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Original Article

Developing an ensemble learning model for slicing 5G networks

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Abstract

Contemporary mobile communication systems require a flexible infrastructure that can accommodate a range of services that require different performance characteristics, so network slicing has become a necessary mechanism for generating multiple isolated virtual networks, built on top of a single physical infrastructure, to provide services best suitable for the application performance requirements. In this paper, an ensemble learning model for network slice allocation in 5G networks is presented based on machine learning techniques. The proposed model combines ensemble learning techniques such as Random Forest (RF), CatBoost (CT), and AdaBoost (ADB), with Logistic Regression (LR) as the final decision-making stage. The proposed ensemble model demonstrated performance with an accuracy of 98.32%, which is over 2% better than the best single model (CatBoost at 96.23%). The proposed ensemble model consistently outperformed Random Forest and AdaBoost by more than 4% and more than 5% respectively. In addition, the proposed ensemble model was balanced and across key 5G slice types (eMBB, mMTC, URLLC) supported the diverse service requirements.

Keywords: 5G Network Slicing, Ensemble Learning, Stacked Model, Service Classification

Introduction

Over the past 20 years, telecommunications network usage has changed dramatically, affecting both the amount of data transferred and the number of connected users [1][2][3]. Owing to a service-oriented design provided through the 5G structure, a multi-service network will be able to accommodate a variety of communication scenarios with heterogeneous performance and service requirements through a range of services to suit each user [2][4]. 5G technology supports scenarios such as high bandwidth, low latency, and wide-area communications, and can provide diverse services such as autonomous driving, industrial control, and cloud gaming, in addition to cloud computing, which presents new challenges in resource scheduling and management [5]. The network environment in which access standards coexist creates new difficulties in network collaboration, and new technologies such as slicing and edge computing pose new requirements for network coordination and deployment [1][6]. The diverse business needs of 5G, complex network forms, and flexible deployment requirements have posed great challenges to network planning, design, provisioning, O&M, and operations, and traditional methods are no longer able to adapt. But at the same time, diverse services and massive network terminals will provide more abundant digital information [7].

Machine learning algorithms have advantages in high-computational data modeling, cross-domain feature extraction, and dynamic strategy generation. 5G networks have massive data, which provides an important basis for model training and data analysis for 5G networks [8][9]. 5G networks serve a wide range of applications and servers that vary in bandwidth, reliability, and latency requirements [10][11]. This diversity requires a model capable of accurate classification [12]. Since the design and operation of network slices require decision-making systems to determine the slice compatible with each application and can extract and model the necessary information, the need arises to design accurate and balanced models for slice classification [13][14]. In machine learning, ensemble learning is a method that combines multiple classification models to provide more reliable and accurate results than a single model [15] [16]. By combining the decisions of more than one model, errors that may arise from relying on a single model can be reduced, enabling better and more accurate performance. Ensemble learning can be applied to network data and to classify the data into slices to increase the accuracy of service classification and select the best slice for each type of service more efficiently. The work presented will explore mixed-stacked ensemble approaches for network slice allocation in 5G scenarios. The model proposes to increase overall classification performance while maintaining balanced performance across different service sets. Our goal is to develop a stacked ensemble learning model that classifies 5G network slices accurately and equitably to improve resource management efficacy and provide the needed quality of service (QoS).

The Network slice is one of the key components in 5G networks. Some works related to network slice are presented. The authors in [17] reviewed a 5G network dataset containing important data attributes which are closely connected to network slicing and developed a multi-level deep learning model to classify optimal slices within a 5G network. The results showed an accuracy of up to 98% when using their dataset. In [18] the authors used fuzzy logic to manage mobility, traffic, and model network slices. In [19] proposed a three-stage model: optimal weighted feature extraction (OWFE), segment classification and data collection. They classified network segments into “eMBB, mMTC, and URLC” using deep learning. In [20], the authors proposed a “DeepSlice” model that uses deep learning to manage network load and predict slices for unknown devices based on device key parameters. The study found that deep learning is a promising solution in this area. The authors in [21] discuss a framework to improve application performance by slicing the network into sub-slices, where some sub-slices focus on spectral efficiency while others focus on providing low latency while reducing power consumption. In [22] they used SDN and NFV techniques that provide the structure for network segmentation. They tested a set of machine learning algorithms such as ("Random Forest", "SVM", " kNN", and "Decision Tree Algorithms") and concluded that random forests are the best for this type of data.

