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Efficient and reliable hybrid deep learning-enabled model for congestion control in 5G/6G networks

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A R T I C L E I N F O

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LSTM

A B S T R A C T

Future generation networks such as millimeter-wave LAN, broadband wireless access systems, and 5th or 6th generation (5G/6G) networks demand more security, low latency with more reliable standards and communication capacity. Efficient congestion control is considered one of the key elements of 5G/6G technology that allows the operators to run various network instances using a single infrastructure for a better quality of services. Artificial intelligence (AI) and machine learning (ML) are playing an essential role in reconfiguring and optimizing the performance of a 5G/6G wireless network due to a vast amount of data. A smart decision-making mechanism is required for the incoming network traffic to ensure load balancing, restrict network slice failure and provide alternate slices in case of slice failure or overloading. To circumvent these issues, a hybrid deep learning-enabled efficient congestion control mechanism is proposed in this paper. This hybrid deep learning model consists of long short term memory (LSTM) and support vector machine (SVM). The applicability of the proposed model is validated by simulating for one week using multiple unknown devices, slice failure conditions, and overloading conditions. An overall accuracy rate of 93.23% is calculated for the proposed hybrid model that reflects the applicability. Apart from this, other performance metrics such as specificity, recall, time consumption, varying training, test sets, true-false rates, and f-score were used for the performance evaluation purposes of the proposed model.

1. Introduction

In the current era of the technological age, mobile communication is considered one of our essential needs. The significant increase in communication devices demands high bandwidth, resource allocation, and the services required to fulfill the basic needs of this generation [1]. The rapid evolution of communication technology from 2G toward 4G and the upcoming 5G and 6G is a prominent example [2]. The current applications of communication devices require high throughput and bandwidth capacity to provide reliable and potential services for all the incoming network traffic. Among the many challenges, seamless operation and management are always considered a big hurdle for the service providers in a heterogeneous wireless networking environment [3]. Service providers continually struggle to develop an ideal model capable of providing reliable services and fulfilling customers' demands. 5G network technology was proposed to fulfill the demands of customers and provide optimum services. The 5G technology is an extended version of the long term evaluation (LTE) or the 4G LTE network, aims to provide higher bandwidth capacity, throughput, and better quality of services. High performance and reliability require reconfigurability to meet optimum network requirements. Apart from the reliability, simplicity and deliberately introducing the redundant information, it is required to gain high load balancing, throughput, reliability and power. Reconfigurability offers three primary services: reliability, performance, and power awareness. It allows the system to adapt two-fold: (1) to recover from a permanent fault and (2) to fulfill the requirements of the running application [4]. Anwar et al. [5,6] proposed a systematic review and developed a resource-efficient model for mobile PMIPv6 networks.

The 5G technology provides a richer mobility experience in terms of its services, infrastructure, and an extensive range of operations. These will open doors for researchers and provide many opportunities to mobilize application areas such as entertainment, seamless mobility, traffic monitory, remote monitoring, IoT services, healthcare, etc. Based on the specification of the third generation partnership, network reconfiguration and slicing is considered to be one of the key elements

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of the 5G network [7,8]. Reconfigurability and network slicing help the operator improve the quality of services by providing a portion of their network based on the customer's specifications. Network slicking ultimately helps the service provider allocate the required number of resources to the incoming network traffic requests instead of offering all the available resources. Prominent applications of network slicing result in reducing the latency as well as the adequate bandwidth required. For example, network slicing in a vehicle-to-infrastructure application where at the same time people may watch a movie and drive an autonomous car. Although a movie may require high bandwidth for surfing, the car sends crucial signals for its normal operations. In such cases, priority should be given to the car's communication instead of allocating high bandwidth to movies [9]. To address such problems, network slicing is the optimal solution for allocating resources based on the needs of a certain application. As a result of network slicing, the operator will use a single infrastructure for allocating available resources to different use cases and applications with improved service qualities [3,10]. All the incoming network traffic and allocated devices must be critically monitored and analyzed to achieve high quality of services and optimum resource utilization. In addition to several challenges, security attacks in a heterogeneous wireless environment are also a severe threat, affecting the network's performance.

In providing optimum decision-making capabilities in many critical environments, machine learning has proven its potential in various application domains such as medical imaging, vehicular networks, traffic monitoring, and so on [11,12]. In 5G network environments, machine learning algorithms are efficient tools in monitoring the status of different devices and performing statistical analysis of network slices, analyzing a vast amount of data generated during communication and important decision-making purposes. Machine learning algorithms are extensively used in many research fields such as traffic management [13], network security [14,15], object detection [16], and many others. It provides an optimized utilization of mobile tower operation based on resources requirements, timely decision-making capabilities in IoT networks, and real-time analysis of incoming traffic and devices [17]. Togou et al. [18] proposed a blockchain-based request provisioning system for the dynamic leasing of network resources among network operators to support cross-domain services. Narsani et al. [19] developed a multihop wireless network inside a factory environment using multiple network devices to evaluate it using Industry 4.0 perspectives. Reconfigurable wireless network slicing is a powerful application for 5G/6G wireless networks, commercial businesses, and mobile operators. It is considered as one of the key elements for 5G technology. It allows the operators to execute numerous network instances using a single infrastructure for a better quality of services. In order to develop an intelligent decision-making mechanism for incoming network traffic, to ensure load balancing, restrict network slice failure, and provide alternate slices in case of slice failure or overloading conditions, a machine learning-based reconfigurable wireless network solution is required. Prime objectives of this research study include:

- To efficiently serve all the incoming network traffic accurately and precisely by providing optimum bandwidth facilities with high satisfaction.
- To ensure no overloading of network slice, restrict slice failure, accurately assignment of network slice to incoming network requests. The main concern of this objective is to ensure no cross-talk or slice failure conditions.
- To allocate alternate slice (master file) during failure of the slices or during the overloading of a slice to ensure no congestion.

