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Machine Learning and Deep Learning Based Network Slicing Models for 5G Network

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Abstract*—5G network can provide high speed data transfer with low latency at present days. Network slicing is the prime capability of 5G, where different slices can be utilized for different purposes. Therefore, the network operators can utilize their resources for the users. Machine Learning (ML) or Deep Learning (DL) approach is recently used to address the network issues. Efficient 5G network slicing using ML or DL can provide an effective network. An endeavour has been made to propose an effective 5G network slicing model by applying different ML and DL algorithms. All the methods are adopted in developing the model by data collection, analysis, processing and finally applying the algorithm on the processed dataset. Later the appropriate classifier is determined for the model subjected to accuracy assessment. The dataset collected for use in the research work focuses on type of uses, equipment, technology, day time, duration, guaranteed bit rate (GBR), rate of packet loss, delay budget of packet and slice. The five DL algorithms used are CNN, RNN, LSTM, Bi-LSTM, CNN-LSTM and the four ML algorithms used are XGBoost, RF, NB, SVM. Indeed, among these algorithms, the RNN algorithm has been able to achieve maximum accuracy. The outcome of the research revealed that the suggested model could have an impact on the allocation of precise 5G network slicing.

Keywords*—5G network, network slicing, 5G slice, deep learning, machine learning, mobile network.

I. Introduction

Fifth-generation (5G) wireless is the most recent iteration of cellular technology, designed to significantly improve the speed and responsiveness of wireless networks. With 5G technology the wireless broadband connections may transfer data at multigigabit speed and the peak rate could reach up to 10 gigabits per second (Gbps) or more. 5G speed is faster than wired network which provides latency of around 5 milliseconds (ms) or less. This is useful for applications that need real-time input. Due to improved bandwidth and antenna technology, 5G is going to transfer more data over the wireless network [1]. Since COVID-19 pandemic, the internet is widely used in various fields and 5G technology is widely used to ensure the speed of the internet [2]. Network slicing is the prime capability of 5G and it enables numerous virtual and independent networks on a shared physical infrastructure. But in 4G and older generations of mobile network were devoid of such facility. Each network slice can contain its particular logical topology, rules of security, and performance characteristics within imposed limit by the underlying physical networks. Various slices can be utilized for different purposes, like confirming priority to specific application/service or segregating traffic for definite users or device classes. The network operators can utilize their maximum network resources for the users and they also have service flexibility.

Slicing technologies on the arena of ethernet networks are as old as virtual local area networks (VLANs). Better network flexibility can be achieved by software-defined networking (SDN) and network functions virtualization (NVF) through partitioning the network architectures into virtual elements [2]. The partitions are dynamically chosen based on requirements and specific purpose. The devoted resource changes according to the change of need. Sometimes, this is done to meet the specific customers' requirements or requirements of network security. Machine learning (ML) approaches have recently made significant strides in a wide range of application domains, particularly by deep learning (DL), reinforcement learning, and federated learning. However, rapid trend is seen in the networking world toward applying ML or DL approach to address difficult issues with network design, management, and optimization. 5G is a new technology and many countries are going to effectively use this technology for future benefit. Efficient 5G network slicing will allow the network to be used effectively. ML and DL approach can provide better solution for data slicing model in 5G technology. In this study, the authors propose an efficient 5G network slicing model by using different ML and DL approach. Therefore, this paper focuses on the purpose of determining the appropriate network slicing method based on the usage pattern, network type, used technology, time, bit rate, packet loss rate, packet delay budget, etc. Different ML and DL algorithms have been applied to the obtained dataset, the most accurate approach has been chosen, and a slicing model has been produced using that algorithm. The rest of the article layout is structured in the following sequences: Section II offers a brief literature reviews on the subject; Section III describes the system architecture and 5G environment; Section IV discusses the proposed methodology; Section V evaluates the performance; Section VI illustrates the analysis of the result; and finally, Section VII draws conclusion including future work proposal.

