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INTEGRATING IOT AND NLP FOR SMART HEALTHCARE: REAL-TIME PATIENT MONITORING AND DIAGNOSIS

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Abstract: The Internet of Things, or IoT, is all the rage these days; it links people's daily lives to small devices like sensors and offers smart applications. In order to analyze a patient's health in real time, smart healthcare applications need remote patient monitoring. Internet of Things (IoT) devices need high-power radio connection, including Fifth Generation (5G), for data transfer in order to provide real-time patient monitoring. The healthcare industry has been transformed by the growing engagement of 5G-enabled IoT technology, which has provided efficient and real-time monitoring and diagnosing capabilities. There are a number of issues that have come to light as a result of the widespread use of 5G-IoT in healthcare applications, a lack of energy-efficient resources; a lack of a standard framework for handling applications; and, most importantly, the potential for malicious data or the disclosure of sensitive medical information. This issue is addressed by proposing a four-module improved system structure. line of new products to improve the 5G-IoT smart healthcare application, the initial module suggests a system structure that gives the general technique. For efficient management of 5G-IoT applications, we outline the suggested smart healthcare system (SHS). It is possible to evaluate the system's efficiency with the use of an automated model called FLAML.

Keywords: Internet of Things, Healthcare, Patient, Monitoring, And Diagnosis.

I. INTRODUCTION

Medical treatment relies on accurate diagnosis and close patient monitoring; integrating sensor networks into the human body would greatly facilitate these tasks. Also, you can get to the data whenever you want, no matter where you are in the globe. When it comes to improving healthcare monitoring systems, the Internet of Things (IoT) has lately emerged as a crucial area for growth. With the help of the Internet of Things (IoT), a healthcare monitoring system can keep tabs on individuals and link all sorts of services and objects to one another online, allowing for the collection, sharing, monitoring, storage, and analysis of data produced by these objects. On the other hand, the Internet of Things (IoT) represents a paradigm shift towards remote control and management of all physically linked things in intelligent applications including smart cities, smart homes, and smart healthcare.

Developing and configuring technology in different situations and conditions is the main focus of most current IoT installations and research. Nevertheless, these methods are not commonly employed in modern times. Hence, the purpose of this study is to assess relevant studies that have focused on the design and implementation of healthcare monitoring systems that enhance quality of life through the use of the internet of things (IoT). Internet of Things (IoT) gadgets and sensors play a crucial role in these systems, which aim to match patients with the most appropriate healthcare providers.

A number of factors, including an ageing population, an increase in the prevalence of serious diseases, and potential global healthcare sector issues, are impacting health outcomes, necessitating real-time monitoring activities in the healthcare business. Diseases get more severe as people become older. Among these conditions include diabetes, heart disease, and major breathing problems. It is crucial to closely observe individuals with these illnesses on a frequent basis in order to prevent serious complications and cut down on needless hospitalizations. The fact that current healthcare systems are unable to meet the urgent medical needs of a rapidly expanding population must also be understood. Additionally, this need for remote therapies was further developed by the scenario following COVID-19.

A wide range of Internet of Things (IoT) devices are available to meet different needs. Wearable sensors and smart implants that allow for remote monitoring from the comfort of one's own home are examples of such technologies. Wearable technology allows patients to monitor major symptoms and any changes in their physical state as they happen in real time. Modern smartwatches, electrocardiogram monitors, and fitness trackers all fall within this category. Any change in blood pressure, oxygen levels, or heart rate may be quickly detected with the use of these sensors. Everyone

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involved, from patients to doctors, stands to gain a lot from the combination of the Internet of Things and artificial intelligence. Patients get comfort in knowing that their health is being closely watched so that they may receive prompt care in the event of an emergency. This is especially helpful for those dealing with long-term health conditions.