In the paper [23], the researchers used a machine learning technique (Lasso Regression) to accurately predict the workload on an enterprise web server. This is done using historical data on the number of requests to the server. The goal is to better allocate network resources and improve the quality of service. An algorithm was developed to select the most important time periods in the data to improve the prediction accuracy. The results showed that this method reduced the prediction error compared to traditional methods. In [24] To manage network slices in 5G networks using machine learning techniques they designed and implemented a system consisting of a gatekeeper that classifies network traffic. It includes a demand forecasting unit and an admission control unit to determine the best slice allocation. The study found that regression trees were better than other machine learning models in accuracy in classification and prediction.

Finally, in the work presented by the authors in [25], it is discussed how machine learning and big data can be used to build a comprehensive framework for network slicing. However, all these studies focus on individual aspects of network slicing without addressing the significant gap related to slice load balancing and future traffic prediction. Machine learning and deep learning techniques have demonstrated their ability to model network data, but they suffer from a balance issue between service classes (eMBB, mMTC, and URLLC). Additionally, they have not adequately addressed ensemble learning models, particularly stacked models. In [26], Wheeb studied VoIP performance in wireless infrastructures, which demonstrated the latency and reliability problems when networks are exposed to dynamic network conditions. In [27], Wheeb et al. enhanced their work with RIS-aided schemes regarding wireless communication efficiency promoting adaptable performance awareness mechanisms in next generation networks. Through the analysis and recommendations of Wheeb et al., we proposed an ensemble learning approach for 5G network slice classification that guarantees Quality of Service (QoS) guarantees for application types such as eMBB, URLLC or mMTC.

5G networks Network Slicing and machine learning

5G is the latest generation of wireless cellular technology, providing enhanced download and upload speeds, Increased stability connections, and greater capacity compared to its predecessors. [1][16]. 5G offers greater speed and reliability compared to 4G networks, with the potential to transform how we access applications, social networks, and information on the Internet. The increasing demand for Internet access, along with the rise of emerging technologies like AI and IoT, and automation, is fueling a surge in data generation. The growth of data is currently occurring at an exponential rate that is expected to reach hundreds of zettabytes within the next 10 years. However, existing mobile networks were not constructed to deal with such large data loads and will certainly need upgrading. [28][29]. Meanwhile, thanks to its high speed, high capacity, and low latency 5G can also help support and enable a diverse range of applications; for example, controlling Cloud connected data traffic, connected drones, videochat, or console quality gaming on the go. A key feature within 5G is Network Slicing, which is a way to transfer data to various applications/services running on the same physical infrastructure. Network slicing can be thought of as independent virtual networks (a slice) designed along performance and response time. The model is that each slice was designed for a particular application or service, for example; industrial applications, high-bandwidth video streaming services, smart device networks, etc [30]. Network slicing is unique in that it can isolate the virtual slices from each other, allowing the slices to be independent from each other and eliminating the impact of failures or performance issues with a particular channel on the rest of the network. [30][31]. This approach helps improve the experience of utilizing applications based on the needs of each category. An example is that network slices can be used for reliable communication with fast latency for a remote surgery case, maintaining productivity in smart factories, or improving traffic management in smart cities, etc. Nevertheless, realizing the full benefits is dependent on various technical and management challenges. Specifically, this includes ensuring complete isolation between virtual slices, dynamically managing network resources and ensuring data security and privacy [28][32]. Moreover, this technology requires ongoing coordination between telecom service providers and beneficiary industries to ensure slices can accommodate differing application needs [33]. Network slicing technologies are a key contributor to achieving the vision of the future of communications, as they enable the provision of flexible and efficient services, making them crucial to the development of communications networks. There are three types of 5G Network Slicing levels See Figure 1.