II. Literature Review

Different articles related to 5G network slicing with ML are consulted. Here some of the relevant articles are briefly illustrated. Those may assist to provide some useful information for the preparation of this study. M. H. Abidi *et al.* [3] intended to develop a hybrid learning algorithm for a

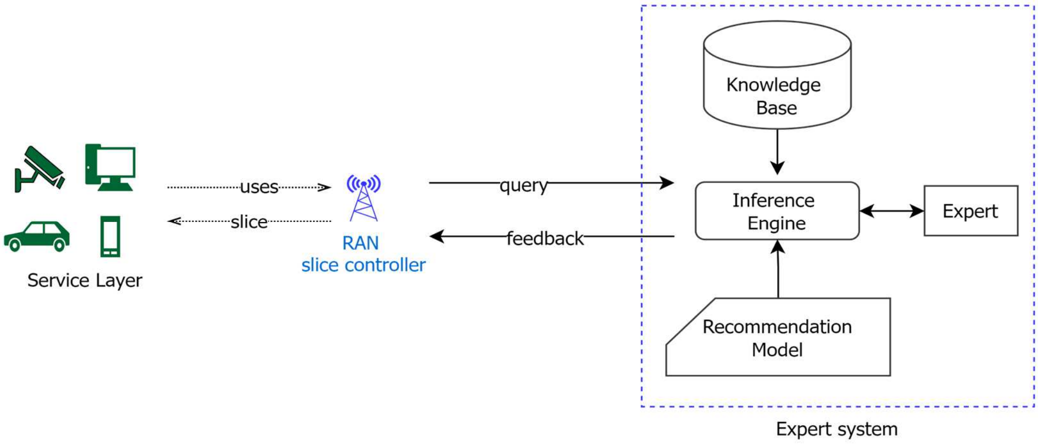

Fig. 1. 5G network slicing model with ML and DL.

successful network slicing. They have hybridized two meta-heuristic algorithms and termed the proposed model as glow-worm swarm-based deer hunting optimization algorithm (GS-DHOA). For each device, a hybrid classifier has classified the precise network slices using DL and neural networks. The GS-DHOA optimizes the weight function of both networks. M. E. Morocho-Cayamcela *et al.* [4] focused on the potential results for 5G from an ML perception. They have established the essential concepts of supervised, unsupervised, and reinforcement learning considering the existing ML concept. They have discussed the likely approaches on how ML can assist to support each targeted 5G network necessities by highlighting its specific use cases and assessing the impact including limitations on the network operation.

Z. Ullah *et al.* [5] described that the UAVs-assisted next-generation communications are highly influenced by various techniques like artificial intelligence (AI), ML, deep reinforcement learning (DRL), mobile edge computing (MEC), and SDN. A review is developed to examine the UAVs joint optimization difficulties to improve the efficiency of system. H. Fourati *et al.* [6] narrated that mobile operators are rethinking their network strategy in order to offer more adaptable, dynamic, economical, and intelligent solutions. They have discussed 5G wireless network background and the challenges including some proposed solutions to manage by ML methods.

T. Li *et al.* [7] discussed that future mobile vehicular social networks (VCNs) are anticipated to be significantly influenced by 5G networks. Higher coverage ratio vehicles are preferred and ML methods are applied to select that. J. Lam and R. Abbas [8] proposed SDS (Software Defined Security) to provide an automated, flexible and scalable network defence system. SDS will connect current advances in ML to design a CNN (Convolutional Neural Network) using NAS (Neural Architecture Search) to detect anomalous network traffic. SDS can be useful to an intrusion detection system to produce a more practical and end-to-end defence for a 5G network. I. Alawe *et al.* [9] proposed different method to scale 5G core network assets by expected traffic load changes through estimation via ML method. Recurrent Neural Network (RNN), more specifically Long Short-Term Memory (LSTM) Cell and Deep Learning Neural Network (DNN) were used and compared. Their replication results confirmed the efficiency of the RNN-based solution compared to a threshold-based solution.