II. LITERATURE REVIEW

Patel, Bhagwat & Pal, Prof. (2024). With the help of the IoT, smart healthcare systems are undergoing a paradigm shift in the way diseases are diagnosed. Now more than ever, artificial intelligence (AI), a lynchpin of computer science, is playing a key role in healthcare by providing complex algorithms to analyse medical data, which in turn helps with prediction and decision-making. Through the Internet of Things (IoT), web-enabled devices, such as wearables and implanted sensors, may continuously gather data, expanding this potential. Smart healthcare systems that use AI and the internet of things improve medical processes, patient experiences, and operational workflows. Rapid and reliable illness detection is made possible by combining AI-driven procedures with IoT data streams. This article aims to overcome the limitations of traditional approaches, which are typically influenced by human biases. Problems with data privacy and security as well as the ethical use of AI are, however, still very much present.

Sujith A.V.L.N. et al. (2022) emphasized the importance of smart health monitoring (SHM) utilizing DL and AI in tackling healthcare difficulties caused by new illnesses and quickly developing technologies in a comprehensive assessment. The rising difficulty of balancing work and health has led to the development of SHM systems, which show great promise as a solution. When contrasted with more conventional methods of healthcare, these solutions have demonstrated to be more dependable, efficient, and quick. Additionally, patients' private information is safe since blockchain frameworks have improved data security and privacy. The use of DL and ML approaches has taken SHM to the next level by improving mortality management, allowing for the early diagnosis of chronic illnesses, and contributing to preventative healthcare. These technologies have been further optimized for real-time, cost-effective services by cloud computing and storage. The evaluation does, however, highlight a number of obstacles, such as problems with scalability and problems with integrating new technology.

Amin et. al. (2022). We talk about how technology and contemporary lives are reshaping the healthcare system. This research looks at how edge computing, 5G, and Internet of Things (IoT) sensors may help with healthcare in real-time while also taking latency and energy consumption into account. In it, healthcare IoT uses are examined. While recognizing difficulties such as computing complexity and security, the study delves into edge intelligence as it pertains to health data processing. We suggest future study directions that might improve healthcare edge computing and, in the end, patients' quality of life. The research also summaries the medical treatment and healthcare industries' overall utilization of IoT technologies on edge platforms.

J. Qi et al. (2023). A transition from conventional hub-based systems to PHS is outlined as a result of the fast growth of the IoT in healthcare. Affordable smart medical sensors are a need, but there are currently no standardized IoT designs, device variety is an issue, data dimensions are complicated, and interoperability standards are not yet in place, all of which limit the potential of the Internet of Things in PHS. This study presents a thorough analysis of IoT-enabled PHS, covering all the bases: recent studies, relevant technology, practical applications, case studies that have been successful, and potential problems and trends down the road. Opportunities and challenges in incorporating Internet of Things (IoT) innovations into individualized healthcare systems are discussed in this paper.

Jones et al. (2019). To foretell upcoming health occurrences, predictive analytics, driven by AI, utilizes both historical and real-time data. Both acute health events and chronic illness management have benefited greatly from this strategy. explore the ways in which proactive healthcare, utilizing patient health records in conjunction with predictive analytics, might decrease hospital admissions and enhance patient outcomes. The significance of combining AI with health monitoring systems to offer individualized healthcare solutions is highlighted by their research.

III. RESEARCH METHODOLOGY

In order to improve treatment and prescription, smart healthcare systems needed findings in real-time. On the other hand, when it comes to smart healthcare applications, the Internet of Things isn't offering very dependable solutions with the current network architecture. Therefore, smart healthcare apps may improve their services with the incorporation of 5G. Common issues that get in the way of improved results and real-time research include delay and latency. Improving critical parameters for subsequent generations is possible, in part, via network slicing. The mobile operator may enhance service quality by using numerous network instances from a single base station.

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This study offered a model that efficiently handles load balancing, overloading, and providing an alternative slice in the event of a slice failure, all in an effort to solve the main issues with network slicing.

Five primary modules make up the suggested model: pre-processing, recursive feature removal, model creation, and parametric assessment. Figure 1 shows the information flow and the operation of all modules. The data set that was gathered is part of the network traffic that includes unique data values from the 5G network. The first module involves applying filters to the data based on certain attributes. The second module, on the other hand, uses a recursive feature elimination approach to extract features from the data. The network slices are managed according to the healthcare system's requirements using a network slicing module. Using Flauto ML methods, which automatically produce effective models depending on performance, the models are built in the fourth module. Parametric testing and assessment are carried out in the final module. The suggested model can manage a bigger healthcare network with an increase in the number of devices since it is based on autonomous modeling.

