Journal of Autonomous Intelligence (2024) Volume 7 Issue 1
doi: 10.32629/jai.v7i1.694

ORIGINAL RESEARCH ARTICLE

An intelligent technique for network resource management and analysis of 5G-IoT smart healthcare application

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ABSTRACT

The transformation of traditional hospitals to a smart healthcare system is a patient-centric, reliable, and smarter way to enhance healthcare facilities for individuals. These healthcare devices are based on the Internet of Things (IoT) and conventional network structures such as 3rd generation (3G) or 4th generation (4G). That did not provide the patient health data in the real-time scenario. Therefore, the integrated 5G-IoT system offers distinct benefits such as remote monitoring, surgery, and real-time data analysis of healthcare system that is operated with slice of dedicated network. It generates huge data with the billions of healthcare equipment that can be evaluated for decision making. This enormous data requires low latency, high-security, capacity, and more reliable techniques for evaluation. In this scenario, network slicing is one of the key solutions that can be considered for isolated end-to-end network structures. Network slicing enables logical and independent network virtual networks to be multiplexed for the same physical network. In this article, we propose an intelligent approach for network resource optimization and analysis of a 5G-IoT based smart healthcare network. We examine the performance of the machine learning algorithm by an automatic model, named A Fast Library for automated machine learning (FLAML). In addition, we perform network slicing to obtain resource optimization in 5G-IoT-based healthcare application.

Keywords: healthcare; 5G; IoT; resource optimization; artificial intelligence; machine learning

ARTICLE INFO

Received: 8 June 2023
Accepted: 17 July 2023
Available online: 9 October 2023

1. Introduction

5G technology offers high-speed, low-latency connectivity that enables healthcare providers to deliver real-time, high-quality care to patients. The Internet of Things (IoT) enables the sensors to communicate with each other and share the information for better results. The data can be communicated through the personal network which may be stored on cloud for further analysis to provide insights that can improve patient outcomes and reduce costs. Machine learning and AI are being used for prediction and monitoring of data in real-time that can recognize the complications in the patient's health. These models can also be used to personalize treatment plans and improve clinical decision-making[1]. By facilitating connectivity between a range of modern medical devices and sensors, the IoT is significantly altering the distinct sub-domains in healthcare such as remote surgeries, monitoring parameters, and remote treatments. This connectivity enables to get the crucial information of a patient's condition and the gathered information can be used for a number of things that include monitoring of patient and enhancement of diagnosis and treatment process[2].

The domain of medical services is fundamentally impacted by 5G innovation. Some of the most important characteristics of 5G communication include quick information transmission, a large coverage area, control of network traffic with low latency, extreme responsiveness, and low cost. The monitoring of patient's health in the real-time is one of the critical factors that is very crucial for providing the treatment to the patient and personalized care. The IoT network is integrated with 5G cell network that provides information size approx. 1 gigabyte quickly with massive clinical imaging documents and better medical treatment[3]. The mHealth is one of the critical units used in medical field integrated with 5G. The term "mHealth" stands for "mobile health", and it has been used to describe how wearable technology, portable communications, and clinical improvements are integrated to give effective and remote medical care[4]. mHealth services and applications are highly vulnerable in case of network failure. In 2015, there is a network failure that caused critical monitoring and connectivity losses in Hillingdon Hospital, Landon. It is a very dangerous situation that may cause deaths, delay in getting help for severe patients, and reason of chronic diseases[5].

The architecture of a 5G-IoT network involves the integration of multiple protocols at different layers to facilitate seamless connectivity and efficient data transfer. This section covered an overview of the architecture along with some commonly used protocols:

Devices and sensors:

IoT devices and sensors communicate using various protocols depending on the application requirements. Some commonly used protocols at the device level include:

- Zigbee: A low-power wireless communication protocol designed for short-range communication in IoT devices.
- Bluetooth low energy (BLE): A low-power wireless protocol commonly used for short-range communication between IoT devices and smartphones.
- Thread: A networking protocol designed for low-power, IP-based communication in IoT devices.

Edge computing:

Edge computing in a 5G-IoT network can use standard protocols for communication between edge devices and the edge server, such as:

- MQTT (Message Queuing Telemetry Transport): A lightweight publish-subscribe messaging protocol that is widely used for IoT communication and supports low-power, low-bandwidth devices.
- CoAP (Constrained Application Protocol): A specialized web transfer protocol designed for resource-constrained devices and networks.

Radio access network (RAN):

The RAN in a 5G-IoT network utilizes advanced cellular communication protocols, including:

- 5G NR (New Radio): The air interface protocol for 5G networks, providing higher data rates, lower latency, and increased capacity compared to previous cellular generations.
- Narrowband IoT (NB-IoT): A low-power, wide-area network (LPWAN) protocol specifically designed for IoT devices, offering long-range connectivity with extended battery life.
- LTE-M (Long-Term Evolution for Machines): A low-power, wide-area network protocol similar to NB-IoT, optimized for IoT applications requiring higher bandwidth and mobility support.

