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Enhanced 6G Network Slicing Classification Using PSO-Based Feature Selection and Ensemble Learning

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***Abstract*—In parallel with technological developments, mobile and wireless communication technologies are advancing rapidly. Today, 5G technology is widely used, while studies on 6G continue. As a result of these developments, the use of internet-connected devices is increasing both in daily life and in industrial areas. This increase in the number of devices brings critical requirements such as additional resources and energy consumption in networks, communication prioritization, and reliable data transmission. In response to these needs, 6G technology offers dynamic, flexible, a nd s cenario-based r esource a llocation based on network slicing. Network slicing makes it possible to support innovative services such as super-eMBB, massive-MTC, and super-URLLC. In this paper, PSO-based feature selection and ensemble learning methods are used to solve the network slicing classification p roblem i n 6 G n etworks. I n a ddition, t he LIME method is applied to help better interpret model predictions and make reliable decisions.**

The main objective of this study is to contribute to the development of autonomous and seamless network systems that are suitable for the dynamic and complex nature of 6G. Thus, it aims to create reliable, flexible, a nd e fficient ne twork solutions by making the best use of the innovations offered by 6G.

***Keywords*—6G, Network Slicing, PSO, Ensemble Learning, LIME**

I. Introduction

Mobile and wireless communication has evolved from generation to generation in light of technological developments and has taken its current form. Recently, studies have been ongoing for the transition from the fifth g eneration (5G) to the sixth generation (6G), and 6G usage is included in some regions. The number of devices connected to the Internet, autonomous systems, and applications such as the Internet of Things are increasing the complexity of networks. Therefore, the need for fast, reliable, efficient, a nd s calable n etworks is increasing daily.

With the increasing complexity of networks comes the need for low latency, high data throughput, and reliable communication. In particular, 6G networks are being considered to solve such situations. In addition, 6G technology is also proposed for operations such as managing network resources and their allocation. When these situations are analyzed and solutions are developed, a new technique emerges, such as network slicing. With the development of 6G technology, network slicing technology is also evolving [1], [2].

6G network slicing enables the dynamic creation of network segments according to predetermined service demands. In the 5G network, slices are made to support new services such as Ultra-Reliable and Low Latency Communications (URLLC), Massive Machine Type Communications (mMTC), and Enhanced Mobile Broadband (EmBB). The 6G network offers various services such as super-eMBB, massive-MTC, super-URLLC, super-precision, and super-immersive. These slices may vary according to the requirements. By using network slices, resources can be allocated flexibly, dynamically, and efficiently according to the scenarios and needs.

Studies are being conducted, especially on 6G, for network slicing, classifying network slices, and allocating resources accordingly. Due to the complex, comprehensive, and dynamic structure of 6G technology, the use of machine learning, deep learning, and artificial intelligence techniques for network slicing operations is increasing. These techniques and technologies have become crucial in slicing, making processes autonomous, and providing uninterrupted service [3], [4].

The literature contains numerous studies on traffic prediction and network slicing [1]–[8]. These studies significantly improve network performance, secure slice allocation, and more effective use of network resources. The reviewed studies generally focus on network slicing, traffic prediction, and secure resource allocation in 5G and 6G networks. Various models are used to classify network packets based on load data, allocate network traffic into secure slices, perform mobile traffic prediction, perform dynamic slicing optimization in the

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network, or perform network slicing classification. For example, CNN, Random Forest, MLP, GRU, LSTM, and hybrid models. The reviewed studies demonstrate the effectiveness of machine learning, deep learning, and artificial intelligence methods for network slicing and traffic prediction in 5G and 6G networks.

In Chen et al.'s study, network packets were classified based on payload data instead of traditional methods. After capturing the packets, 1D and 2D images were generated, and Convolutional Neural Network (CNN) models were trained. eMBB, mMTC, URLLC, and internet applications (4K video, NB-IoT, UAV, Facebook) in 5G technology were tested [3]. Immadisetti et al. aimed to allocate specific network slices to specific applications in 5G mobile networks. The fine-grain network slices approach provides network resilience, analysis, and fault detection. The study used traffic data from more than 50 applications, such as Google, YouTube, Facebook, and DDoS attack data. A Random Forest-based two-stage method is proposed for secure slice allocation, and an accuracy of 86% is achieved [5]. Gupta et al. used deep learning models for mobile traffic prediction to optimize resource utilization in 5G network slicing. A dataset of six days of internet usage data was used to predict which network slice belonged to the streaming, messaging, calling, or cloud categories. In tests with sequence learning techniques, MLP and Encoder-Decoder models performed moderately, while GRU and LSTM models performed better [6]. Hussain et al. developed an approach combining different dynamic slicing optimization models in 5G networks. A large amount of configuration and performance data was collected with an experimental 5G prototype, and the LSTM model played a critical role in the dynamic slicing correction process using time series predictions. Grey Wolf Optimization (GWO) method is applied for resource allocation optimization [7]. Dangi and Lalwani developed an efficient 5G network slicing method based on a hybrid learning algorithm. The study has three phases: data set loading, hyperparameter optimization with HHO, and slicing classification with a hybrid deep learning model [1].