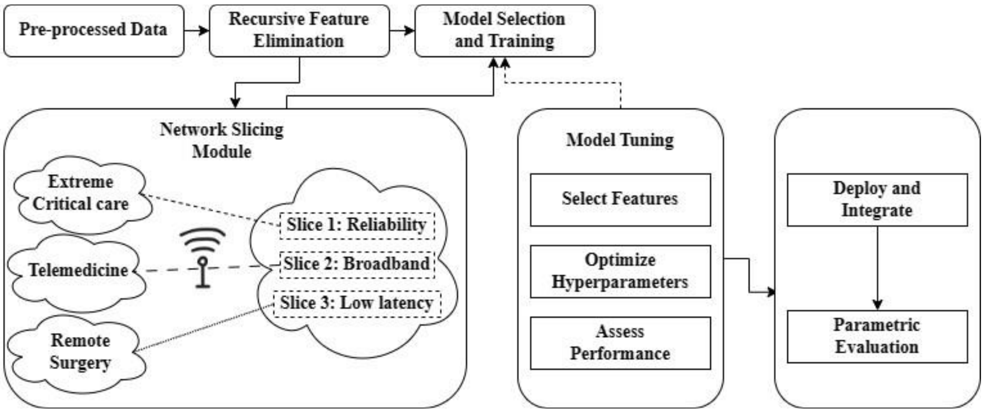

Figure 1: Methodology for the System to Be Implemented

Here is a brief synopsis of the modules that were mentioned:

- The primary function of the pre-processing module is to clean and filter data that has been retrieved from different medical equipment. After that, sort the feature matrix according to the dependent and independent variables. As the data gives the models false leads, dealing with missing data is the next stage. Either assessing the mean value for the column or removing the data row will do this. In the end, it converts the categorical data to a numerical format for better data processing.

- The Recursive feature Elimination (RFE) Module Some dataset characteristics may be completely irrelevant to the model and thus provide the lowest possible outcomes. So, either removing features from the original dataset or extracting them is necessary. You have the option of doing this by hand or using an automated approach called RFE. The first method relies on picking certain characteristics, while the second on picking an algorithm to choose those traits. The RFE wrapper class takes the estimator value and the features chosen for the algorithm as inputs and returns an output. Resampling and recursive feature elimination are carried out in accordance with the parameter improvement.

- Depending on the needs and importance of the data, the Network Slicing Module creates network slices. It checks that the network function is being controlled and managed correctly in order to identify whether slices are created correctly. The data is partitioned into three sections: first, for remote surgery; second, for telemedicine; and third, for really critical care monitoring. Communication with minimal latency and maximum dependability form the basis of the first slice's requirements. A network slice with improved broadband access is provided to telemedicine for the purpose of patent monitoring. Thirdly, remote surgery required great security, dependability, and minimal latency. Method 1 is the foundation upon which the network slicing is built.

Model Building Despite the fact that there are a number of approaches available, the dataset can only be adequately represented by a machine-learning-based model. Feature selection, estimators, and performance may all be put into these models manually. But with a machine learning model that runs automatically, all of the human work in creating the prediction model is gone. It also makes it easier and requires less experience to construct a reliable model. Feature selection, hyperparameter optimization, and model performance assessment are all parts of the model tuning process that FLAuto ML assists with. To measure the model's efficacy, this model additionally considers the user-specified value of the epochs.

