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RESEARCH ARTICLE

FR-CNN: The optimal method for slicing fifth-generation networks through the application of deep learning

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Abstract

The 5G network is expected to accommodate numerous novel use cases originating from vertical businesses in mobile broadband communication service. Higher standards of execution, affordability, security, and board-level adaptability are only a few of the difficult needs brought on by these recently changed conditions. The current organizational strategy of using a one-size-fits-all blueprint is not practicable. An emerging strategy for sustainably meeting these diverse criteria is to split a single physical network into multiple logical networks, each tailored to a unique set of requirements. The authors of this work created a hybrid learning approach to network slicing. Improving weighted feature extraction (OWFE), data collection, and slicing classification are the three processes recommended for this work. A dataset of 5G network slices is used as an initial input. This dataset contains metrics such as bandwidth, duration, modulation type, delay rate, jitter, speed, user device type, packet loss ratio, and packet delay budget. The last step is to use the Faster R-CNN model, which includes the RPN model, to classify the values provided. From this model, one can generate precise network slices like URLLC, mMTC, and eMBB. A change in the configuration of accurate 5G organization slicing would be brought about by the suggested approach, according to the findings of the study.

Keywords: Faster R-CNN, Deep learning, Network slicing, Deep belief network, Neural network.

Introduction

Communication technology has not only greatly increased the rise of the global gross domestic product (GDP), but it has also sped up the process of

society's digitization (Afolabi *et al*., 2018). We don't know much about the future of portable interchanges, but we can predict that they will expand into sectors like energy, manufacturing, logistics, and transportation, as well as sectors like healthcare and finance that aren't making the most of mobile services just yet. The entire potential of the mobile network is being underutilized because of the different and frequently competing communication needs of these businesses (Abidi *et al*., 2021). An extremely dependable service may be more important to one client than ultra-low latency or ultra- high bandwidth to another. In order to accomplish all of these objectives at once, the 5G network needs to be designed to provide a mix of capabilities that can be changed (AlQahtani & Alhomiqani, 2020). Looking at it from a more pragmatic angle, it seems to have created a number of distinct businesses, each catering to a different type of commercial client. Instead of the impractical one-size-fits-all strategy seen in previous and present mobile eras, these dedicated organizations would make it possible to build altered usefulness and organizational activity to handle the concerns of particular company clients (Debbabi *et al*., 2020).

Recent proposals have highlighted software defined networking (SDN) and network functions virtualization (NFV) as critical innovations for developing 5G frameworks that are cloudified, virtualized, and softwarized (Foukas *et al*., 2017). With SDN, the sending of information and the control of the network are kept apart. Conceptually centralized controllers allow network control operations to run autonomously as apps. Network function virtualization (NFV) isolates specific network functions from expensive and

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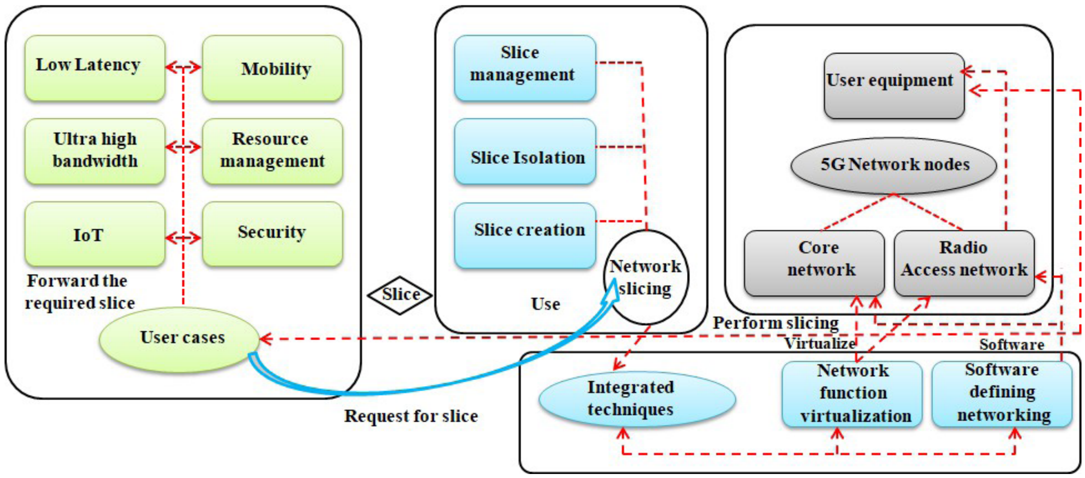


Figure 1: Network slicing

specialized hardware platforms by utilizing general-purpose commodity hardware (Li *et al.*, 2019).