Core network:

The core network in a 5G-IoT architecture utilizes various protocols for different functionalities:

- IP (Internet Protocol): The foundational protocol for network communication, enabling data exchange between devices and networks.
- IPv6 (Internet Protocol version 6): The latest version of IP that provides a larger address space to accommodate the vast number of IoT devices.
- MQTT and CoAP (mentioned earlier): These lightweight protocols are commonly used for communication between IoT devices and the core network.

Cloud infrastructure:

In the cloud infrastructure layer, protocols used for data storage, processing, and analytics include:

- HTTP (Hypertext Transfer Protocol): The standard protocol for transmitting data over the web, commonly used for cloud-based services and APIs.
- MQTT and CoAP: These protocols can be used for communication between cloud-based servers and IoT devices.

Applications and services:

IoT applications and services can utilize a wide range of protocols depending on the specific use case. Some commonly used protocols include:

- HTTP and HTTPS (HTTP Secure): These protocols are widely used for communication between applications and servers, enabling data retrieval and control.
- MQTT and CoAP: These lightweight protocols are often used for real-time data exchange and control in IoT applications.

It is important to note that the selection of protocols may vary depending on the specific requirements of the IoT use case, and new protocols may emerge as technology evolves. Network slicing is a technique used in modern telecommunications networks to create multiple virtualized network instances over a shared physical infrastructure. Each of these virtualized networks, or "slices", can be customized to support different applications, services, or user groups with varying performance and security requirements. Network slicing recognition refers to the ability of a network to detect and identify the different network slices that are running on it. This is important because it allows the network to properly manage and optimize each slice based on its unique requirements. There are several techniques and protocols that can be used for network slicing recognition, including:

Software-defined networking (SDN): Control plane and data plane is separated through SDN which allow the network to be more programmable and flexible. With SDN, network slices can be created, configured, and managed dynamically, making it easier to recognize and differentiate between them.

Network function virtualization (NFV): NFV replaces specialized network hardware with virtualized network functions (VNFs) that can be deployed and scaled as needed. By using NFV, network slices can be instantiated as virtual networks, making them easier to recognize and manage.

Multi-protocol label switching (MPLS): MPLS is a protocol used to route traffic across networks based on labels rather than IP addresses. By using MPLS, network slices can be identified and managed based on their unique labels, making it easier to differentiate between them.

Enhanced mobile broadband (eMBB): The 5G deployment is based on greater bandwidth and improvement on 4G LTE. It will provide the low latency and high bandwidth for the latest applications like ultra-HD and high-resolution videos.

Massive machine type communication (mMTC): The main utilization of mMTC is to provide connectivity large number of devices that may connect usual or IoT devices. It supports several IoT applications such as smart city, smart healthcare, and many others for the reduction of energy consumption and improves the human lives.

Ultra reliable low latency communication (URLLC): The major aim of URLLC is to provide ultra-reliable low latency and more bandwidth to meet the expectations of a 5G network. It will require end-to-end latency reduction for the deployment of a 5G core network.

The results can be analyzed using machine learning techniques after network slicing to estimate the performance of the medical devices. Because of the enormous amount of data and complexity of the IoT devices that are 5G enabled, ML computations have shown to be of tremendous value in medical treatment. These calculations enable us to distinguish important facts from the information we have gathered and make decisions based on those realities. The use of ML-based frameworks has several advantages. They can be trained to process huge amounts of data called preprocessing of information and then applied in clinical settings to aid inductive reasoning-based risk assessment and treatment planning. AI estimates the productivity and reliability of the a 5G network. By focusing on clinical science data from textbooks, journals, and clinical practices information that is tiresome for people computerized reasoning (AI) can help clinicians with counselling and give the best understanding consideration[5]. Current AI is getting closer, but it cannot make decisions like a human brain can. The combination of AI and IoT devices based on 5G in healthcare makes it easier to observe, make do, and investigate clinical data. Current AI is getting closer, but it lacks the conclusions that a human psyche can come to. The integration of AI and IoT devices based on 5G in medical services makes checking, making do, and deconstructing clinical data easier. **Figure 1** shows the growth of 5G in healthcare industry may reached $459.71 that is a CAGR of 36.8% from 2022 to 2030.

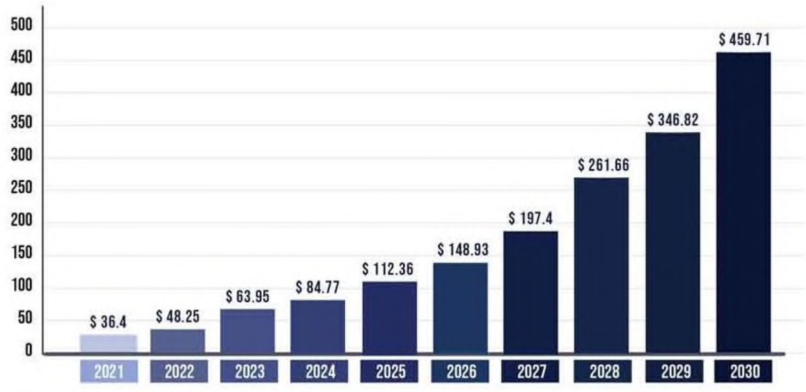

Figure 1. Growth of smart healthcare till 2030[6].