S. K. Singh *et al.* [10] suggested their concept, where each logical slice of the network is separated into a virtualized sub-slice of available resources, to address the problem of network load balancing. By choosing the feature with the Support Vector Machine (SVM) technique, they were able to determine the requirements of various connected device applications. Sub-slice clusters for the similar applications were created by using K-means algorithm. The proposed framework performs better in their comparison analysis than in the current experimental evaluation research. L. Le *et al.* [11] have developed a useful and effective framework for clustering, predicting, and managing traffic behaviour for a large number of base stations with different statistical traffic characteristics of various types of cells by combining big data, ML, SDN, and NFV technologies.

P. Subedi et al. [12] proposed that network slicing enables network design to have flexible and dynamic features. To enable network slicing in 5G, the pre-existing network architecture must undergo domain modification. They enhanced network flexibility and dynamics to suggest a network slicing architecture for 5G.

Idris Badmus *et al.* [13] proposed that, the local 5G micro-operator concept will likely be deployed in a variety of ways that involve end-to-end network slicing. The anticipated architecture incorporated with multi-tenancy layer, service layer, slicing management and orchestration layer. S. S. Shinde *et al.* [14] proposed a different network function allocation issue for multi-service 5G networks. It will be able to set up network functionalities in a distributed computing environment on the service request. In their proposal, the core network (CN) and radio access network (RAN) are both taken into consideration.

S. A. Alqahtani and W. A. Alhomiqani [15] proposed an architecture on network slicing for 5G involving cloud radio access network (C-RAN), MEC, and cloud data centre. Their proposed model is created on queueing theory. The results of the investigation and the simulation model proved that the projected model has a significant influence on how many MEC and C-RAN cores are needed to meet the quality-of-service goals for 5G slices.

The background study on various publications were mostly related to network slicing and some publications have described the slicing using ML and DL. ML algorithms used SVM while DL algorithms used RNN and LSTM. In addition,