The rest of the paper is organized as follows; Section 2 outlines the related work reported in the proposed field. Section 3 outlines the proposed methodology. Section 4 details the experimental setup of the proposed model. Section 5 outlines the performance analysis of the proposed model. In contrast, the results and discussion are explained in Section 6, followed by Section 7.

2. Background study

The following subsections show the background study of the proposed research.

2.1. 5G/6G network slicing

5G network is the evolution of the LTE network with a wide range of operations and functionality. Compared to the LTE, it is more flexible, scalable to be adopted for diverse use cases. Network slicing in the 5G network provides flexibility and ease of creating multiple logical networks over shared physical infrastructure. AI and machine learning are considered decision-making tools for predicting and making various decisions in a slicing-based network environment [12,20,21]. Detail of the efforts made in the literature is given as follow.

Oladejo and Falowo have explored 5G network slicing by examining the effect of the number of transmit power and the users on the MVNO's capacity [17]. The study conducted by Ma et al. [22] has defined the NFV and the SDN 5G core network architecture. Furthermore, Du and Nakao [20] have applied deep learning models for radio spectrum scheduling in RAN-oriented problems. Finally, Abhishek et al. [23] have proposed a priority management solution for smart cities where the prioritization of network traffic is managed.

A study conducted by Yoo [10] provides information for selecting network slices, their standardization, and different slice-independents functions. Furthermore, for slicing and RRC frame, the author also proposed architecture. Kurtz et al. [24] have worked on the 5G new radio air interface. The proposed study uses the NFV and SDN work on slicing to show the potential ability to provide service guarantees and the dynamic data rate allocation in the radio air interfaces. In a study, the matrix exponential distribution represents handovers for emergency communications and the public's safety [25]. Their work has provided a more accurate decision regarding handovers by including different parameters in their decision process. Finally, Abhishek et al. proposed a framework that represents network virtualizations with multiple providers that necessitate the network slicing in the 5th generation network [26].

Another study performs the selection and assignments of virtual networks or its slices and then assigned based upon the QCI. The security requirement associated with the service requested [8]. Campolo et al. [27] provided their vision on V2X network slicing by identifying the major requirements and then a set of guidelines for network slicing. These guidelines are aligned with the standards of 3GPP specifications. Addad et al. [7] have proposed a model that provides a cost-efficient deployment of network slices. The model allows mobile network operators in allocating underlying resources according to the requirements of their associated users. However, the requirement of multiple services requested from the same device has not been considered in their work. An another study provides mathematical model for providing demand based slice isolation in addition to the guarantee end-to-end delay in 5th generation network slices [28]. Their proposed solution also reduces the chances of distributed network attack such as denial of service in 5th generation core.

Furthermore, several provisional models are introduced for third party slices by [29]. Their study also provides detailed discussion regarding the isolation properties. A more safe, efficient, service-oriented authentication framework that supports fog computing and network slicing for the 5th generation enabled IoT services are provided by Ni et al. [30]. In addition to their proposed framework, a mechanism for preserving configured types of slices and accessing service types of users. Thantharate et al. [31] demonstrated three variant models by using MQTT and CoAP protocol. The main aims of their demonstrations are to provide better mechanisms for OTA delivery of security patches and the software updated to IoT devices. For the detection of intrusion or attacks in the 5th generation network, internet of thing (IoT) network for flooding, injection kind of threads and impersonation, Rezvy et al. [21] proposed a neural network algorithm based solution named as deep auto-encoded dense neural network algorithm.

2.2. Role of machine learning in 5G/6G network slicing

Machine learning has shown tremendous potential in various application domains for solving decision-making problems and predictions. Such examples include health care, medical imaging, route selection, data manning, decision support system, and resource allocation in the network environment [11,12]. Rapid growth in devices and user demands regarding mobile communication results in high-speed 3G, 4G, and upcoming 5 G networks. Due to the richer mobility, reliability, and services associated with the 5G network, the operators are constantly working to cooperate with these features to attract more users and provide a better quality of services [3,32]. Among the prominent feature of 5G technology, network slicing is one of the critical elements which will allow the operator to customize their capabilities and services according to the need of use cases in the networking environment [10,17]. Network slicing provides a cost-effective solution for resource efficiency and improves the quality of services (QoS). A 5G network will revolutionize the shape of communication in many areas include media, entertainment, healthcare, social media interaction, networking capabilities, autonomous driving due to its high support for bandwidth and richer set of services [3]. All of these services and a huge amount of data during communication will require intelligent decision-making supports and predictive decision making for better resources utilization and performance efficiency.