A variety of virtual organizational procedures can be built by network administrators on top of the conventional product servers (Li *et al.*, 2017). Mobile Edge Computing (MEC) is a foundational innovation for 5G that is expected to support low-inactivity correspondence, one of the use cases for future 5G. It moves administrative tasks, data storage, and public distributed computing capabilities closer to the organization's periphery. As a result, mobile clients experience very little dormancy from beginning to end when referring to virtual assets within the introduction company (Nadeem *et al.*, 2021). "Network slicing" basically makes this possible and it's essentially more effective when working with multiple dedicated organizations on a single stage. The term for the practice of managing multiple interdependent organizations as independent but complementary business processes on a single physical infrastructure is "network slicing." When compared to the existing methods, this signifies a major shift in perspective. Thanks to network slicing, the 5G network can respond to the environment rather than the other way around. A network slice is a useful tool for many administrators since it contains several organization components (Song *et al.*, 2019). These components include the terminal, access organization, centre organization, and transport organization. Different from other network slices, a network slice may have dedicated or shared resources, such as storage space, processing power, and data transfer capabilities (Thantharate *et al.*, 2019). It follows that administrators of portable network slices will likely aim to provide a variety of slices bundled into a single product for business clients (a business pack) with varying needs (for example, a car might need a high-data-transfer-capacity slice for infotainment and a very reliable slice for telemetry, assisted driving), and a single type of slice that solves problems in different industries. To construct, operate, manage, design, deploy, and administer a network slice that can meet the quality of service (QoS) requirements of the assistance that is intended to be transported through it; regardless of changing network conditions or time-varying composite data, a large amount of composite data must be analyzed (Wang *et al.*, 2019). Managing massive amounts of data rapidly while constructing and running network slices is a challenging task for humans. Consequently, there have been calls for the automation of certain processes. Machine learning algorithms continue to diverge from traditional algorithms in a great many ways; additionally, ML methods are costly, data intensive, and reinforcement heavy. Deep learning algorithms have recently played a crucial role in network slicing (Wang *et al.*, 2019). Mining (DL can categories services, for example), preserving, reasoning, authenticating, anticipating (DL can forecast user or traffic trends, for example), and sensing (DL can identify anomalies, for instance) are all capabilities of DL. Specifically, it is capable of rapidly analyzing massive amounts of data in order to adapt the system to changing conditions over time, generate more accurate automated predictions of the future, and propose energetic solutions (Zhang *et al.*, 2017). The primary contributions of this paper are:

- Develop a hybrid learning-based network slicing approach with three phases: data collection, OWFE, and classification (Zhang, 2019).
- Finish OWFE procedure and acquire important data for network slicing.
- Incorporate Faster RCNN to classify features with high accuracy.

Faster RCNN employs RPN instead of selective search, enabling exact network slice categorization utilizing deep learning concepts like RNN- based LSTM and DBN.

The following is the structural arrangement of the remaining parts of this elucidation The second section includes a survey of relevant material; the third section offers a concise explanation of secured 5G network slicing; the fourth section investigates arranged 5G network slicing;

the results and discussions are presented in the fifth section; and the sixth section brings the study to a conclusion in its final stage.