Despite the fact that a number of studies have been conducted related to 5G, and AI in medical fields, most of them have concentrated on the design on behalf of the scope of calculations or the way the information is presented by 5G-IoT devices. As a result, we tried to find solutions by looking into a few ideas for both ML models and IoT frameworks. The fundamental commitments of this work are what will happen next. In this article, we have used an automated machine learning model for building the machine learning algorithms for building the model. Some of the major contributions of the current article are as follows:

- The proposed model is built with the help of automated removal of features using the recursive feature elimination technique.
- The network slice is proposed based on the critical care units, remote surgery, and telemedicine.
- The major problem with the network service providers to assign the network slicing in the 5G network. So, we proposed an algorithm for network slicing in a 5G network.
- The model building is done with an automated machine learning model, named FLAutoML tool that executes the programs till it generates the optimized results in terms of accuracy and time delay.

The following sections make up the remaining portions of the paper: section II analyses the review of the literature on machine learning-related 5G IoT applications. We have concentrated on the proposed methodology and its process in section III. The description of the dataset and its key components were the focus of section IV. The results and their explanation in terms of the evaluation criteria were covered in section V. The paper is then concluded with future scope in section V.

2. Literature review

In this section, we give an overview of a few former dispersed businesses that involved the use of AI in healthcare, 5G, and IoT. The focus is on recent work in the field of healthcare application derived from 5G-IoT. Paramita et al.[7] suggested a smart healthcare system that is useful to collect patient physiological parameters such as blood pressure, body temperature. It is based on WSN. The proposed system is used to enhance human life values by using newest technologies like IoT, 5G and machine learning. Technology that is used to monitor patient parameters is IoT and the parameters are forwarded to the monitoring station using 5G. Efficiency to predict the critical condition of patients is improved by using machine learning models. Rghioui et al.[8] suggested for monitoring diabetes patients makes use of AI computations. Smart devices, sensors, and cell phones were used in the design to collect body estimates. The clever framework collected the data obtained from the patient and used AI to do information grouping in order to create an analysis. Several AI based calculations were used to evaluate the forecasting framework that was suggested. Lloret et al.[9] outlines a strategy for intelligent observation of health monitoring of periodic patients in their publication. Wearable technology is utilized to take parameter values from the body, and the patient manages the data using a mobile phone[9].

Based on data, Jain et al.[10] suggested a virtual real time digital support system for COVID-19 pandemic situation that is based on 5G network slice. Wearable devices will collect the biometric data and forwarded it through the 5G network. Then data analytics is used for fast prediction and direction to build a knowledge graph. Charleonnan et al.[11] provide an algorithm based on AI to forecast chronic illness. Among the AI methods studied are decision tree classifiers, support vector machines, strategic relapse models, and K-closest neighbors (KNN). The suitable classifier to forecast kidney chronic illness was discovered by comparing the output of several prediction models, which were developed using a dataset of continuing kidney disease. In order to predict CKD, Wang et al.[12] explored several AI techniques, particularly characterization and affiliation methods, and dissected the effects of combining the methods by choosing tactics with grouping methods. With the use of WEKA-based characterization techniques, the CKD dataset is benchmarked. Yoo et al.[13] give a model for individualized heart state depiction, a fast and efficient system based on deep neural network to handle stable data obtained from bio sensor. This model can also aid clients in recognizing potentially dangerous situations, collect input information, and nurture a predicted work.

Pradhan and Chawla[14] examined 65 revised publications for using AI computations to predict various illnesses. The analysis primarily focuses on various AI calculations used for diagnosing a few diseases in an effort to find a gap in the future development of clinical IoT's ability to detect biological breakdown in the lungs. Zhang et al.[15] provides a general way to design and implement an E-Health system which is based on 5G. Author has refined two use cases which are 5G based E-Health system for remote health and 5G based system for COVID-19 pandemic. Also present the comparable study among 4G LTE and 5G and defined the challenges related to 5G in healthcare. The late developments in the 5G-IoT field are summarized in the articles by Cheng et al.[16]. In order to enable smart 5G-IoT administrations, Ullah et al.[17] created a deep learning model to manage the control flow graph (CFG).

3. Proposed methodology

Smart healthcare systems required real-time results for better treatment and prescription. However, IoT is not providing highly reliable solutions with existing network infrastructure in smart healthcare applications. So, the integration of 5G can enhance the services provided by smart healthcare applications. Latency and delay are two common factors that become a hurdle for a better outcome and real-time investigation. Network slicing is one of the key factors through which important parameters can be enhanced for future generations. The mobile operator can improve the quality of services by using multiple instances of the network from a single base station. To address the key problems of network slicing, we proposed an efficient model that can be utilized for load balancing, and overloading conditions, and provide an alternate slice in case of slice failure.