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Algorithm 1: NetworkSlicing (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<= l till
   /* Load balancing for network slice */

4. Percentage utilization of the network slice
   M1= eMBB_l / sizeof(eMBB) *100

   M2= URLLC_l / sizeof(URLLC) *100

   M3= mMTC_l / sizeof(mMTC) *100

   M4= MF_l / sizeof(MF) *100

5. 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.
```

In order to find the optimal hyperparameters for a certain machine learning problem, FLAML employs a mix of methods such as bandit-based algorithms, random search, and Bayesian optimization. It is compatible with many different ML methods, including SVMs, gradient boosting, random forests, and deep learning models. The capacity to get competitive outcomes with FLAML is a major characteristic. Required very little time and computing resources. It does this by eliminating the requirement for exhaustive search and intelligently allocating computing resources to the most promising hyperparameter combinations.

To handle the hyperparameter sensitivity, FLAML's optimization approach is built for parametric evaluation. Regardless of how sensitive the hyperparameter configuration is to changes, FLAML attempts to find it by intelligently exploring the hyperparameter space using methods like Bayesian optimization. To make sure FLAML models are robust and generalizable, it's a good idea to try out alternative hyperparameter values and do cross-validation. Consequently, separate metrics including accuracy, precision, recall, support, and average time form the basis of the parametric assessment. Evaluating the association