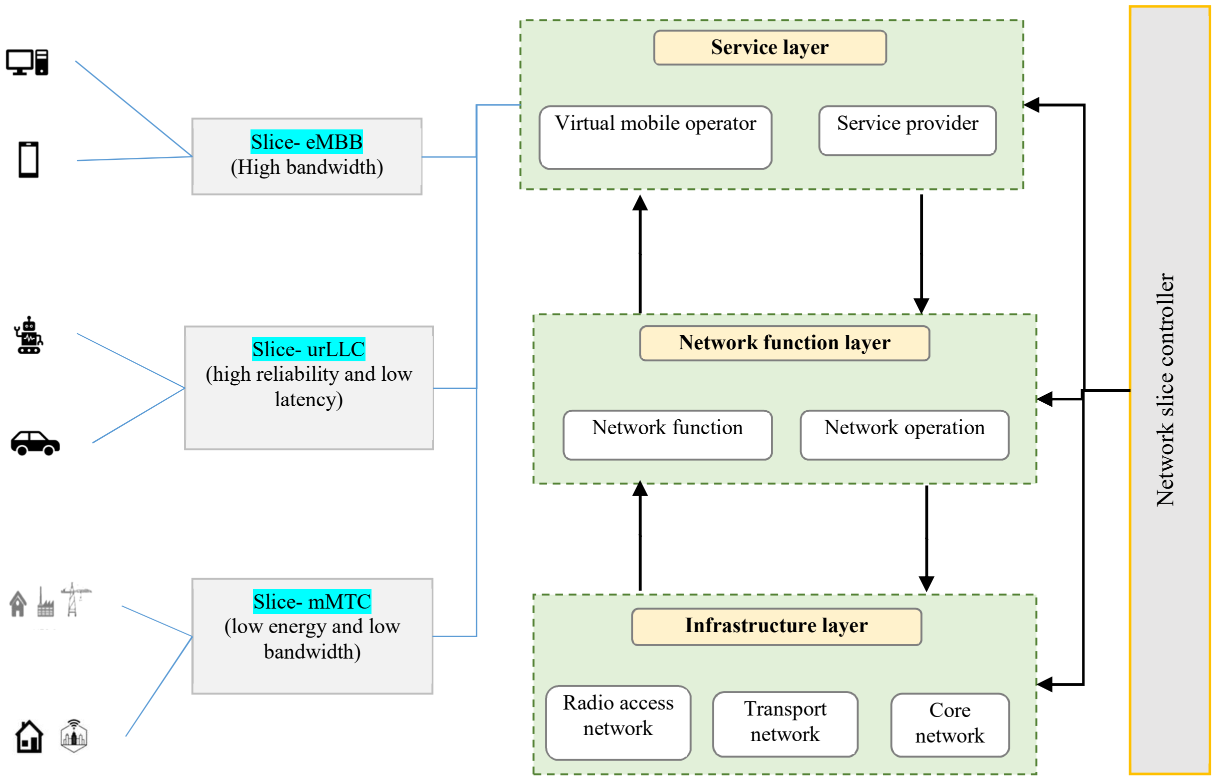

Fig. 2. Graphical overview on generic 5G network slicing procedure.

various feature extraction methods have been used by various researchers. 5G network is currently expanding its scope. The research and development activities are ongoing in this regard. Therefore, the study is conducted to develop acceptable model for 5-G network slicing by applying different ML and DL algorithms.

III. System Architecture and 5G Environment

To develop the network slicing model, the connected devices in the network including their services and services delivery requirements need to be collected for detail review. Data collection should be based on network type, network strength, bandwidth, latency, etc. Figure 1 shows an expert system approach of the network slicing model with ML and DL. Depending on the type of devices or equipment and method of use, each RAN controller will determine or recommend specific slice sizes for users based on the expert system results.

Network slicing is an end-to-end concept that covers all of the prevailing network segments. It significantly converts the entire perception of networking by extracting, isolating, arranging, and separating the logical network components from the original physical network resources, which enhance the principles of network architecture including capabilities [2]. In a network slicing, the operators can allocate the required amount of resource as per the slice. It immensely improves the operational efficiency of the network. Network operators can physically isolate the traffic of different radio networks, slice a network, blend the multiple network capacity and slice the shared resources [10]. This enables 5G network operators to choose the characteristics needed to support their target levels of spectrum efficiency, traffic capacity, and connection density, which is how many devices can connect from a given space. The generic framework of 5G network slicing and device connectivity with layers is presented in Figure 2.

Three categories have been established by the International Telecommunication Union (ITU) for 5G mobile network services [16]:

- Enhanced Mobile Broadband (eMBB): It offers mobile data access to: (i) densely populated of users, (ii) immensely mobile users and (iii) users spread over large areas. It depends on structures such as large ranges of multiple input, multiple output (MIMO) antennas and the combination of spectra beginning with 4G conventional wavelengths and extending into the millimetre band.
- Massive Machine-Type Communications (mMTC): The facilities are made to serve enormous quantity of devices in a small zone with the belief that they produce little data (about tens of bytes/ second) and can stand high latency (up to ten seconds on a round trip).
- Ultrareliable Low-Latency Communications (URLLC): It can provide secure communications with 1 ms latencies and higher reliability with zero or low packet loss. It can be achieved through a combination of: optimization of physical device, instantaneous multiple frequency handling, packet coding with process techniques and optimized signal management.

IV. Proposed Methodology

The usage of ML and DL algorithms in prior research studies on 5G network slicing has been quite limited. In this paper, ML and DL algorithms have been used based on the characteristics of the 5G network, i.e. type of uses, equipment, technology, day time, duration, guaranteed bit rate (GBR), packet loss rate, packet delay budget, slice, etc. 5G slicing dataset is collected from open source and different ML and DL algorithms are applied on it. Some processing methods are adopted to convert the obtained dataset into a utility set for application in the model. To prepare the data for processing, text data is first converted to a numerical dataset using level encoding. The original dataset is divided into two different parts with 80% of the original dataset as the training dataset and the remaining 20% of the data as the test dataset. Later, CNN, RNN, LSTM, bidirectional LSTM (Bi-LSTM), CNN-LSTM, eXtreme gradient boosting (XGBoost), random forest (RF), naïve bayas (NB) and SVM algorithms are applied with 80% of the dataset and their accuracy is determined. Figure 3 shows the whole process along with data pre-processing methodology.