The proposed model consists of five main modules: pre-processing, recursive feature elimination, network slicing module, model building, and parametric evaluation module. The functionality of all modules is shown in **Figure 2** along with the information flow. The collected dataset is belonging to network traffic that consists of distinct data values based on the 5G network. In the first module, the data is filtered with certain features. While, in the second module, the data is extracting the features with a recursive feature elimination algorithm. A network slicing module is used to manage the network slices based on the requirement of the healthcare system. The fourth module is utilized to build the models using FLautoML algorithms that are used to generate effective models automatically based on the performance. Finally, the last module is used for parametric evaluation and testing purposes. The proposed model is based on the automatic modelling so it can handle larger healthcare network if the number of devices is increased.

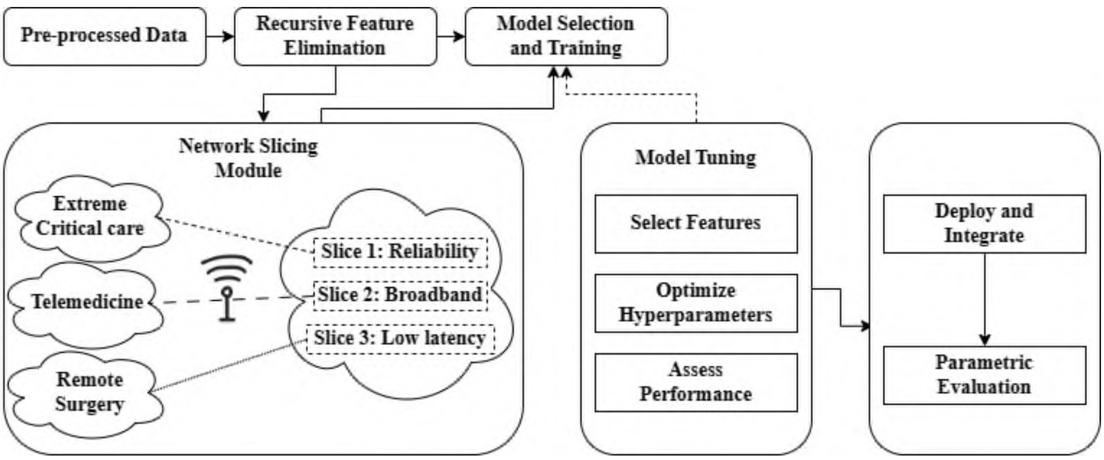

Figure 2. Proposed methodology of the system.

The detailed description of the mentioned modules can be summarized as:

Pre-processing module: This module is mainly utilized for the filtration and cleaning of data collected from various healthcare devices. Then classify the matrix of features based on dependent and independent variables. The next step is to handle the missing data as the data creates misleads to the models. It can be done by using deleting the data row or by evaluating the mean value for the column. Finally, encodes the categorical data in numerical form so that the data handling can be improved.

Recursive feature elimination (RFE) module: There are some features that exist in the dataset that may generate the worst results due to their irrelevance from the model. Therefore, there is a requirement for feature extraction or elimination from the original dataset. This process can be done either manually or by an automatic method named RFE. It can be implemented in two distinct ways first is based on the choice of selected features and another is the choice of the algorithm used to select features. RFE is a wrapper class that works based on the estimator value, and a number of features selected for the algorithm. According to the parameter improvement, resampling is done and features are eliminated recursively.

Network slicing module: This module is utilized to create the network slices based on the requirements and criticalness of the data. It verifies the controlling and managing of the network function for the recognition of appropriate slice creation. The whole data is divided into three different slices, one is extremely critical care monitoring, the second is telemedicine, and the last is for remote surgeries. The requirement of the first slice is based on ultra-reliability and low-latency communication. Telemedicine is used for patent monitoring and receives a network slice with enhanced broadband connectivity. While the third slice, named remote surgery, required low latency, high-reliability, and high security. The network slicing is based on the proposed algorithm as follows (Algorithm 1):

Algorithm 1 Network slicing (eMBB, URLLC, MF, mMTC)

Begin:
1) mMTC, eMBB, NS, MF, URLLC = 0/* initialize network parameters with vector length l. */
2) Initiate the looping variable $k = 0$;
3) Loop: $k \leq l$ till
/* Load balancing for network slice */
1) Percentage utilization of the network slice
$M1 = eMBB_l/\text{sizeof}(eMBB) \times 100$
$M2 = URLLC_l/\text{sizeof}(URLLC) \times 100$
$M3 = mMTC_l/\text{sizeof}(mMTC) \times 100$
$M4 = MF_l/\text{sizeof}(MF) \times 100$
1) Perform the slicing with conditions
If ($M1 < 90$) && (high throughput):
    assign critical care unit for eMBB
Else if ($M3 < 90$) && (reliability and broadband connectivity):
    assign telemedicine unit for mMTC
Else if ($M2 < 90$) && (low-latency, high reliability, and high security):
    assign remote surgeries for URLLC
Else:
    MF = in case of network slice fails.
End loop.