In 5G network slicing, AI and ML support will pave the way in taking the automatic decision making and prediction regarding resource assignments, identifying application requirements by monitoring the network traffic and devices status. Machine learning has shown its potential in many applications. A huge amount of data traffic will be involved in 5G mobile communication from a large number of devices [32]. Automatic network analysis will effectively analyze network traffic and make the most optimal decision and prediction to efficiently adjust the services to different slicing. Analysis of big data will provide helpful insight for the adaptability of network services to avoid network congestion. Deep learning for automation in 5G slicing will achieve the task of resources utilization without the intervention of human. Furthermore, automatic monitoring and real-time data analysis will improve the slice network performance, detection fraud, security of the communication, and load management. Experts are actively exploiting machine learning and deep learning to improve the reliability, efficiency, and performance to provide cost-effectively and improve the quality of services to the end-users [8,21,30]. A typical deep neural network (DNN) model is shown in Fig. 1. It consists of an input layer, hidden layer(s) and output layer.

In the proposed study, a hybrid AI-based solution is provided for optimizing the efficiency of 5G network slicing in the context of load balancing, accurate resource allocation and restriction of network slice failure and alternate assignment of devices involved in the communication process. Furthermore, researchers are actively working in providing AI and Deep learning-based solutions for improving the efficiency of 5G network slicing.

3. The proposed hybrid model for reconfigurable network slicing

Reconfigurable wireless network slicing is an innovative feature of the next-generation wireless networks that encourages mobile operators and commercial business tycoons to ensure no traffic congestion. It is considered as one of the key elements for 5G/6G technology. An intelligent decision making architecture is required to ensure load balancing, restrict network slice failure and provide alternate slices in case of slice failure or overloading conditions. To address these critical problems and present a model to predict unknown network requests efficiently, perform load balancing, optimum utilization of resources, and restrict network slice failure, a hybrid deep learning-based model is proposed in this research work which consists of LSTM and SVM algorithms. The LSTM algorithms are handy in detecting network traffic, allocation of network slice and accurate resource assignment, while the SVM algorithms are used for statistical performance like; load balancing in the network slices, assignment of an alternate slice (master file) in case of a network slice failure, accurate assignment of network resources. After validating the proposed model for varying training and test sets, time consumption, unknown devices requests, slice failure, slice overloading, imbalanced allocation of resources and accuracy. The proposed model outperformed by generating an accuracy rate of 93.23%, reflecting the proposed model's applicability for the defined different scenarios. Fig. 2 depicts the proposed hybrid model consisting of input unknown devices and LSTM and SVM based recognition models.

Mostly, the SVM showed high capabilities for classifying both linear and non-linear classification problems [33,34]. Based on the quadratic function, the optimum recognition results can be calculated using the regularization parameter. Different kernel-based functions are suggested in the proposed work, including radial-based functions, polynomial Kernel, sigmoid, and linear functions.

- Linear Kernel – $H(i,j) = i \times j$
- Sigmoid Kernel – $H(i,j) = \tanh\langle \beta_0 ij + \beta_1 \rangle$
- RBF (Radial Basis Function) Kernel – $H(i,j) = e^{(-\gamma \|i-j\|^2)}$
- Polynomial Kernel – $H(i,j) = [(i \times j) + 1]^d$

With d, β_0, β_1 and γ are the metrics that are empirically measured using Eq. (1).

$$f(x) = W^T \theta x + j \tag{1}$$

Where $w \in R$ and $b \in R$ and $\theta(x)$ is feature set.

Besides many application of the SVM classifier, one of the reasons for using this technique is it is easy to implement, provide optimum results within a limited time, and is computationally smart. Transformation can be performed using the non-linear operator $\theta(x)$ to draw inputs a_i, b_i into high dimensional space. Eq. (2) reflects the optimum hyper-place represented below.

$$f(x) = sgn(\sum b_i x_i M(a_i, a) + y) \tag{2}$$

while $M(a_i, a) = e^{(-\gamma \|a_i - a\|^2)}$ is the Kernel-based function. The algorithm for the proposed hybrid model is given below.

4. Experimental setup

The neural network plays a prime role in the industrial revolution and has shown extensive applications, including; internet security [35,36], text recognition [37,38], wireless localization for indoor navigation purposes [39,40], healthcare [41], and many others. However, accurate analysis and quick decisions regarding a particular input device are too difficult for a human. A machine learning-based hybrid model is proposed to address this problem, which is given in Fig. 3, capable of deciding which network slice is suitable for a new connected device. The proposed hybrid model also aims to detect network load, slice failure and the decision to adjust a particular network slice for the newly connected unknown device. For calculating and statistical purposes, a support vector machine is used in this research work. In contrast, an artificial neural network based on the LSTM model is proposed for deep slice purposes. These classification models (SVM and LSTM) are trained using the same dataset [42] consisting of 65000 unique entries.