Top Layer eMBB (Enhanced Mobile Broadband), where applications in this layer need high speeds and reliable connectivity such as smart cities, smart transportation, and enterprise applications [34][35][36].. Middle Layer URLC (Ultra-Reliable Low-Latency Communication), where applications in this layer need very low latency & reliability, such as telehealth and hospitals [37][38]. Bottom Layer mMTC (Massive Machine Type Communication), where applications in this layer support massive low-power communications, such as entertainment and printing applications. Machine learning model[40][41].

Machine learning methods such as CatBoost (CT), Random Forest (RF), and AdaBoost (ADB) are used for slice allocation. The algorithms' performance is evaluated using a dataset divided into training and test units.

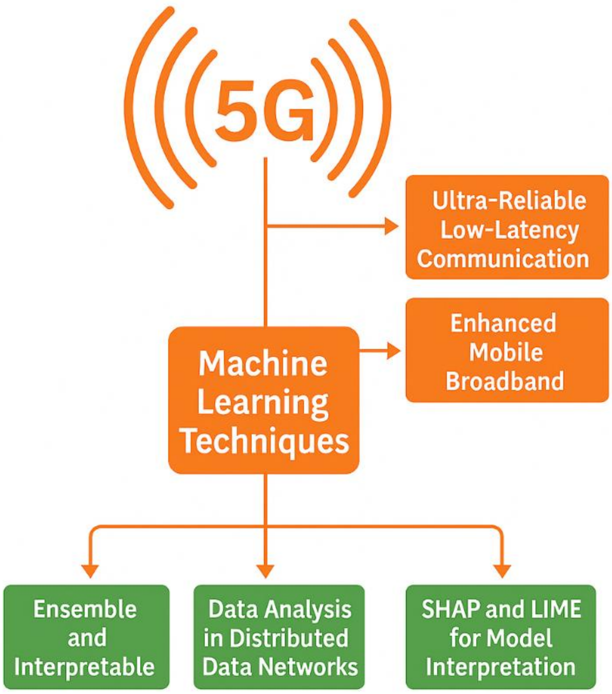

Figure 1. The virtual network of slices

CatBoost algorithm works on the concept of categorical boosting, which gradually grades the class variables through the boosting process to reduce the classification error rate. It is an algorithm that works with categorical data. It is suitable for data that includes heterogeneous categorical data [41][42].

Random Forest is a decision tree-based algorithm that partitions recurring data into distinct random clusters within a specified range. The advantage of this model is its ability to handle missing data and RF can handle a variety of features [42].

AdaBoost is an algorithm that works as a strong classifier by training a set of weak learners to improve their performance on labeled data, where a model is built on top of a model, each model being trained on the mistakes of the previous model. It may be less suitable than other learning algorithms in some cases. To demonstrate convergence with a strong learner, the weak learners must perform slightly better than a random guess [42][43][44].

PROPOSED MODEL

The proposed model has an ensemble learning approach, combining the clustering and boosting methods with Random Forest (RF), CatBoost (CT), and AdaBoost (ADB) as base learners, and Logistic Regression (LR) as an overlearner for final decision making. The base learners selected provide complementary strengths and different learning approaches: RF optimizes clustering methods for variance reduction, while CT and ADB minimize bias through iterative corrections of errors. Specifically, CatBoost has attractive advantages with categorical features, with little preprocessing of data. The choices accommodate a balanced ensemble with variance and bias reducing mechanisms with manageable computation costs.

Let $X = [x_1, x_2, ..., x_n]$ represent the set of input features, and $Y = [y_1, y_2, ..., y_m]$ denote the target variable indicating the slice type in the 5G network.