Model building: Although, there are several algorithms to generate a model based on machine-learning for the dataset. These models can be built based on the manual understanding of the feature selection, estimators, and performance. However, an automated machine learning model automates the process and eliminates the manual steps for building the predictive model. It also minimizes the efforts and level of expertise for the building of an accurate model. The FLAutoML works with the model tuning process that selects feature, optimizes the hyperparameters, and assess the model performance. This model also takes the variable number of epochs for evaluating the performance of the model. FLAML uses a combination of techniques, including Bayesian optimization, random search, and bandit-based algorithms, to efficiently search the hyperparameter space and identify the best set of hyperparameters for a given machine learning task. It supports a wide range of machine learning algorithms, such as gradient boosting machines, random forests, support vector machines, and deep learning models. One of the key features of FLAML is its ability to deliver competitive results with minimal computational resources and time. It achieves this by intelligently allocating computational budget to the most promising hyperparameter configurations, effectively reducing the need for exhaustive search.

Parametric evaluation: FLAML's optimization methodology is designed to address the sensitivity of hyperparameters. By intelligently searching the hyperparameter space using techniques like Bayesian optimization, FLAML aims to identify the best hyperparameter configuration regardless of its sensitivity to changes. It is always recommended to experiment with different hyperparameter values and perform cross-validation to ensure robustness and generalization of the models produced by FLAML. Therefore, the parametric evaluation is done based on distinct parameters such as accuracy, precision, recall, support, and average time. First, we evaluate the correlation among the selected features. The distribution of LTE5G needs to be evaluated. The distribution of the target variable slice type is measured. Then distinguished parameters are evaluated for the final performance.

4. Dataset description

The telecom industry gained a lot of popularity with the massive digital transformation. It shows unprecedented growth with the assimilation of artificial intelligence and machine learning. The ability of data analytics and productivity with resource optimization with the growing amount of data is one of the critical issues over the 5G-IoT network. Network slicing datasets[18] play a vital role in demand bandwidth, coverage, latency, and reliability of the 5G network. The dataset is having two files, one is for training purpose that contains total 17 attributes with 32 k records while other file is used for testing purpose contains about 31 k records with 17 attributes. The dataset is providing the information about multitude of 5G applications, services, and resource allocation[19]. The dataset is processed with the following steps such as handling of missing data, removal of duplicate data, cleaning of data values, and balancing of dataset. The description of some attributes is shown in the **Table 1**.

Table 1. Dataset description.

Attributes	Description
LTE5G	Indicates the user equipment categories or specification.
Packet loss	It provides the ratio of number of packets dropped out of total transmitted packets.
Slice type	It allows multiple network configurations for virtual and independent.
GBR	It indicates the guaranteed bit rate.
IoT devices	Distinguished IoT devices used or not for application.
Healthcare	Indicates 0 or 1 for usage or non-usage.
Packet delay	The time difference between packet sent from one end and received at another end.
Industry 4.0	Usage or not (0 or 1).
Smartphone	Smartphone cellular data usage or not.

Dataset can be defined in terms of the given Equation (1):

$$D = \{(\vec{p}_1, q_1), (\vec{p}_2, q_2), \dots, (\vec{p}_n, q_n)\}, \vec{p}_1 = (p_i^1, p_i^2, \dots, p_i^m)^T \tag{1}$$

For the evaluation of regularization, we need to calculate the L_p norm with the Equation (2):

$$L_p(\vec{p}_i) = (|p_i^1|^p + |p_i^2|^p + \cdots |p_i^m|^p)^{\frac{1}{p}} \tag{2}$$

The regularization of the dataset can be evaluated in terms of the Equation (3):

$$\vec{p}_i = (\frac{p_i^1}{L_p(\vec{p}_i)}, \frac{p_i^2}{L_p(\vec{p}_i)}, \dots, \frac{p_i^m}{L_p(\vec{p}_i)})^T \tag{3}$$

where *m* indicates the number of features present the dataset, *p* and *q* are the values present the feature vectors.

5. Results and discussion

A model is designed and implemented in Python that includes the Keras library and TensorFlow for the evaluation of the performance of the model. This can be achieved by using several steps: i) first split the dataset in train and test dataset in the ratio of 80:20 for a better outcome. Then visualize the dataset by pair-wise scatter plot for continuous variables. **Figures 3–6** show the distribution of the dataset in the form of the scatter plot, histogram, distribution of slice type, and target variables. **Figure 7** demonstrates the co-relation among all the parameters in terms of the heatmap.