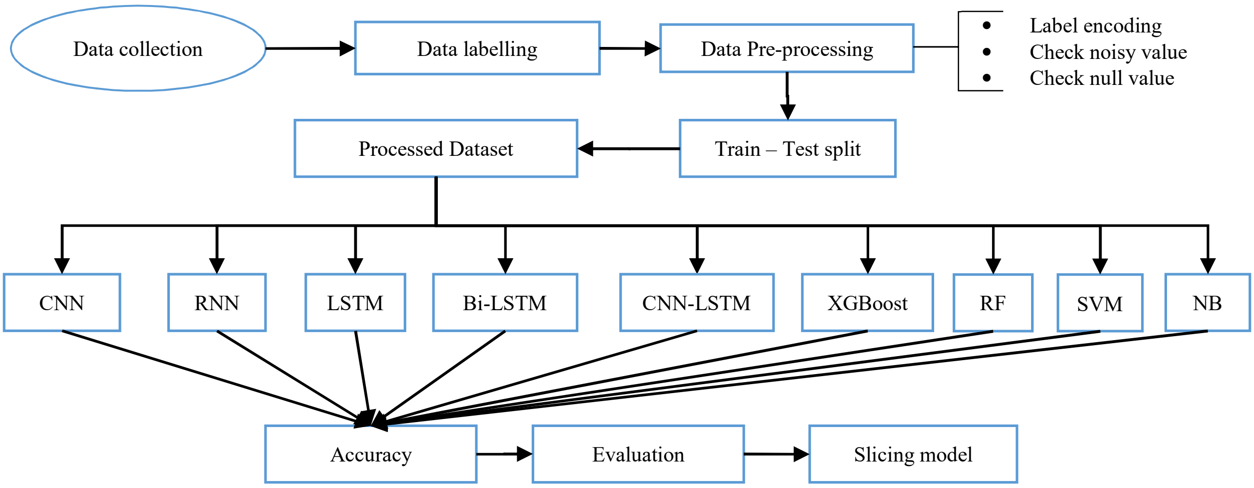

Fig. 3. Methodology used for 5G network slicing by using DL, ML models.

CNN: It is a special neural network for processing data with a grid-like topology. CNN has many layers and one of the layers is the convolution layer which is used to extract various features from the input images. Filter is applied on the input matrix and the output is received as feature map which is used in the feature extraction stage. The pooling layer is an additional layer that is utilized to reduce the dimensions without sacrificing quality. This layer also reduces overfitting as there are fewer parameters. Finally, the model becomes more tolerant towards variations and distortions.

RNN: In the field of natural language processing, it is mostly employed. RNN can process sequential data, accepting both the present and past input data. RNNs are able to recall previously obtained data, which aids in their ability to anticipate what will happen next. The RNN requires a lot of effort to train. Long sequences cannot be handled when Rectified Linear Unit (ReLu) or Hyperbolic Tangent (TANH) are used as activation functions.

LSTM: The data is modified slightly by LSTM using additions and multiplications. In LSTM, information is communicated through a method called cell states. This allows LSTM to selectively remember or forget information. LSTM networks are well-suited to processing, categorizing, and producing forecasts based on time-string data.

Bi-LSTM: It is an extension of traditional LSTM that can improve model performance on sequence classification problems. It trains two LSTMs on the input sequence as opposed to only one, where first one is the original copy and second one is the reversed copy. This can give the network an extra context and lead to a quicker and even more thorough learning process for the problem.

CNN-LSTM: Convolutional layers and maximum pooling or maximum overtime pooling layers are used in CNN models to extract high level features. Although LSTM models are more suited to text categorization because they can identify long-term connections between word sequences.

XGBoost: Recently XGBoost has topped Kaggle competitions for structured or tabular data. A distributed gradient boosting toolbox with an emphasis on portability, flexibility, and efficiency is called XGBoost. It develops machine learning algorithms utilizing the Gradient Boosting architecture. To swiftly and accurately address a variety of detection and analysis difficulties, XGBoost uses parallel tree boosting.