In the first stage, the base learners (RF, CT, and ADB) are trained independently on the same dataset:

- **Random Forest (RF):**

$$h\_RF(X) = (1/T)\ \Sigma\ (\text{from } t=1 \text{ to } T)\ h\_t(X) \qquad (1)$$

- **CatBoost (CT):**

$$h\_CT(X) = \Sigma\ (\text{from } i=1 \text{ to } M)\ \alpha_i \cdot g_i(X) \qquad (2)$$

- **AdaBoost (ADB):**

$$h\_ADB(X) = \text{sign}(\Sigma\ (\text{from } j=1 \text{ to } N)\ \beta_j \cdot f_j(X)) \qquad (3)$$

The outputs from the base learners are passed to the meta-learner, Logistic Regression, which aggregates these results to make the final decision:

$$P(Y=1|X) = \sigma(w_0 + w_1 \cdot h\_RF(X) + w_2 \cdot h\_CT(X) + w_3 \cdot h\_ADB(X)) \qquad (4)$$

Where $\sigma(z) = 1 / (1 + e\hat{}(-z))$ is the Sigmoid function. The Binary Cross Entropy loss function is used to measure the model's performance:

$$L = -\ (1/m)\ \Sigma\ (\text{from } i=1 \text{ to } m)\ [\ y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)\ ] \qquad (5)$$

To revise the weights, the derivative of the loss function Regarding each weight is calculated:

$$\partial L/\partial w_j = (1/m)\ \Sigma\ (\text{from } i=1 \text{ to } m)\ (\hat{y}_i - y_i) \cdot h_j(X_i) \qquad (6)$$

The weights are updated using the Gradient Descent algorithm:

$$w_j := w_j - \eta \cdot \partial L/\partial w_j \qquad (7)$$

Where η represents the learning rate.

Figure 2 illustrates the practical steps and the proposed model.

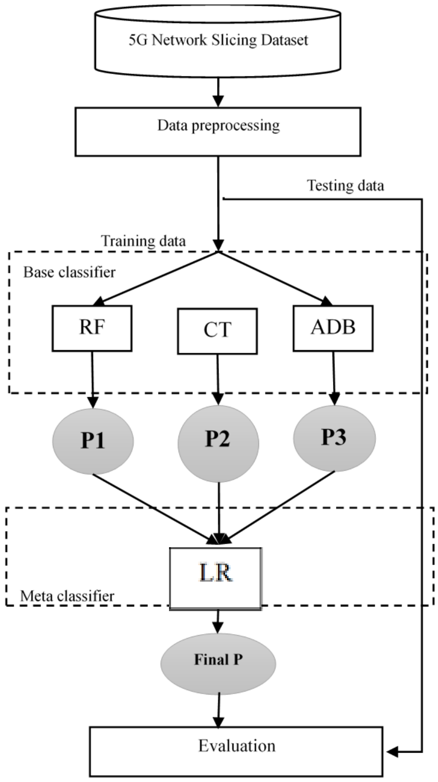

Figure 2. Proposed model architecture

Dataset And Preprocessing

This study relies on a dataset obtained from the source "CRAWDAD umkc/networkslicing5g", which contains information about network slicing in 5G network environments [43]. The dataset contains 466,739 records distributed across eight input features plus a target variable. The features include the type of supported access technology, device class (LTE/5G UE Category), day and time, Quality of Service Identifier (QCI), packet loss rate, and maximum packet delay budget. The dataset was split into a training set and a test set at a ratio of 80:20, respectively. Table 1 describes the features in the dataset.

Table 1. Description of features in the dataset

Features	*Description*	*Data Type*
Use CaseType (Input 1)	Represents the type of use case for which the service is provided.	Object
LTE/5GUE Category (Input 2)	Classification of devices supporting LTE or 5G networks.	Object
Technology Supported (Input 3)	The technology supported by the devices or services, either LTE or 5G.	Object
Day (Input 4)	The day on which the data was collected.	Object
Time (Input 5)	The time at which the data was collected.	Object
QCI (Input 6)	Quality of Service Class Indicator used to define the required service quality level.	Object
Packet Loss Rate (Reliability)	Represents the packet loss rate, indicating the reliability of the connection.	Float64
Packet Delay Budget (Latency)	The packet delay budget, indicating the time taken to send and receive packets.	Object
Slice Type (Output)	The type of network slice to be assigned for each service, used as the target variable for classification.	Object