among the characteristics that have been chosen is the first step. It is necessary to assess the rollout of LTE 5G. We take a look at the target variable's slice type distribution. The last step is to assess the performance based on the identified parameters.

IV. DATA ANALYSIS

For the purpose of evaluating the model's performance, a Python model is developed and deployed using the Keras library and Tensor flow. There are a number of ways to do this:
i) To begin, for optimal results, divide the dataset in half, 80 percent for training and 20 percent for testing. After that, for continuous variables, use a pair-wise scatter plot to see the data. Using scatter plots, counted packet delays, probability of IoT devices and LTE/5G with Slice type, and goal variables, Figures 2, 3, 4, show the dataset distribution.

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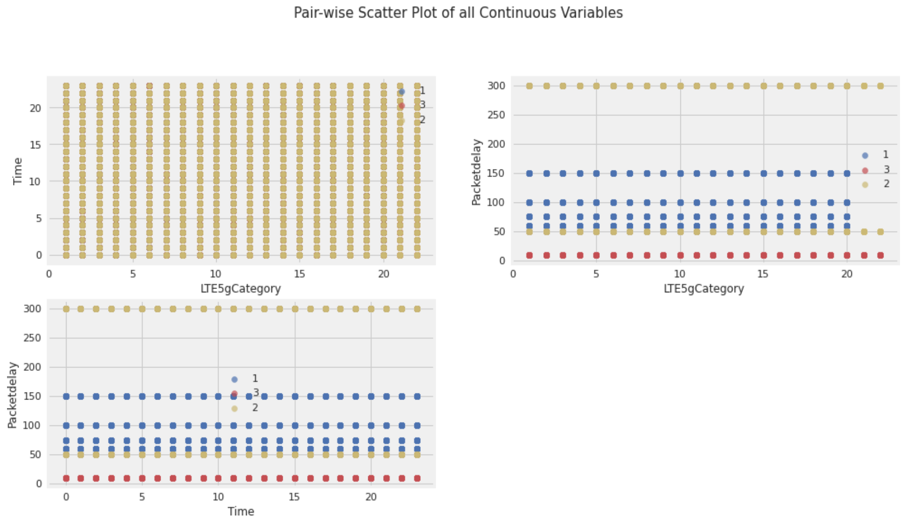

Figure 2: Pairwise scatter plot of a continuous variable

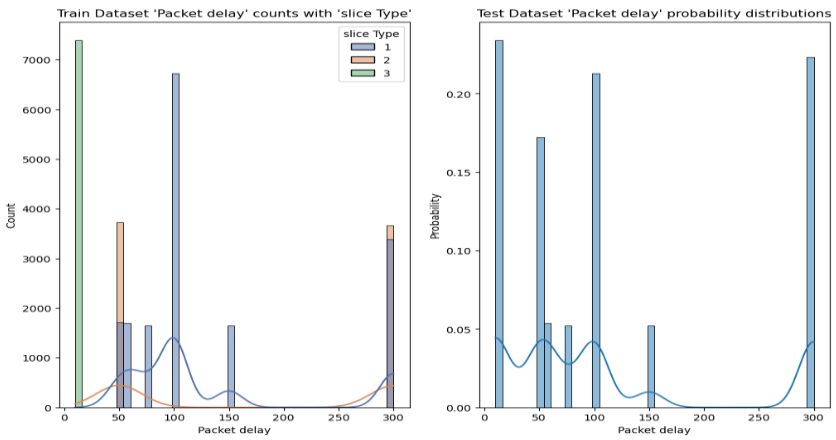

Figure 3: Distribution of Probability and Slice Type on Packet Delay

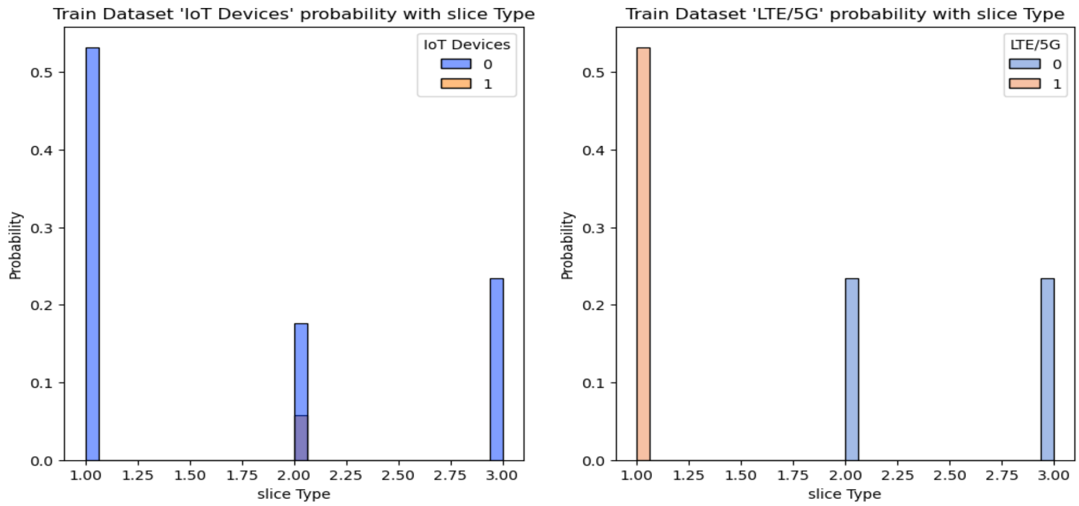

Figure 4: Slice type and the Internet of Things (IoT) as well as LTE and 5G

Figure 5 show the dataset distribution. Figure 6 uses a heatmap to show how all of the factors are related to one another.

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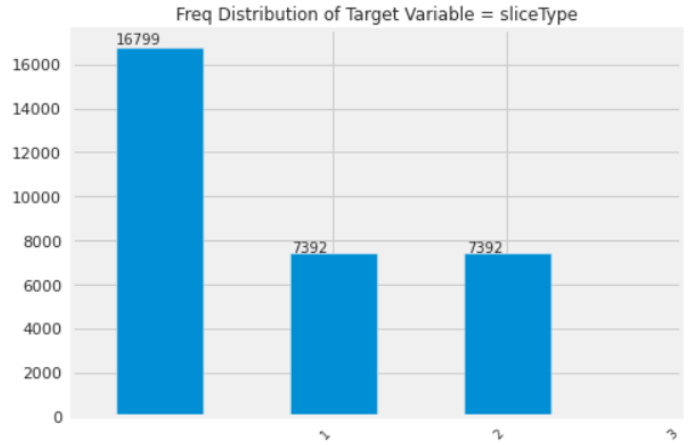

Figure 5: Distribution of the desired variable's frequency Category of Slice

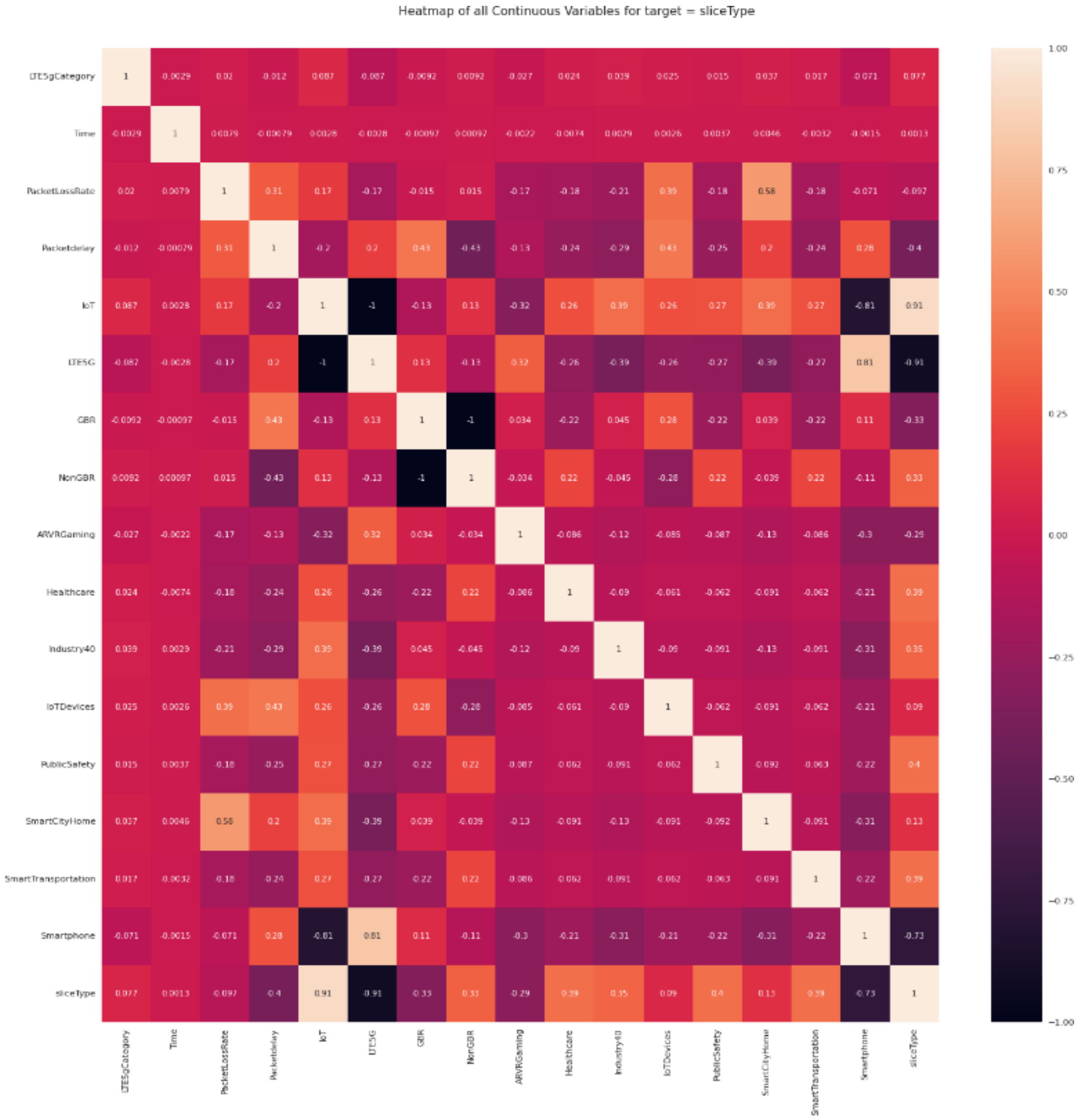

Figure 6: The target variable's heatmap displaying all continuous variables