This dataset consists of the key performance indicators (KPIs) regarding networks and devices. It consists of the type of devices (IoT-based devices, smartphones, URLLC devices, and many others) connected to the internet, user equipment (UE) category, QoS class identifier (QCI), maximum packet loss, packet delay budget, day and time information, weather conditions (normal condition or harsh conditions) and many others. As depicted in Fig. 3, multiple devices include healthcare to personal use devices, smartphones to vehicle systems, athletes'

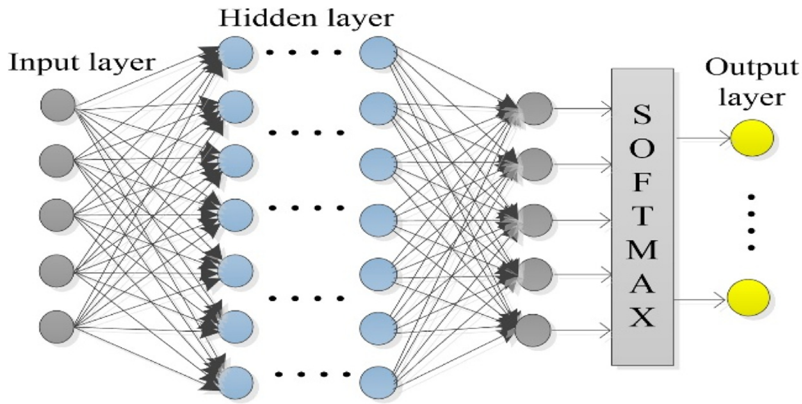

Fig. 1. Typical DNN model.

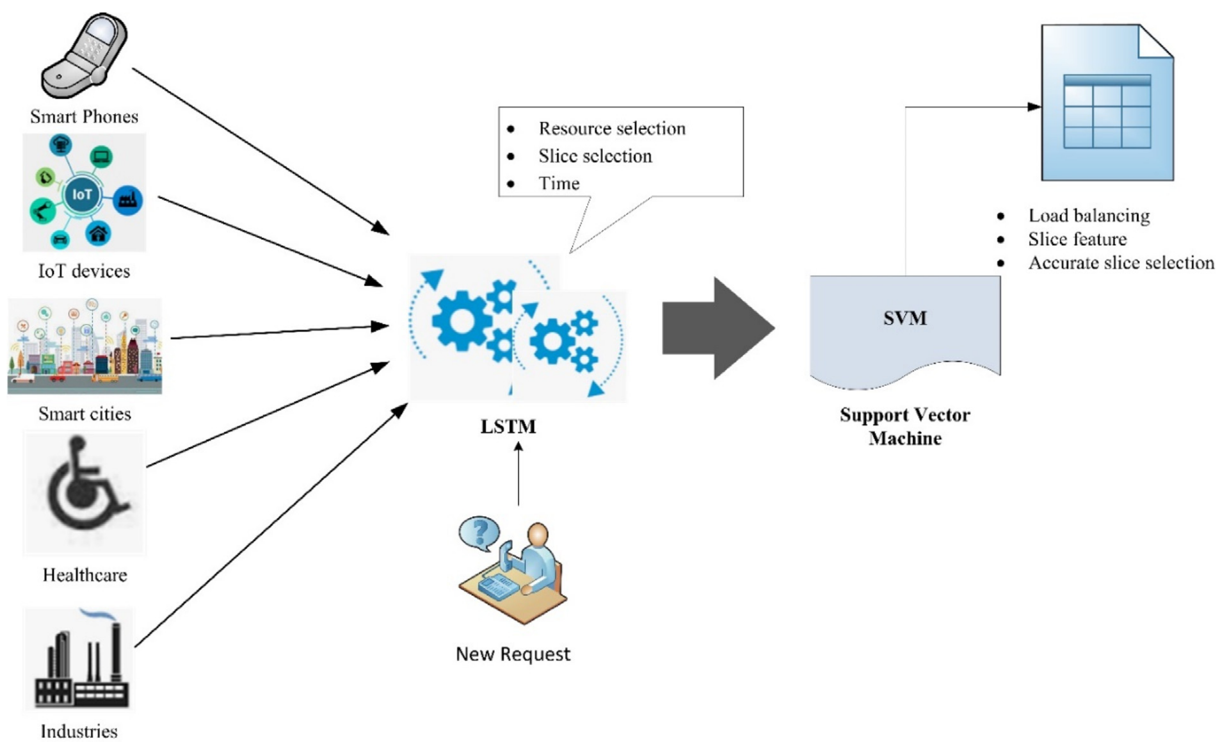

Fig. 2. Proposed hybrid model.

performance measures to physical performance measures, and requests for one or multiple sources. The proposed hybrid model will also keep weekly information regarding multiple requests received in the system. Resultantly, this information will be used by the proposed hybrid model for future allocation and available resource reservations.

LSTM model is an enhanced version of the back-propagation neural networks. In this study, the LSTM model is used to decide the network slice for the incoming new network request. At the same time, the SVM checks the network slices' resource utilization. Different parameters used to develop the LSTM model in the proposed research work are detailed in Table 1.

Table 1
Parameters of the LSTM model.

Parameter	Value
Total number of layers	5
Number of hidden layers	3
Activation function	Rectified linear unit
Performance metrics	Load balancing, slice failure, alternate slice allocation capabilities, time, F-measure, specificity, accuracy, true-false values, varying training and test sets

5. Performance evaluation

The performance of this hybrid deep learning-based model is evaluated by developing a simulating model in python using Tensor-Flow and Keras libraries. These libraries are the best practicing tools for neural network-based architectures development purposes. Performance of multiple connected devices is tested based on request duration, packet-loss rate, packet-delay budget, and slice prediction. Overall performance results are depicted in Table 2. During the simulation phase, some variations are considered in the traffic types; MTC devices are further classified into two broad classes (1) the devices that require a non-interrupted connection and (2) the devices that require a momentary-based connection to send data periodically. Common people mostly use smartphone devices for calling, web-browsing.