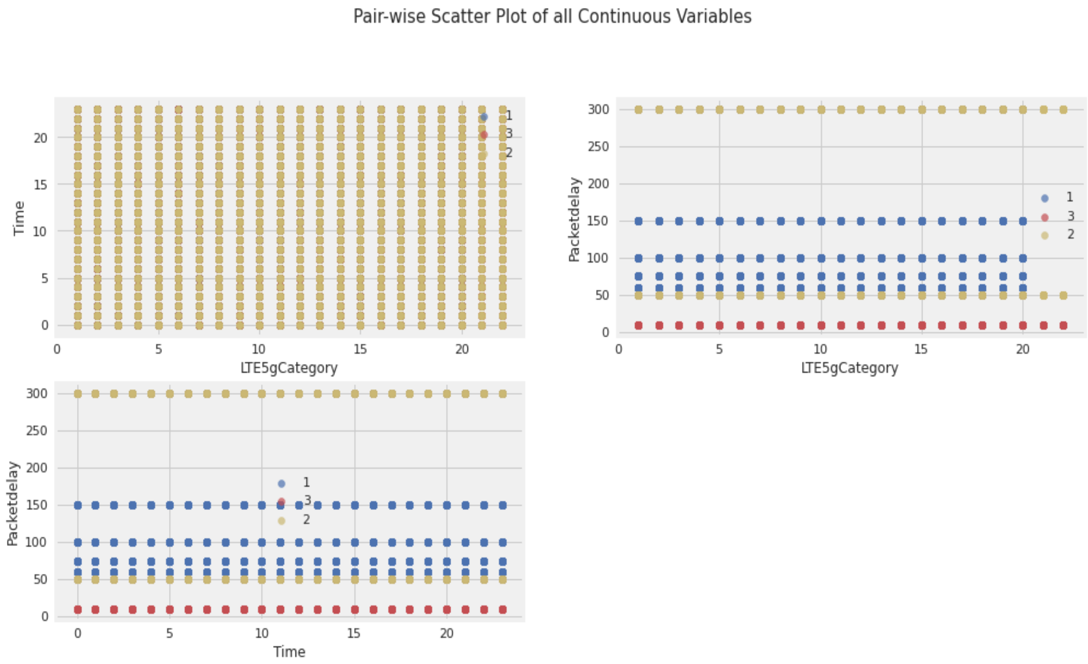

Figure 3. Scatter plot pair-wise for continuous variable.

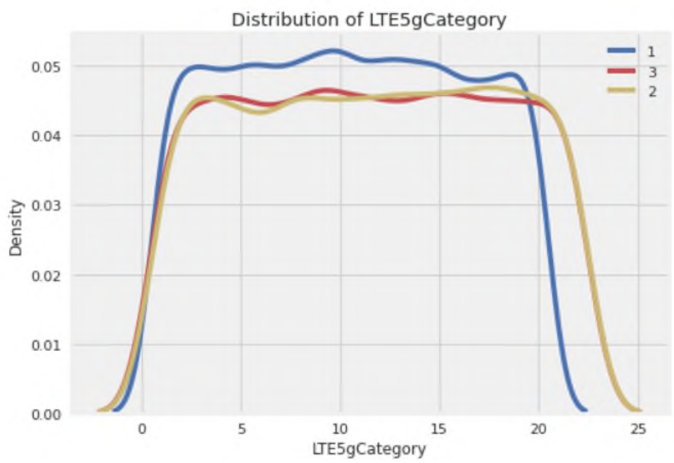

Figure 4. Histogram for distribution of LTE5G category.

Figure 5. Distribution of slice type target.

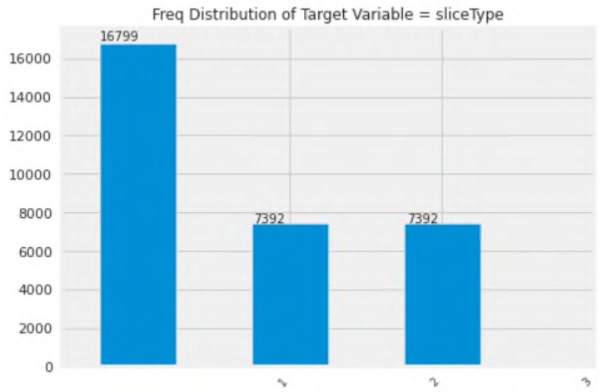

Figure 6. **F**requency distribution of target variable slice type.