Healthcare equipment' average LTE5g category, time, and packet delay are shown in Figures 7, 8, and 9. One automated machine learning tool that identifies the correct ML model with minimum computing resources is FLAML, which stands for Fast Library for Automated Machine Learning and Tuning.

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This program is primarily used for creating accurate models, easily customizing classification and regression, and generating data. The XGBoost, lgbm, random forest, and extra_tree algorithms were used. Machine learning models produced by FLAML may have different levels of interpretability and explainability based on the technique used and the difficulty of the challenge. With improved training data and epochs, FLAML supports a variety of ML techniques.

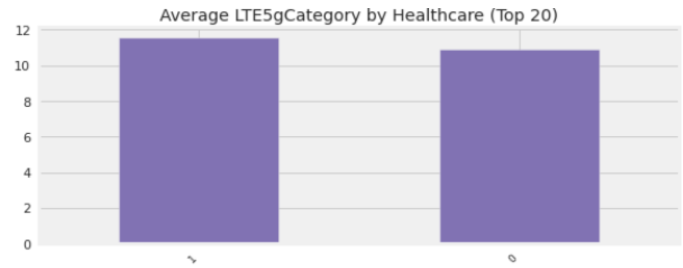

Figure 7: Average Healthcare LTE5g Category

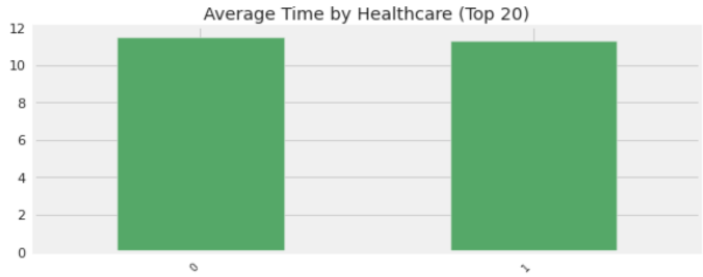

Figure 8: Healthcare Industry Standard Time

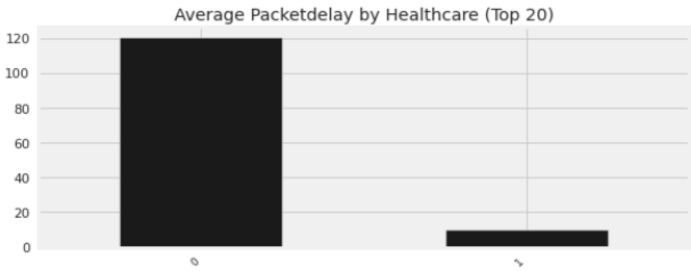

Figure 9: Healthcare industry average packet latency

While certain algorithms, like deep neural networks, are notoriously difficult to understand, others, like decision trees and rule-based models, have a more naturally interpretable quality. Which method is best will be determined by the unique collection of healthcare problems and their representation. Name of the ML learner, hyperparameter settings, best roc auc ovo, and time it took the best algorithm are all part of the findings returned by FLAML.

Table 1: Analysis of previous studies in relation to ongoing investigations

Algorithm/Classifier	**Dataset**	**Time Delay**	**Accuracy/ Throughput**