Algorithm: To model reconfigurable wireless network slicing in 5G network

Input: Different device types (smartphones, healthcare devices, IoT devices, smart homes, automotive, industrial devices, and so on)
Output: Network slicing, load balancing, no network slice failure, alternate network slice for incoming network traffic in case of slice failure

```
Start
Step 1: initialize eMBB as an empty vector of length k
        initialize mMTC as an empty vector of length k
        initialize URLLC as an empty vector of length k
        initialize mFile as an empty vector of length k      // mFile represents "master file"
Step 2: initialize function = 0                 // to check the functionality of a certain network slice
Step 2: initiate network request based on different input types, req

  for i = 1 … k do

// to control load balancing in different network slices
        s1 = eMBB_k/sizeof(eMBB) × 100      // returns the % age size utilized for eMBB slice
        s2 = mMTC_k/sizeof(mMTC) × 100      // returns the % age size utilized for mMTC slice
        s3 = URLLC_k/sizeof(URLLC) × 100    // returns the % age size utilized for URLLC slice
        s4 = mFile_k/sizeof(mFile) × 100    // returns the % age size utilized for mFile slice

     if (function)
        if (high throughput && s1 < =93%)      // above 93% is followed as overloading in our case
          eMBB_k = req_i                       // in case of high throughput device should be assigned eMBB slice
        ElseIf ((reliability && low latency) && s2 <=93%)
          mMTC_k = req_i
        ElseIf ((low throughput && high density) && s3 <=93%)
          URLLC_k = req_i
        Else
          mFile_k = req_i                      // if size exceeds 93% then master file resources must be allocated   // to the incoming network traffic
    Else
     mFile_k = req_i                           // if a certain network slice fails then the requests are automatically    // assigned to master file
    End if

  End for
```

Meanwhile, these devices also act as first responders in emergencies (requiring lower packet loss and packet delay scenarios). The proposed pre-defined slice categories contain enhanced Mobile Broadband (eMBB), massive Machine Type Communication (mMTC), Ultra-Reliable Low Latency Communication (URLLC), and the Master slice. The Master slice has the network functionalities of all the corresponding network slices. This slice can be followed as a backup slice in hot standby and provides resources to other slices based on hard load situations on other slices.

Using the incoming traffic information and track records of the corresponding output network slice (utilization), the statistical information on a specific network slice can be accurately identified using the proposed hybrid model. It also helps in efficiently allocating all the incoming network traffic to the desired network slice. Deep neural network (DNN) architecture is handy when there are no clear rules to deal with each incoming device type. For example, cellular handover depends upon various network factors, including timely allocations, accurate resource allocations, etc. With each new incoming request, a smart decision model must automatically learn and adapt very quickly to meet the incoming requests' changes or the new requirements. DNN can help in such cases to accurately identify and accommodate the unknown requests in the corresponding network slices.

For training, in the proposed model, 70% of the data is used for training purposes. In comparison, the remaining 30% is used for testing purposes. Fig. 4 depicts the simulation results of the hybrid deep learning model executed for the first 20 h. After completion, it provides the number of users being served at a particular interval of time. To test the applicability of the proposed model, the model is tested consecutively for three days for 24 h and outperformed by generating efficient results.

In a 20-hour simulation, approximately half a million unknown user connections were requested and generated 40% for eMBB, 25% for mMTC and 35% for URLLC. For the proposed model, the plot begins when the model reaches a steady state. In Fig. 3, it is marked as 1st hour. As depicted in Table 2, all the new traffic has a pre-defined time-to-live (TTL) value, and so a request remains alive for a small value (a fraction value of a second). For example, at any particular interval, eMBB active user average count was 200. URLLC and mMTC users were allocated short TTL compared to the eMBB because there are more active users for broadband services in our case. This will ultimately help analyze user patterns and make optimum decisions using the accumulated information retrieved from the requested unknown devices.

A hybrid deep learning model will finally decide which device will be assigned to which one slice. It will ultimately help the network model prepare for any new incoming connections to be allocated appropriate resources in advance to ensure no delays laterally.

6. Results and discussions

This section of the paper outlines the performance analysis of the proposed hybrid model in terms of load balancing, slice prediction and