RF: For the aim of prediction, RF creates a vast collection of de-correlated trees. By adding randomization to the tree-growing process, it lessens tree correlation. It performs split-variable randomization. At each tree split in the RF, the feature search space is reduced [17].

NB: One of the earliest machine learning algorithms is NB. Basic statistics and the Bayes theorem form the foundation of this approach. The NB model employs class probabilities as well as conditional probabilities. To expand characteristics Gaussian distribution is used [17]. The Gaussian distribution with mean and standard deviation is described in (1).

$$p\left(x=v \mid C_k\right)=\frac{1}{\sqrt{2\pi\sigma_k^2}}e^{-\frac{\left(v-\mu_k\right)^2}{2\sigma_k^2}} \quad (1)$$

SVM: An algorithm for supervised ML is the SVM. Both classification and regression issues are addressed using this. N-dimensional space is used to hold the data items, and the values of the features are used to show the specific coordinate. Because it produces the most homogeneous points in each subsection, it is known as a hyperplane [18]. A maximum margin separator is created by SVM and is used to create decision boundaries with the greatest feasible distance. W is for weight vector and X is for is the set of points. By using (2), we can find out the separator.

$$W.X+b=0 \quad (2)$$

V. Performance Evaluation

Five DL algorithms and four ML algorithms are used in this research work. The data slicing model is chosen based on which of the nine applied algorithms will offer the highest accuracy. The performance of different ML and DL methods are displayed in Tables I and II respectively. Here it is seen that among the five deep learning algorithms, RNN has achieved the highest accuracy with 86.43%, while among the machine learning algorithms, XGBoost has been able to achieve the highest accuracy with 85.28%. Parameters used in the applied algorithms are shown in Table III.

TABLE I. Performance of DL Algorithms

Algorithm	Accuracy (%)
CNN	84.92
RNN	86.43
LSTM	83.91
CNN-LSTM	87.41
Bi-LSTM	78.32

TABLE II. Performance of ML Algorithms

Algorithm	Accuracy (%)
XGBoost	85.26
SVM	82.95
Random forest	81.93
Naïve Bayes	80.27

TABLE III. Detailed Specifications of the Algorithms Used

Algorithms	Specifications
SVM	$C = 1.0$ Kernel: radial basis function = $exp(-\gamma \, \|x - x_n\|^2)$ Gamma: scale = $\frac{1}{number\ of\ features \times X.var()}$
XGBoost	Distribution measure: Gini index, $\text{Gini}(D) = 1 - \sum_{i=1}^{m} p_i^2$ Maximum depth = 0, Minimum samples split = 2
Naïve Bayes	Distribution: Gaussian distribution = $f(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$ Mean, $\mu_y = \frac{1}{N}\sum_i x^{(i)}$, Variance, $\sigma_y = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}$
Random forest	Estimator number = 100, Maximum depth = 2, Random state number = 0
CNN	Filters = 176, Kernel size = 4, Loss function = Mean square error, Activation = rectified linear unit
RNN	Sample RNN = 156, Optimizer = Adam, Loss function = Mean square error, Input dim = 1000
LSTM	Recurrent dropout = 0.2, Spatial Dropout1D = 0.4, Loss function = Mean square error, activation = SoftMax
CNN-LSTM	CNN activation = sigmoid, Optimizer = Adam, LSTM activation = rectified linear unit
Bi-LSTM	Recurrent dropout = 0.3, activation = SoftMax, Loss function = Mean square error

VI. Result Analysis

Now a day's different expert systems, recommendation systems, detection systems, etc. are built using models created by various ML or DL techniques. The performance of the algorithms utilized in the models reveals its variation. DL is composed of neural networks and its layers interact more with each other. Therefore, the accuracy is relatively good in the case of DL or neural networks. Figure 4 shows the relative accuracy of the nine algorithms used in this study.

