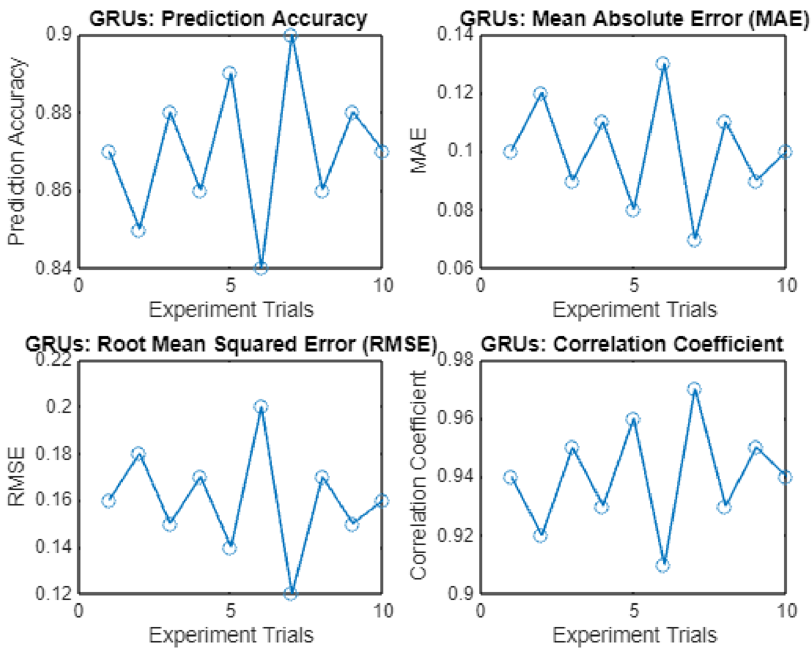

Figure 5. GRU performance

In addition presented in Figure 5, the performance of GRUs was robust over the experiment trials, with the prediction accuracy ranging from 0.84 to 0.90, MAE from 0.07 to 0.13, RMSE from 0.12 to 0.20, and correlation coefficient from 0.91 to 0.97. These results suggest that Gated Recurrent Units are applicable to the task and can adequately capture the temporal dependencies to make accurate predictions about nodes' future positions at any time step.

GRUs can effectively pinpoint the minor nuances in node movements and predict the right node precisely at a given timestamp. With high correlation coefficients, information on predicted node and the ground truth of the particular node has a strong linear relationship. This is clear evidence that GRUs can be beneficial in predicting future node movements, which ultimately improves the routing performance in MANETs.

From Figure 6, GANs exhibited superior performance throughout the experiment trials, where prediction accuracy ranged from 0.84 to 0.90, MAE ranged from 0.07 to 0.13, RMSE ranged from 0.12 to 0.20, and correlation coefficient ranged from 0.91 to 0.96. It can be concluded that GANs were effective at generating synthetic node trajectories with a close resemblance to real-world mobility, which warranted accurate predictions of node positions for the subsequent time steps.