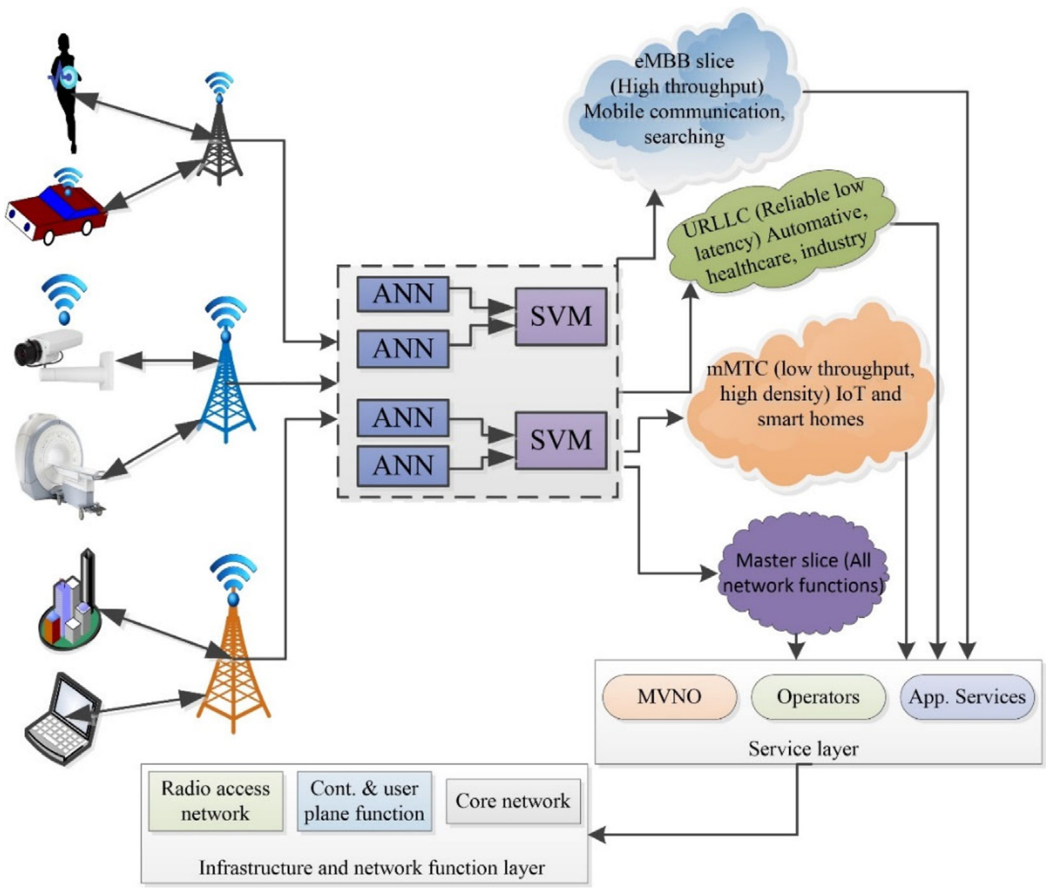

Fig. 3. Proposed methodology.

Table 2
Performance evaluation of proposed hybrid slicing model.

S.no	Devices	Packet loss rate	Packet delay budget (ms)	Duration (s)	Slice identified
1.	Healthcare	10^{-6}	10	200	URLLC
2.	Intelligent transportation	10^{-6}	10	50	URLLC
3.	Smart cities	10^{-3}	50/300	90	mMTC
4.	IoT devices	10^{-3}	50/300	50	mMTC
5.	Smart phones	$10^{-3}/10^{-6}$	60/75/100/150/300	250	eMBB
6.	Industry 4.0	$10^{-3}/10^{-6}$	10/50	160	mMTC/ URLLC
7.	Unknown devices	$10^{-3}/10^{-6}$	10/50/60/75/100/150/300	40/110/190	eMBB/ mMTC/ URLLC

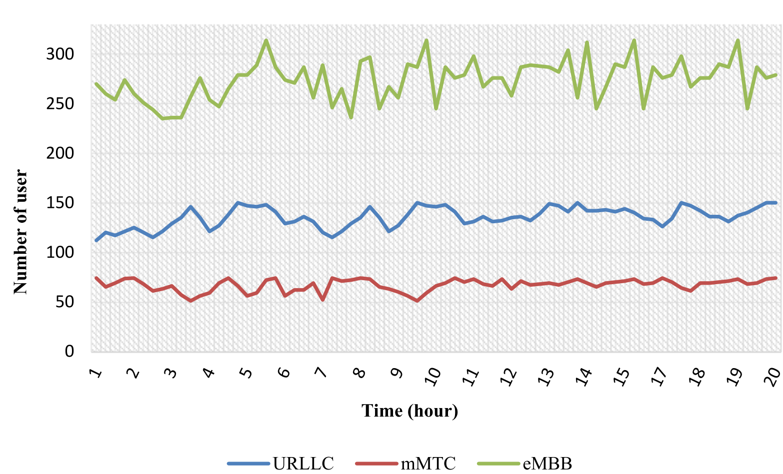

Fig. 4. Number of active users observed after every 10 min.

Table 3
Slice prediction and assignment for unknown devices.

S.no	Device type	Technology	Packet		Slice identified
			Loss-rate	*Delay-budget*	
1.	Requested device – 1	LTE/5G or IoT	10^{-2}	100	mMTC
2.	Requested device – 2	LTE/5G	10^{-6}	10	URLLC
3.	Requested device – 3	LTE/5G	10^{-3}	50	eMBB/mMTC
4.	Requested device – 4	IoT	10^{-6}	150	eMBB
5.	Requested device – 5	IoT	10^{-3}	180	eMBB

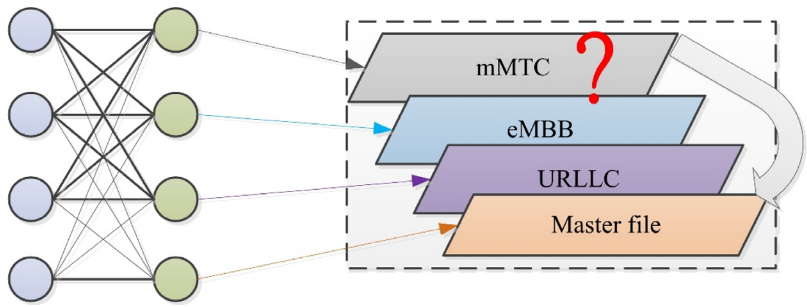

Fig. 5. Load balancing model for slice overloading conditions.