CNN	NSL-KDD	0.1872	98.3%
Enhanced Spectrum Sensing	Simulated Environment	0.87	97.8%
Hierarchical Cognitive Engine Architecture	Conceptual Framework	--	--
POSENS	Experimental	0.754	98.6%
Reinforcement Learning	Simulated Environment	0.3600	94.6%
FLAML	Network Slicing	0.03724	98.65%

V. CONCLUSION

A more efficient, dependable, and patient-centered approach to improving healthcare facilities for people is the smart healthcare system's transition from conventional hospitals. The healthcare sector stands to gain a lot from the combination of the Internet of Things (IoT) and 5G technology, which will allow for remote patient monitoring, linked

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ambulances, and robotic surgery. With 5G-IoT, many medical devices may communicate and generate massive amounts of data for analysis. More trustworthy assessment methods, capacity, low latency, and high security are needed for this massive data. An insightful method for analysing and optimizing the resources of a smart healthcare network based on 5G-IoT is presented in this chapter. A Fast Library for Automated Machine Learning (FLAML) is an automated model that evaluates the algorithm's performance. The results of the parametric assessment reveal that the LGBM algorithm achieves the best accuracy with a time delay of 0.3724 ms and an accuracy of 98.65%. With the integration of 5G and the Internet of Things (IoT), the outcomes will be attainable in the future. Data ownership, privacy, sharing, and data protection regulations are some of the possible ethical concerns that aren't given enough attention.

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