To determine whether the suggested network slicing system is good or not, it needs to compare with some current and pertinent studies. The suppositions used by researchers when gathering samples and disclosing the findings of their research activities when processing those samples will have a strong indication in the effort of comparing performance evaluation. Since the 5G network has not yet been fully launched in Bangladesh, it has become difficult to simulate with real-time data. The majority of the literature review of various research works revealed that only a small number of works had been done specifically for the 5G network slicing model. But there had been a sizable amount of work done on the ML scope on 5G network, 5G network features including advancement and network intrusion. Nonetheless, an effort has been made in this study to evaluate this proposed model against other studied models using criteria like accuracy and algorithm. A comparison between proposed work and other works is shown in Table IV. Since very little previous work found on 5G network slicing, therefore the comparison of proposed work is done with few other methodologies.

VII. Conclusion and Future Work

A proposed 5G network slicing model is developed using ML and DL algorithms. This model has three distinct phases: collection, preparation, and application of data. Initially the data about 5G network slicing is collected. The dataset included attributes linked with various network devices such as "type of uses, equipment, technology, day time, duration, GBR, packet loss rate, packet delay budget, and slice". With the help of nine prominent classifiers, 5G network slicing has been classified. The accuracy of the classifiers has been used

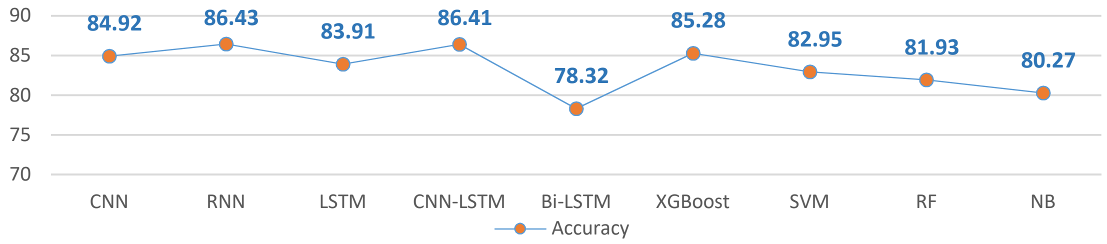

Fig. 4. Performance of algorithms used to build models for 5G network slicing.

TABLE IV. DETAILED SPECIFICATIONS OF THE ALGORITHMS USED

Articles	Problem domain	Algorithms	Outcome	Accuracy
M.H. Abidi et al. [3]	5G network slicing	GS-DHOA-NN+DBN	classified network slices using hybrid classifier using DBN	94.44%
M. E. Morocho-Cayamcela et al. [4]	Discussion on 5G network requirement, emphasizing 5G/B5G mobile and wireless communications	NM	Stimulate discussion on the role of ML on a wide deployment of 5G/B5G	NM
I. Alawe et al. [9]	Traffic forecasting for 5G core network scalability	RNN, LSTM	Load forecast on traffic arrival in a mobile network	RNN has better performance
Idris Badmus et al. [13]	end-to-end network slice architecture and distribution	NM	architecture incorporated with multi-tenancy layer, service layer, slicing management and orchestration layer	NM
Proposed Methodology	5G network slicing with ML and DL	CNN, Bi-LSTM, CNN-LSTM, RNN, LSTM, XGBoost, SVM, RF, NB	5G network slicing based on user performance	86.43% (RNN)

to gauge their merits. By examining the outcomes of subsequent identical works, the relative qualities of the results obtained have been evaluated. The study achieved an accuracy of 86.43% with RNN classifier, which is good as well as promising. There remains a potential future work with a very large set of 5G network data.

REFERENCES

[1] N. Al-Falahy and O. Y. Alani, “Technologies for 5G Networks: Challenges and Opportunities,” IT Professional, vol. 19, no. 1, pp. 12-20, February 2017.

[2] X. Li, M. Samaka, H. A. Chan, D. Bhamare, L. Gupta, C. Guo, and Raj Jain, “Network Slicing for 5G: Challenges and Opportunities,” IEEE Internet Computing, vol. 21, no. 5, pp. 20-27, September 2017.