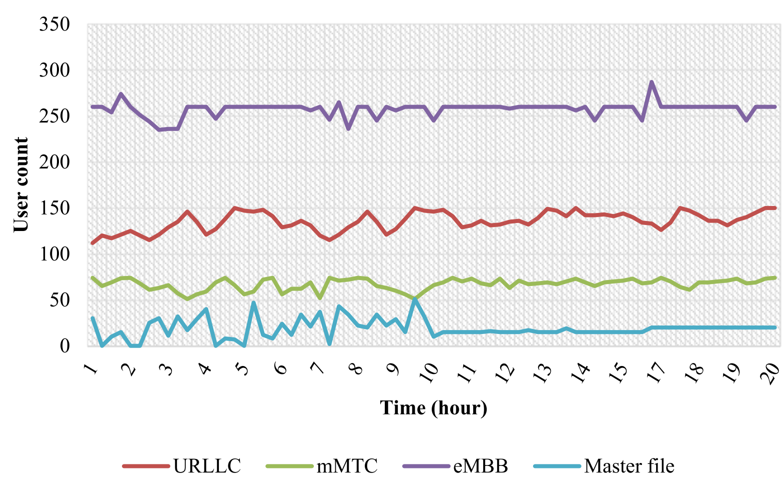

Fig. 6. Load balancing when connection requests exceed a certain pre-defined limit.

network availability. To test the applicability of the proposed model, three different scenarios are calculated in this research work:

- **Accurate slice assignment –** To define criteria to accurately assign the network slices to an unknown device type, requesting network resources.
- **Load balancing –** Load balancing aims to utilize the available network slice resources efficiently. All the incoming new requests will be directed to the master file if a particular network slice is reported to exceed a certain threshold defined. Suppose the limit is below that particular threshold value. In that case, our model will assign the request to that particular network slice until it reaches that particular limit. In our case, we have selected a threshold value of 93% of its total utilization.
- **Slice failure scenario** – If a slice fails to allocate required resources to the newly requested connection, all these connections will be routed to the master slice instead of resisting any connection.

The hybrid model will capture the time and other relevant information regarding slice failure in a specific situation that will ultimately make the model smart in deciding before assigning a slice to the requested device types. Also, it helps in advance preparing for the proposed model.

These scenarios are discussed in detail below to validate the proposed model.

6.1. Accurate slice assignment

The proposed hybrid deep learning model is trained for multiple input types (smartphones, smart cities, healthcare devices, and so on) based on network and device KPIs. An overall accuracy rate of 93.23% is calculated, as depicted in Fig. 8. The model is also tested for unknown input types with random parameters. Slice prediction accuracy was 96.46% for unknown requested devices. Table 3 reflects 5 unknown devices requested and the corresponding information regarding network slice assigned, packet loss measured, the technology used, and packet budget rate recorded.

6.2. Load balancing

The proposed hybrid model is also validated for overloading scenarios. If the newly requested connections exceed a certain threshold value, we select 93% utilization of the slice. For example, Fig. 5 shows that an mMTC slice exceeds 93% utilization i-e exceeded the defined threshold value. The incoming traffic is automatically assigned to the master slice (a backup file for any new mMTC requests/connections).

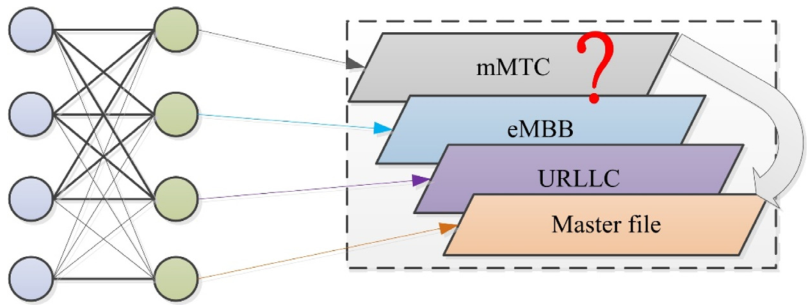

Fig. 7. mMTC slice failure and redirection to master file to overcome failure conditions.

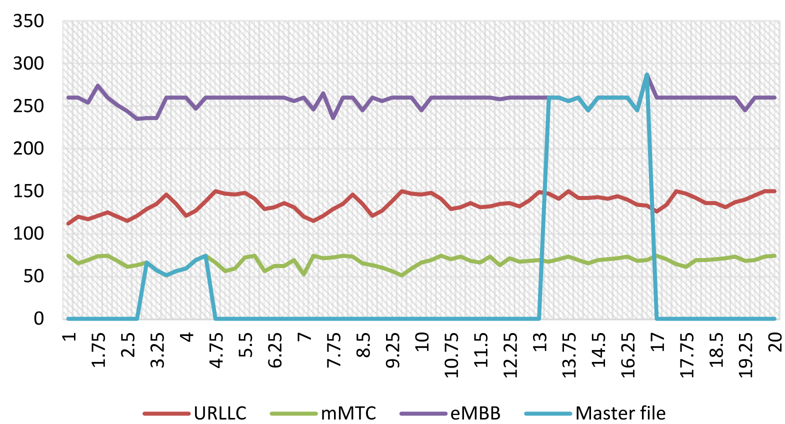

Fig. 8. mMTC slice failure and redirection to master slice.