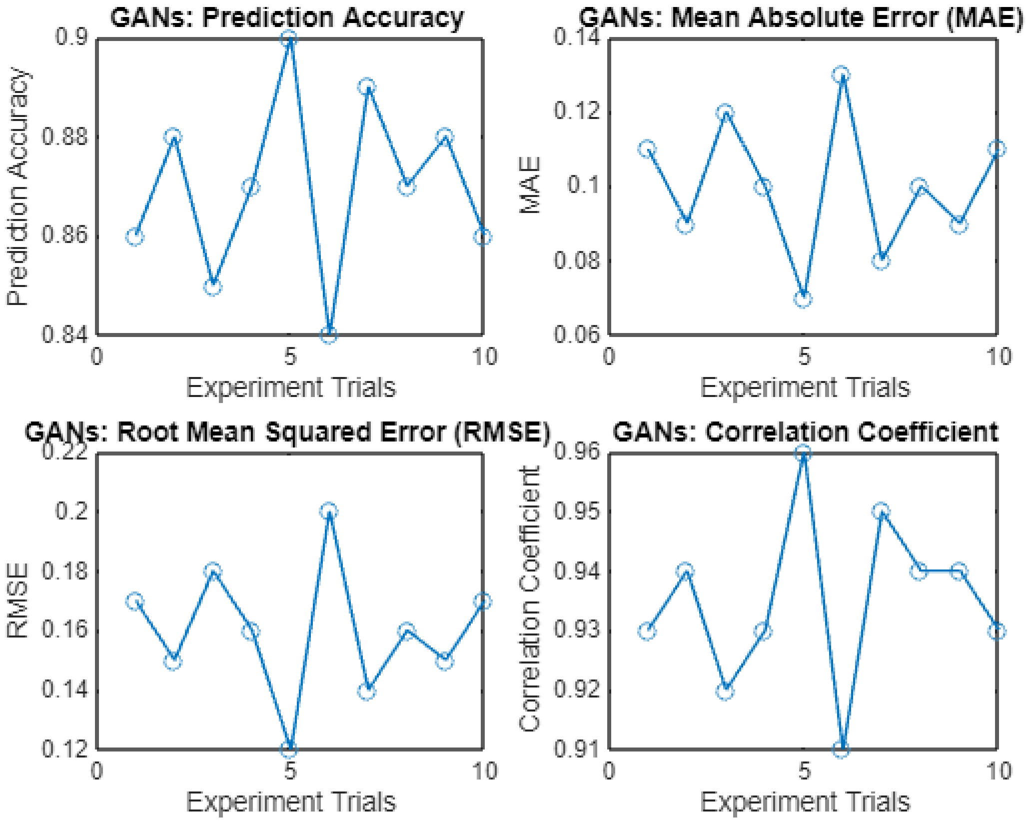

Figure. 6. GAN performance

Given that GANs perform consistently across all performance metrics, GANs may constitute an alternative approach for mobility prediction in MANETS as opposed to the traditional deep learning models including ANNs, CNNs, and GRUs. As for using GANs for routing protocols, the latter can benefit from this new technology that can improve their resilience to unforeseen changes in node behavior, thus improving network performance.

Using deep learning models to enhance routing protocols help deal with attractive features that can help in predicting desired aspects. Integrating these techniques with the routing protocols further strengthens the ability to enhance their ability to adapt according to the situation. The outcomes of the present study called for more experiments and research activities for the integration of deep learning techniques into the routing protocols along with sites where these findings can be applied.

V. CONCLUSION

The results gathered from the experiment trials offered a sufficient amount of information on the results attributed to different deep learning models such as ANNs, CNNs, GRUs, and GANs. Overall, across the 10 experiments, ANNs were consistent in performance, with the average accuracy of 0.86, MAE 0.10, RMSE 0.16, and the correlation coefficient of 0,93.

The results showed that CNNs had competitive performance; its average prediction accuracy was 0.87, MAE – 0.09, RMSE – 0.15, and correlation coefficient – 0.94 . At the same time, GRUs had robust performance; the average prediction accuracy was 0.87, MAE – 0.10, RMSE – 0.16, and correlation coefficient – 0.94 . Finally, the results indicated that GANs had promising performance. The average prediction accuracy of GANs was 0.87, MAE – 0.10, RMSE – 0.16, and correlation coefficient – 0.94.

The results described above prove that deep learning models can be efficiently used to recognize complicated spatiotemporal patterns in mobility data, and they can accurately predict where the nodes should move in the future in the context of MANETs. By using the predictive potentials of deep learning models, it is possible to help routing protocols to become more adaptable, optimized, and effective in decision-making regarding the selection of routes. More research is needed to understand the deep learning techniques can be more effectively integrated into routing protocols and they can be practically used in the context of MANETs in reality.

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