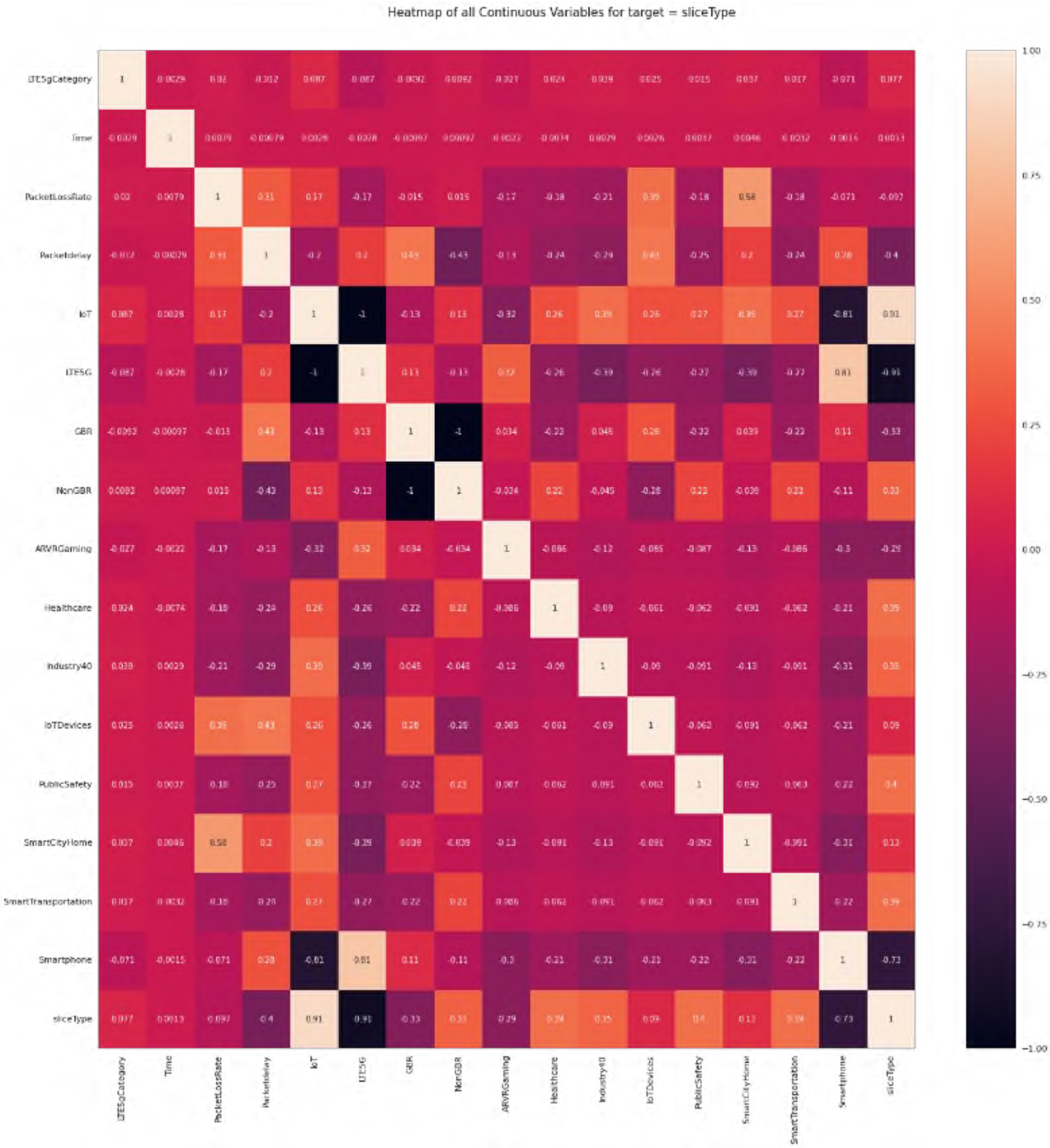

Figure 7. Heatmap of all continuous variable for target variable.

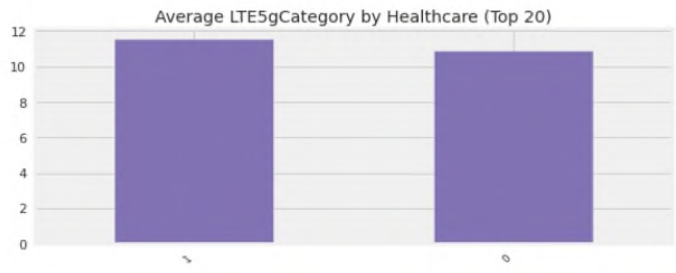

Figure 8. Average LTE5G category by healthcare.

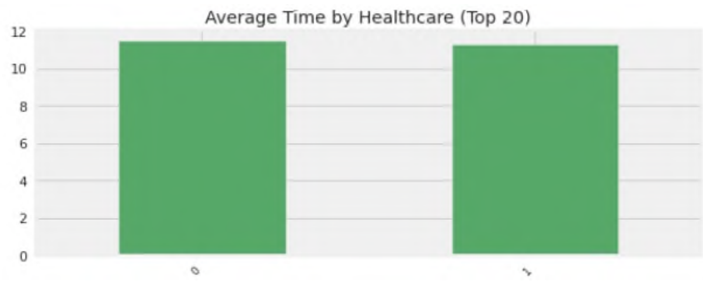

Figure 9. Average time by healthcare.