Our hybrid model can accurately identify this overloading scenario and redirect new incoming traffic to the master slice to avoid resulting overloading conditions. After comparing the overloading condition in Fig. 5, the master slice assigns the required resources to the overloaded new connections, as depicted in Fig. 6.

6.3. Slice failure conditions

To check the applicability of the proposed model, a complete slice failure condition is tested using the proposed hybrid model. For experimental analysis, we assumed the failure of an mMTC slice, as depicted in Fig. 7. The proposed model will route all the new mMTC related traffic to the master slice to handle this scenario while avoiding any transmission loss. However, this process will impact all the ongoing communication on that particular slice. It also results in sudden slice failure conditions because of connection loss.

Fig. 8 depicts that the proposed model showed a failure state for the mMTC slice for two hours and fifteen minutes ranging from 2:30 h to 4:45 h on the mMTC slice for one period and another four hours 13 h to 17 h. During this experimental analysis, the master slice was found as a backup file that accurately routed all the network traffic during these failure conditions.

The model is also tested for the whole week for both day and night timings based on varying training and test sets and time information to ensure the model's applicability in both of these conditions. As a result, an overall accuracy rate of 93.23% is achieved for the proposed model, as depicted in Fig. 9. This high accuracy rate of the proposed hybrid reflects the applicability of the proposed model in 5G network slicing.

The proposed hybrid model is based on different performance metrics of accuracy, recall, precision, F-score and misclassification rate concluded that the model outperforms by concluding an identification rate of 93.23% for the network slice. The results generated are shown in Fig. 10.

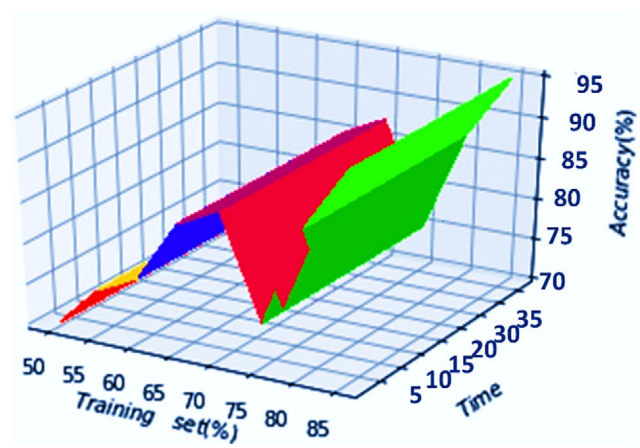

Fig. 9. Hybrid model accuracy results.

7. Conclusion

Traffic congestion control in 5G/6G wireless network technologies is a challenging task. It is considered a critical problem for mobile operators and commercial businesses for the next generation of communication technology (beyond 5G/6G technologies). A smart decision-making mechanism is required for the incoming network traffic to ensure load balancing, restrict network slice failure and provide alternate slices in case of slice failure or overloading conditions. To address these problems, the proposed research presents an approach for accurate network slicing using a hybrid deep learning mechanism for the optimum prediction of the optimum network slice using the proposed hybrid model. The applicability of this model is validated by simulating for one week using multiple unknown devices, slice failure conditions, and overloading conditions. An overall accuracy rate of

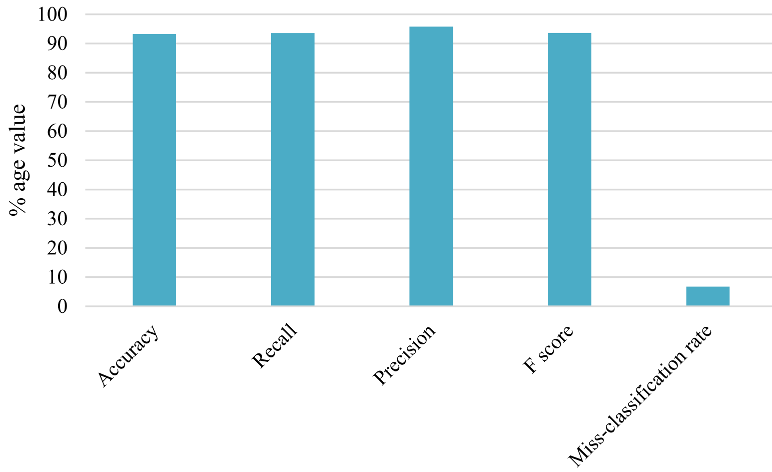

Fig. 10. Proposed model efficiency based on different performance metrics.

93.23% is calculated for the proposed hybrid model that reflects the applicability of the model. Apart from this, other performance metrics such as specificity, recall, time consumption, varying training, test sets, true-false rates, and f-score were used for the performance evaluation purposes of the proposed model.

In future, we want to test the applicability of the proposed model in a real production environment once the 5G ecosystem is commercially available for the consumers along with devices and networks facilities. Also, we will further enhance this research work to significantly address handovers, identify incoming future traffic and assignment of accurate resources accordingly, and borrow network resources from other slices.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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