[3] M. H. Abidi, H. Alkhalefah, K. Moiduddin, M. Alazab, M. K. Mohammed, W. Ameen, and T. R. Gadekallu, “Optimal 5G network slicing using machine learning and deep learning concepts,” Computer Standards and Interfaces, vol. 76, pp. 103518, June 2021.

[4] M. E. Morocho-Cayamcela, H. Lee, and W. Lim, “Machine Learning for 5G/B5G Mobile and Wireless Communications: Potential, Limitations, and Future Directions,” IEEE Access, vol. 7, pp. 137184–137206, September 2019.

[5] Z.Ullah, F. Al-Turjman, U. Moatasim, L. Mostarda, and R. Gagliardi, “UAVs joint optimization problems and machine learning to improve the 5G and Beyond communication,” Computer Networks, vol. 182, pp. 107478, December 2020.

[6] H. Fourati, R. Maaloul, and L. Chaari, “A survey of 5G network systems: challenges and machine learning approaches,” International Journal of Machine Learning and Cybernetics, vol. 12, no. 2, pp. 385-431, August 2020.

[7] T. Li, M. Zhao, and K. K. L. Wong, “Machine learning based code dissemination by selection of reliability mobile vehicles in 5G networks,” Computer Communications, vol. 152, pp. 109–118, February 2020.

[8] J. Lam and R. Abbas, “Machine Learning based Anomaly Detection for 5G Networks.” arXiv, 03474, March 2020.

[9] I. Alawe, A. Ksentini, Y. Hadjadj-Aoul, and P. Bertin, “Improving Traffic Forecasting for 5G Core Network Scalability: A Machine Learning Approach,” IEEE Network, vol. 32, no. 6, pp. 42–49, November 2018.

[10] S. K. Singh, M. M. Salim, J. Cha, Y. Pan, and J. H. Park, “Machine Learning-Based Network Sub-Slicing Framework in a Sustainable 5G Environment,” Sustainability, vol. 12, no. 15, pp. 6250, January 2020.

[11] L.V. Le, D. Sinh, B.S. P. Lin, and L.P. Tung, “Applying Big Data, Machine Learning, and SDN/NFV to 5G Traffic Clustering, Forecasting, and Management,” 2018 4th IEEE Conference on Network Softwarization and Workshops (NetSoft), pp. 168–176, June 2018.

[12] P. Subedi, A. Alsadoon, P. W. C. Prasad, S. Rehman, N. Giweli, M. Imran and S. Arif, “Network slicing: a next generation 5G perspective,” EURASIP Journal on Wireless Communications and Networking, vol. 2021, no. 1, pp. 102, 2021, April 2021.

[13] I. Badmus, A. Laghrissi, M. Matinmikko-Blue and A. Pouttu “End-to-end network slice architecture and distribution across 5G micro-operator leveraging multi-domain and multi-tenancy,” EURASIP Journal on Wireless Communications and Networking, vol. 2021, no. 1, pp. 94, April 2021.

[14] S. S. Shinde, D. Marabissi, D.Tarchi, “A network operator-biased approach for multi-service network function placement in a 5G network slicing architecture,” Computer Networks, vol. 201, pp. 108598, December 2021.

[15] S. A. AlQahtani and W. A. Alhomiqani, “A multi-stage analysis of network slicing architecture for 5G mobile networks,” Telecommun Syst, vol. 73, no. 2, pp. 205–221, February 2020.

[16] P. Popovski, K. F. Trillingsgaard, O. Simeone, and G. Durisi, “5G Wireless Network Slicing for eMBB, URLLC, and mMTC: A Communication-Theoretic View,” IEEE Access, vol. 6, pp. 55765–55779, September 2018.

[17] J. Han, M. Kamber, J. Pei, Data Mining Concept and Technique, 3rd Edition, Morgan Kaufmann, 2012, pp. 332-398.

[18] S. J. Russell, and P. Norvig, Artificial Intelligence a Modern Approach, 3rd Edition, Upper Saddle River, NJ: Prentice Hall, 2010, pp. 725-744.