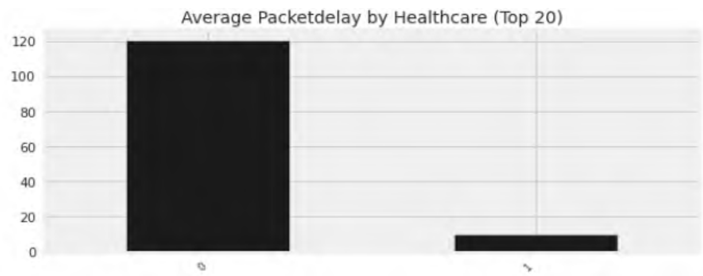

Figure 10. Average packet delay by healthcare.

Figures 8–10 show the average LTE5G category, time, and packet delay by healthcare devices. We have used an automatic machine learning tool named Fast Library for automated machine learning and tuning (FLAML) that finds the accurate ML model with low computational resources. The main utilization of this tool is easy customization of classification, regression, and generation of accurate model building. It utilized the XGBoost, random forest, LGBM, and extremely randomized tree classifier (extra-tree) algorithms. The interpretability and explainability of machine learning models generated by FLAML can vary depending on the specific algorithm used and the complexity of the problem. FLAML supports a wide range of machine learning algorithms, including gradient boosting machines, random forests, support vector machines, and deep learning models. Among these, certain algorithms, such as decision trees and rule-based models, tend to be more interpretable by nature, while others, like deep neural networks, are generally considered less interpretable. The selection of algorithm will depend on the specific set of healthcare problem and representation. The FLAML returns the following results that contain the ML learner name, hyperparameter configuration, best roc_auc and time taken by the best algorithm.

Best ML leaner: LGBM

Best hyperparmeter config: {'n_estimators': 4, 'num_leaves': 4, 'min_child_samples': 20, 'learning_rate': 0.09999999999999995, 'log_max_bin': 8, 'colsample_bytree': 1.0, 'reg_alpha': 0.0009765625, 'reg_lambda': 1.0}

Best roc_auc on validation data: 1

Training duration of best run: 0.03724 s

The training and testing parameters of the model is as follows:

	precision	recall	f1-score	support
1	1.00	1.00	1.00	13439
2	1.00	1.00	1.00	5913
3	1.00	1.00	1.00	5914
accuracy			1.00	25266
macro avg	1.00	1.00	1.00	25266
weighted avg	1.00	1.00	1.00	25266

(a)

	precision	recall	f1-score	support
1	1.00	1.00	1.00	3360
2	1.00	1.00	1.00	1479
3	1.00	1.00	1.00	1478
accuracy			1.00	6317
macro avg	1.00	1.00	1.00	6317
weighted avg	1.00	1.00	1.00	6317

(b)

Figure 11. **(a)** parameters evaluation for training dataset; **(b)** parameters evaluation for testing dataset.

Figure 11a,b shows the evaluation of distinct parameters for training and testing datasets for the best-optimized model (LGBM). While the training time for the best run is 0.03724 seconds retrieved from the model. **Table 2** shows the comparative analysis of the proposed work with the existing work conducted by researchers.

Table 2. Comparative analysis of past work with current research.

Reference	Algorithm/classifier	Dataset	Time delay	Accuracy/throughput
[20]	CNN	NSL-KDD	0.1872	98.3%
[21]	Enhanced spectrum sensing	Simulated environment	0.87	97.8%
[22]	Hierarchical cognitive engine architecture	Conceptual framework	-	-
[23]	POSENS	Experimental	0.754	98.6%
[24]	Reinforcement learning	Simulated environment	0.3600	94.6%
Proposed model	FLAML	Network slicing	0.03724	98.65%

6. Conclusion

The transformation of traditional hospitals to a smart healthcare system is a patient-centric, reliable, and smarter way to enhance healthcare facilities for individuals. The integration of IoT and 5G technology endeavor several benefits to the healthcare system that incorporates remote patient monitoring, connected ambulances and robotic surgery through remotely. 5G-IoT supports uncountable healthcare equipment that produced tremendous amount of data that can be evaluated. This enormous data requires low latency, high-security, capacity, and more reliable techniques for evaluation. In this article, we propose an intelligent approach for network resource optimization and analysis of a 5G-IoT based smart healthcare network. We examine the performance of the machine learning algorithm by an automatic model, named A Fast Library for automated machine learning (FLAML). The parametric evaluation shows the results for best accuracy with the LGBM algorithm that provides 98.65% accuracy and 0.3724 ms time delay. In the future, the results can be obtained with the real-time implementation of IoT integrated with 5G. In this paper, we have assumed the ideal conditions and not focused about the potential ethical issues such as data ownership, privacy, data sharing, and data protection laws.

Author contributions

Conceptualization, NG; methodology, NG; validation, PKJ; formal analysis, PKJ; data curation, UG; writing—original draft preparation, SS; writing—review and editing, NG, SS and UG; visualization, SS and UG; supervision, PKJ. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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