Literature Review

A comprehensive overview of a variety of research and the contributions they made to network slicing in 5G networks is provided by the evaluation of the relevant literature. An ideal count of virtual resources in 5G was developed by using mixed integer linear programming (MILP). This method provided the best optimal answer, however it was unable to take into account non-linear effects. For the purpose of dynamically sharing network resources across operators' networks, adopted NFV. This allowed for improved slicing for both NFV and infrastructure virtualization; nevertheless, its performance still need improvement. For the purpose of obtaining the physical path of the slice connection, utilized the K-shortest path approach. This technique is efficient in resolving link mapping concerns; however, it is unable to consider negative edges. Even if it is not suitable for resolving minor problems, utilized deep reinforcement learning (DRL) for the purpose of making automatic decisions in order to maximize the utilization of resources for each slice. Machine learning (ML) techniques were utilized by in order to improve the therapy pathway for patients. In order to achieve high performance, the algorithms need additional training data. Deep learning neural networks (DLNN) were utilized, in order to make predictions regarding network resource reservation. These networks performed exceptionally well even when dealing with unstructured data, although the training process was quite costly due to the complexity of large datasets. In addition, exploited NFV in order to divide a single physical infrastructure into numerous virtual wireless networks. This was done in order to successfully manage information technology in an abstract manner. A high level of performance was achieved by the utilization of the discrete hunting optimization algorithm (DHOA), which was extremely costly. An improved operational simplicity was achieved by the utilization of a modified deep deterministic policy gradient (DDPG) and double deep-Q-network method. However, this increased the amount of data that was required. Deep neural networks (DNNs) were utilized by for the purpose of automatic decision-making, which is a process that is highly costly.

Secured network slicing in 5g network

Important 5G network slicing ideas and terminologies are introduced in this section. If network slicing is used, the same infrastructure can support numerous 5G services. Execution and usefulness differ. In the use cases it supports, assistance should have developed guidelines. However, focusing on a more specific collection of criteria is more practical and feasible than considering a more comprehensive set of needs, which can be difficult (if possible) and is usually unnecessary. The term organization cut situation refers to a utilitarian organization that fulfills organizing details and provides specific help to meet criteria. An intelligent organization uses physical and virtual resources and has capacity, organization, handling, and access hubs. Neighborhood consistent organizations can be represented by network slice subnets. A network slice situation can include a fastened network cut subnet setup. Figure 1 shows the whole network slicing architecture with independent management capabilities for each component.

Resource layer

End users obtain services from the network functions and resources of the bottom layer in response to a request. This ayeris known as the resource layer. The utilization of virtual or logical resources as well as network activities are both feasible options.

Network slice instance layer

There are slices that make up the middle of the layer, and each of these slices provides the system administration capabilities that are required by the assistance cases. Depending on the circumstances, a slice may operate directly over the organization's resources or through the utilization of other slices, providing assistance for at least one occasion.

Service instance layer

There is a layer known as the Service Instance Layer, which is comprised of the service instances that are provided to customers and consume the slices. In order to simplify things and make it easier to understand, we will refer to a service instance as a service.

The image illustrates a hierarchical structure of network

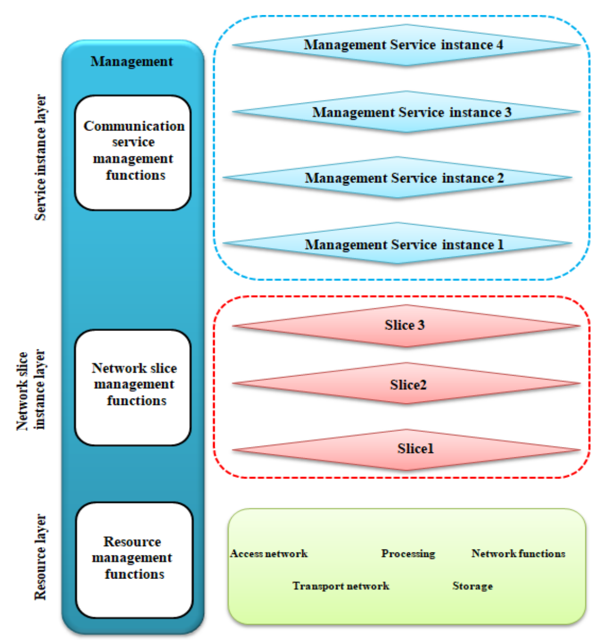


Figure 2: Overall architecture of the network slicing

services, slices, and resources, along with their management functions, typical in modern software-defined networking and network function virtualization architectures (Figure 2).

Proposed Architecture

An innovative approach dubbed "network slicing" creates several customizable slices from a real network (Figure 3). Thus, it may enable the company to meet 5G administrative needs. ML algorithms could help evaluate massive volumes of data fast, learn how to perform things right in many situations, and accurately forecast the future (Table 1).