The data was preprocessed by processing missing values and converting text types into variables suitable for use in machine learning models. An encoding process was also performed to convert the text data into numbers, which facilitates its use in the various classification models included in the proposed model .The classification process is divided into two main stages:

Phase 1 (Base Learners): In this stage, several base models (Base Learners) are used that rely on ensemble learning techniques such as Bagging and Boosting. The Random Forest (RF) algorithm is used within the Bagging models to improve classification performance by training several independent models and merging their results. On the Boosting side, the CatBoost (CT) and AdaBoost (ADB) algorithms are used to gradually enhance the model and correct errors in previous predictions.

Phase 2 (meta-learner): After obtaining the outputs of the models in the base layer, these results are sent to the meta-learner, which is logistic regression. This learner aggregates the outputs from the base models and makes the final decision. The default hyperparameter settings provided by the Scikit-learn libraries were adopted.

Results

Machine learning models were tested for slice allocation in 5G networks. The results show varying performance of the models, as shown in Table 2, where accuracy and other performance metrics were calculated based on the test data.

Table 2. Model performance

Model	*Accuracy*	*Error Rate*	*Precision*	*Recall*	*F1-Score*	*Weighted Averag*
RF	94.12%	5.88%	93.67%	92.45%	92.96%	93.41%
CT	96.23%	3.77%	94.89%	95.47%	95.18%	96.15%
ADB	93.41%	6.59%	92.36%	91.54%	91.95%	91.76%
proposed model	98.32%	1.68%	98.24%	97.81%	98.02%	98.14%

To determine the efficiency of the models for each class, the models were evaluated on three major network use cases: eMBB, mMTC, and URLC. Table 3 shows the Performance of model by category.

Table 3. Performance of model by category

Model/Category	*eMBB*	*mMTC*	*URLLC*
Random Forest (RF)	93.45%	92.12%	94.67%
CatBoost (CT)	96.32%	94.75%	97.38%
AdaBoost (ADB)	92.12%	91.54%	91.62%
proposed model	98.34%	97.82%	98.27%

Discussion

The results of the tested models show differences in performance, with the proposed model achieving the highest prediction accuracy of 98.32%, outperforming all other models, namely CatBoost, Random Forest, and AdaBoost. The overall performance of all models is relatively good, but combining them into a stacked ensemble model significantly improved accuracy and reduced the error rate to 1.68%.

One advantage of the proposed model is that it combines strengths from each algorithm separately. Random Forest alleviates the variance present in the data and Boosting algorithms, as in the case with CatBoost and AdaBoost, gradually address errors to increase accuracy. The final layer of the ensemble model is a logistic regression that provides balance in all of the predictions, while allowing the layer to adapt to generalize better when predicting new data. When observing performance across the three 5G service categories eMBB, mMTC, and URLLC, the ensemble model shows balanced performance with accuracies over 97% in all categories, the highest of any model investigated. This performance shows that the model is learning to optimize for the needs of each service category, whether that be speed, reliability, or supporting a significant number of low-powered devices. Furthermore, when comparing the current model's performance to previous work, the model outperformed accuracy, as well as class balance. Work in [17] displayed 98% accuracy, but relatively low-class diversity. Work in [22] indicated random forest showed the best accuracy among the traditional machine learning algorithms, although there was some overlap in accuracy, the stacked ensemble learning in this case was able to achieve accuracy of 98.32% and perform significantly better at balancing classes as well.

Conclusion

This paper proposes a stacked ensemble learning model for the classification of 5G segments. The results demonstrate that the suggested models outperform existing ensemble models, including Random Forest, CatBoost, and AdaBoost. The stacked ensemble models achieve balanced performance across the three classes (eMBB, URLLC, and mMTC) and therefore demonstrate that the model can be used for classifying diverse services along with quality of service (QoS) assurance. These results demonstrate that not only does the stacked ensemble methodology achieve higher accuracy, however it also achieves a higher level of fairness when considering imbalanced data, which may be useful for resource allocation in complex environments with 5G networks.

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