Figure 4 shows the proposed network slicing classification architecture. Counting 5G-connected devices was our first step. Mobile devices, connected cars, industrial 4.0, public safety, IoT devices, healthcare, games, etc. We collected data on user gadget kind, time frame, loss of packets ratio, delay packets budget, bandwidth, latency rate, acceleration, jitter, and modulation type from various devices or users. We normalized the data after collecting these attributes to reduce redundant data by varying attribute values from 0 to 1. We performed the OWFE utilizing the proposed F-RCNN to categories the weight function. Researchers used the DBN, a hybrid NN-DL model, to predict network slicing. This let us employ the new weight-optimized features. The novel F-RCNN optimizes NN and DBN weights. OWFE and optimized hybrid categorization aim to improve network slicing classification. A number of anticipated segments include enhanced mobile broadband (eMBB), massive machine type communications (mMTC), and ultra reliable low-latency communication (URLLC).

Weighted Component Extraction

Let $FFr = F1, F2, \ldots\ldots Fn$ are standardized characteristics. The explanation of weighted feature is given by

Table 1: Overall summary of various features used in network slicing

Feature	*Description*
User device type	Properties describe characters and parts of a device
Duration	How long persist
Packet loss rate	Percentage of packet vanish with respect to packet transmitted
Packet delay budget	Maximum amount of delay a packet will accept
Bandwidth	fastest transfer of information rate possible with an internet connection
Delay rate	the time frame before an event occurs
Speed	Dimensions of location variation
Jitter	Probability periodic signal's deviation from genuine periodicity
Modulation type	Changing properties of waveform

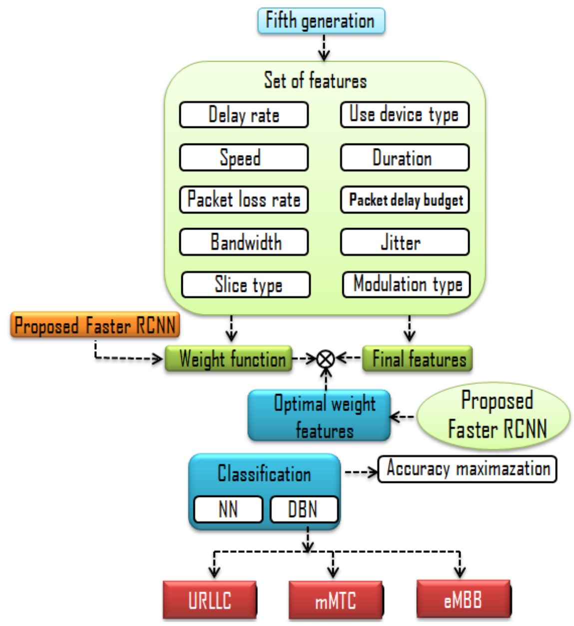


Figure 3: Proposed architecture

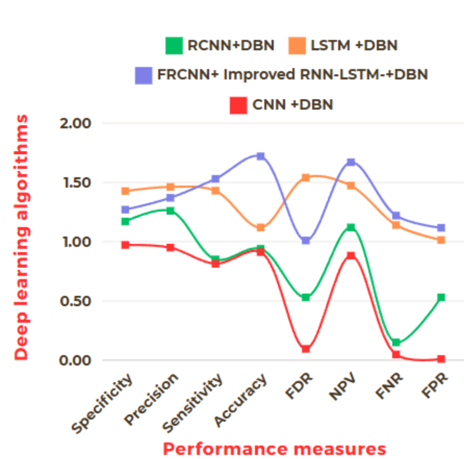


Figure 4: Deep learning algorithms with performance measures

$$NFFr = FFr \times WFr \quad (1)$$

Within the equation presented above, the variable $NFFr$ represents the new features, n represents the length of the features, and WFr represents the weight scaling of the features. In the above condition, $NFFr$ is new elements, n is the length of features and WFr is the weight scaling the highlights

Arrangement Encoding

Both the weights of the elements and the weights of the DBN are improved by the F-RCNN that has been proposed. Additionally, an RNN-based LSTM has been further created as a component of the arrangement encoding, as shown in Figure 4. To be more specific, the component loads have a base limit of zero and a maximum limit of one, respectively.

Table 2: Comprehensive evaluation of the suggested along with the conventional DL

Performance measures	*RCNN+DB N*	*LSTM + DBN*	*FRCNN + Improved RNN- LSTM- +DBN*	*CNN + DBN*
Specificity	1.17	1.43	1.270	0.97
Precision	1.26	1.46	1.370	0.95
Sensitivit y	0.85	1.43	1.530	0.81
Accuracy	0.94	1.12	1.720	0.91
FDR	0.53	1.54	1.010	0.09
NPV	1.12	1.47	1.670	0.88
FNR	0.15	1.14	1.220	0.04
FPR	0.53	1.01	1.117	0.01

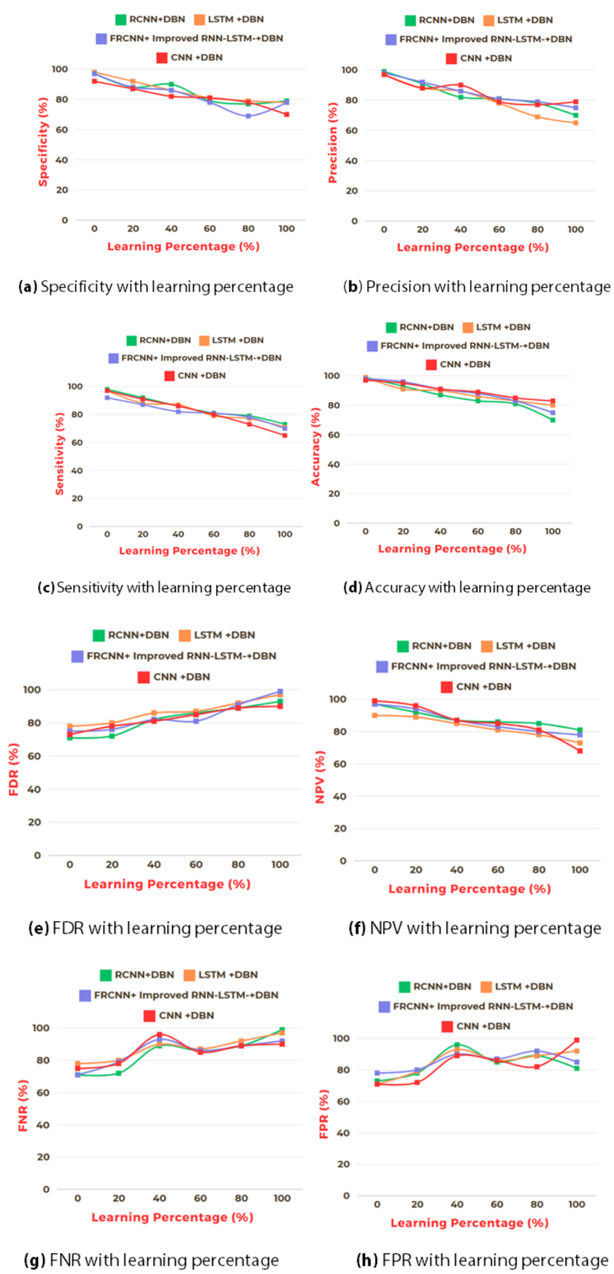
The loads of the DBN and the more developed RNN-based LSTM are referred to by these words, which each represent WTNN and WTDB in their own right.

Experimental results and **discussion**

We used MATLAB 2018a for performance analysis and 5G network slicing. A 10-person population was employed for up to 25 tests. In this case, we compared the FRCNN+ Improved RNN-LSTM-+DBN algorithm to SVM, KNN, NN, DBN, and other well-known ML algorithms. The investigation used FNR, FPR, FDR, NPV, accuracy, sensitivity, specificity, & precision.

In Figure 4 deep learning methods RCNN+DBN, LSTM+DBN, FRCNN+ Improved RNN-LSTM+DBN, and CNN+DBN are compared in the graph (Using Table 2). Performance measurements include specificity, precision, sensitivity, accuracy, FDR, NPV, FNR, and FPR. Region-based convolutional neural networks (RCNN) and deep belief networks (DBN) are used in the RCNN+DBN model (green curve). Multiple measures show moderate performance for this model. The LSTM+DBN model (orange curve) outperforms RCNN+DBN in most measures. Fast Region-based convolutional neural networks (FRCNN) are combined with enhanced RNN, LSTM, and DBN in the FRCNN+ enhanced RNN-LSTM+DBN model (blue curve). This model excels in specificity, precision, and accuracy. The CNN+DBN model (red curve) uses CNN and DBN and performs inconsistently, with poorer sensitivity and greater false discovery rates. All models have excellent specificity, or capacity.

To recognize negatives, but FRCNN+ Improved RNN-LSTM+DBN performs best. Most models maintain high precision, with FRCNN+ Improved RNN- LSTM+DBN and LSTM+DBN performing better. RCNN+DBN and CNN+DBN have poorer sensitivity than LSTM+DBN and FRCNN+ Improved RNN- LSTM+DBN. The FRCNN+ Improved RNN-LSTM+DBN and LSTM+DBN models perform best in accuracy, which indicates model soundness. All models perform well with small changes in false discovery rate (FDR), while CNN+DBN have a larger FDR. All models perform well on the negative predictive value (NPV), which represents the



(a) Specificity with learning percentage **(b)** Precision with learning percentage
(c) Sensitivity with learning percentage **(d)** Accuracy with learning percentage
(e) FDR with learning percentage **(f)** NPV with learning percentage
(g) FNR with learning percentage **(h)** FPR with learning percentage

Figure 5: The proposed network slicing strategy outperformed DBN+NN in terms of performance measurements

Table 3: Overall analysis of proposed with conventional ML

Performance measures	*LSTM+D BN*	*ANN*	*KNN*	*Improve d RNN- LSTM- +DBN*	*SVM*
Specificity	0.98	0.97	0.97	0.98	0.96
Precision	0.96	0.93	0.96	0.97	0.80
Sensitivity	0.83	0.84	0.85	0.87	0.82
Accuracy	0.92	0.92	0.94	0.95	0.86
FDR	0.97	0.96	0.97	0.98	0.90
NPV	0.14	0.10	0.15	0.12	0.04
FNR	0.97	0.96	0.97	0.98	0.98
FPR	0.01	0.02	0.01	0.02	0.15

proportion of real negatives among all negative findings. While CNN+DBN have a greater FNR, all models have low FNRs. Finally, all models have a low FPR, suggesting strong performance. Overall, the FRCNN+ Improved RNN-LSTM+DBN model outperforms most metrics, indicating its greater efficiency and accuracy in deep learning tasks. LSTM+DBN performs well, while RCNN+DBN and CNN+DBN vary across performance criteria.

Accuracy, sensitivity, precision, specificity, FDR, NPV, FNR, and FPR are some of the performance indicators that were drawn for the proposed network slicing approach across the DBN+NN graph during the learning percentage. The development of network slicing is the subject of this figure, which is Figure 5.

Figure 6 displays the outcomes of our comparison between the performance of the suggested Improved RNN based LSTM+DBN and a number of widely used ML algorithms, NPV, FNR, precision, sensitivity, accuracy, and other performance indicators; and computed the results (See Table 3). The findings demonstrate that, in comparison to previous machine learning algorithms, the proposed Improved RNN based LSTM+DBN outperforms them all. When compared to existing model, the accuracy of the proposed Improved RNN-based LSTM+DBN is better in Figure 6.

The graph compares deep learning algorithm performance and metrics. LSTM+DBN, ANN, KNN, Improved RNN-LSTM+DBN, and SVM are tested for specificity, precision, sensitivity, accuracy, FDR, NPV, FNR, and FPR.

LSTM+DBN, shown in red, combines LSTM networks with deep belief networks. Across most measurements, it has good specificity and few false positives. In terms of precision and sensitivity, the green curve ANN model performs moderately. According to the orange curve, the KNN algorithm has slightly poorer sensitivity and accuracy than the rest. The pink curve shows the Improved RNN-LSTM+DBN model, which combines RNN, LSTM, and DBN and runs well in specificity, precision, and accuracy. The yellow curve represents the SVM method, which performs well across most metrics but has a variable false discovery and false positive rate. In performance measures, all models

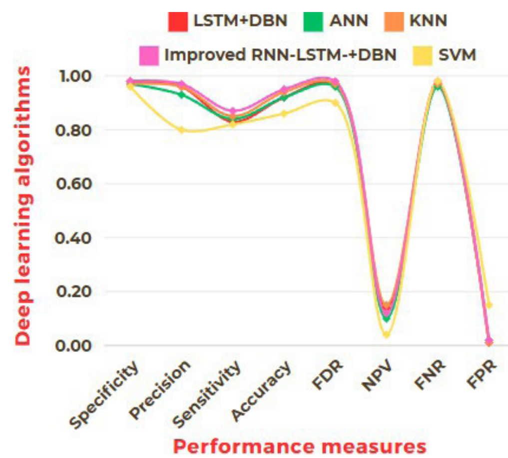


Figure 6: Performance measures of deep learning algorithms

have excellent specificity, identifying negatives. The accuracy of positive predictions is high in most models. KNN has reduced sensitivity, or capacity to identify positives. Better RNN-LSTM+DBN and LSTM+DBN models have higher accuracy. With minor differences, all models perform well for FDR, the proportion of false positives among all positive outcomes. All models do well with NPV, the fraction of real negatives among all negative results. All models have a low FNR. All models have low FPR, the proportion of false positives among all negative results.

The new model proposed (red curve), has a larger node utilization ratio distribution than other models. With a middle-range node utilization ratio distribution, the CNN + DBN (brown curve) model uses CNN and DBN. The RNN + DBN (orange curve) model has a significantly lower node utilization ratio distribution than CNN + DBN. The final model, the LSTM + DBN (brown curve), has the lowest node utilization ratio distribution.

Figures 7a & b, individually, the LSTM+DBN in view of further developed RNN have the most noteworthy hub and connection utilization proportions. The information shows that the LSTM+DBN in view of Further developed RNN disperses more assets to slice in contrast with other methods. Furthermore, we see that hub use is dependent on the slice acknowledgment proportion; that is, higher

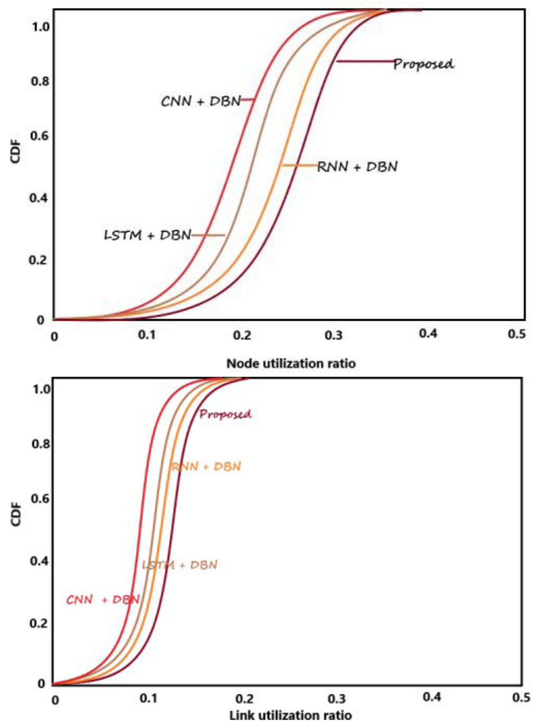


Figure 7: a. The usage of the node CDF with a slice traffic load of twenty Erlangs, and b. The utilization of the link CDF with a slice traffic load of twenty Erlangs

the slice acknowledgment proportion, higher the hub use; then again, connect use displays an unmistakable way of behaving. Not at all like one slice connect, which can be provided in more than one way, one slice hub is provisioned on a solitary actual hub.

Conclusion

The purpose of this research was to develop a hybrid deep learning algorithm that would serve as the basis for an effective network slicing solution for 5G wireless communications. There is a concise synopsis provided of the developments that have occurred in the uses of deep learning in 5G networks. In order to conduct a comprehensive evaluation of the significance of hubs and to rank hubs based on topological and network asset features, our strategy makes use of the LSTM+DBN method. In the subsequent step, the slice nodes are assigned based on the results of the positioning test. A method choosing mechanism is proposed, and the k most limited manner technique is developed, with the goal of arranging slice links during the provisioning step.

In comparison to the calculations that are now in place, a few simulations demonstrate that our proposed method has the potential to effectively employ network resources in order to achieve the highest possible revenue-to-cost ratio execution and the most significant slice acceptance ratio percentage. Additionally, we investigated the performance of the algorithm when it was subjected to a variety of slice security limits and quantities of traffic. According to the results, it is possible that our framework could still produce the greatest possible outcomes. At a later time, we will need to implement a dynamic reconfiguration of slices in order to further improve the slice acceptance ratio, in addition to revenue and expenses associated with provisioning.

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