Dangi et al. studied flexible and scalable network slicing in 6G networks. Data preprocessing was performed using the Unicauca IP Flow Version2 dataset, and 78 tags were transformed into five network slices (super eMBB, massive-MTC, super-URLLC, super-precision, super-immersive) based on device demands. A hybrid model based on CNN and BiLSTM is proposed for reliable network slice allocation. CNN is used for automatic feature selection, and BiLSTM is used for network slice classification [8]. Botez, Zinca, and Dobrota discuss AI-based network slicing methods in 6G networks. A synthetic dataset obtained from recent papers was created and shared. The dataset includes features such as Use Case, Packet Loss, Latency, Jitter, Data Rate, Mobility, Connectivity, and Predicted Slice, and feMBB, umMTC, mURLLC, ERLLC, and MBRLLC slices are used. By analyzing the quality of service parameters, Random Forest, Decision Trees, kNN, Naïve Bayes, SVM, XGBoost, and FNN models are trained for network slice prediction [2]. Mahmoud et al. conducted a 6G network slicing study using a real-world DeepSlice dataset. The dataset has nine features: use case (XR/gaming, healthcare, industry 4.0, IoT, public safety, etc.), connection technology, packet loss, delay, and Slice type. Feature selection was performed with CNN, and a hybrid deep learning approach was used for network slice classification [4].

This study aims to study 6G, evaluate it using real-world traffic data, improve resource utilization, and ensure network resilience. For this purpose, the Unicauca IP flow version 2 dataset, which is widely used in the literature for different purposes, is selected. Labeling and preprocessing were performed on the dataset for network slice classification. A practical approach of PSO-based feature selection and ensemble learning methods was used to determine the most compelling feature list. The LIME method improves the interpretability of model decisions, and detailed analysis is presented for each class label. A promising solution for efficient and scalable network slicing in 6G networks is presented.

The paper consists of 4 sections. The first section discusses 6G and network slicing technologies and presents the literature on this area. The second section presents the materials and methods of the study. The third section presents the experimental results and evaluations. The last section presents the conclusions and contributions of the study.

II. Material and Method

1) Dataset description: The open-access Unicauca IP flow version2 [9] dataset was used in the study. The data set contains IP network traffic flows labeled for different applications. In particular, researchers use the data set in network management, cybersecurity threat detection, and application identification. The dataset contains 3,577,296 observations, 87 features, and 78 tags that hide information about IP flow.

A. PSO

Particle Swarm Optimization is a population-based heuristic optimization algorithm developed by Kennedy and Eberhart [10]. Inspired by swarm behavior in nature, it uses a population of particles to find the best solution. The optimization process is based on the process of sharing information between each candidate particle. Here, each particle adjusts its position to the best position in the swarm. These particles also use their previous speed and position information. Updating the velocity and position information of particles in systematic equations can be done as follows:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t) \quad (1)$$

where w is the inertia weight controlling the influence of the previous velocity, c_1 and c_2 are acceleration coefficients guiding the particle toward its personal best position $pbest_i$ and the global best position $gbest$, respectively. The random numbers r_1, r_2 (uniformly distributed in $[0, 1]$) introduce stochastic behavior. The new position of the particle is then updated as:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (2)$$

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This iterative process continues until an optimal or satisfactory solution is found [11].

B. Ensemble Learning

Ensemble Learning is an approach that aims to make more substantial and more generalizable predictions by combining multiple machine learning models [12]. Bagging (e.g., Random Forest) separates data samples into different subsets and runs models in parallel [13], while Boosting (e.g., AdaBoost, XGBoost) reduces errors by training weak models sequentially [14]. Stacking improves prediction accuracy by building a new model from the outputs of different models. These methods are used to improve model performance and reliability, especially for complex data sets.

C. LIME

LIME (Local Interpretable Model-Agnostic Explanations) is a method for explaining the predictions of complex machine learning models [15]. In order to understand how the model makes a particular prediction, the contribution of each feature to the prediction is determined by generating the model result on given test instances. This makes the model's decision-making more transparent and interpretable.

III. Methodology

This study uses PSO feature selection and ensemble learning methods for the 6G network slicing classification problem. First, missing and outlier data are corrected by data preprocessing steps, and then the most compelling features are identified by PSO, and unnecessary variables are eliminated. Then, classification was performed with ensemble models such as Random Forest, XGBoost, AdaBoost, and KNN, and performance metrics were compared. To analyze the effect of feature selection on model performance, metrics such as accuracy and F1-score are evaluated before and after PSO. Furthermore, the LIME method is used to visualize the features based on the model predictions for each slicing category to make sense of the model's decision mechanisms.

1) Dataset preprossessing: The dataset was preprocessed to improve data quality and classification performance for 6G network slicing. The preprocessing steps are as follows:

The dataset is labeled into five separate classes corresponding to different 6G network slicing categories. These labels are super-eMBB, massive-MTC, super-URLLC, super-precision, and super-immersive. This labeling enabled the classification model to learn meaningful patterns based on predefined slice types. The distribution of the data set is shown in Figure 1.

To avoid ambiguity and to ensure that the supervised learning model is trained on well-defined classes, unknown or incompletely labeled examples were removed from the dataset. The size of the dataset was reduced from 3,577,296 to 724,517 instances.

Features with constant values in all examples were identified and extracted. In the raw dataset, 11 features had constant values. Since these features do not provide any discriminative information for classification, their removal helped to reduce the data dimensionality without losing relevant information.

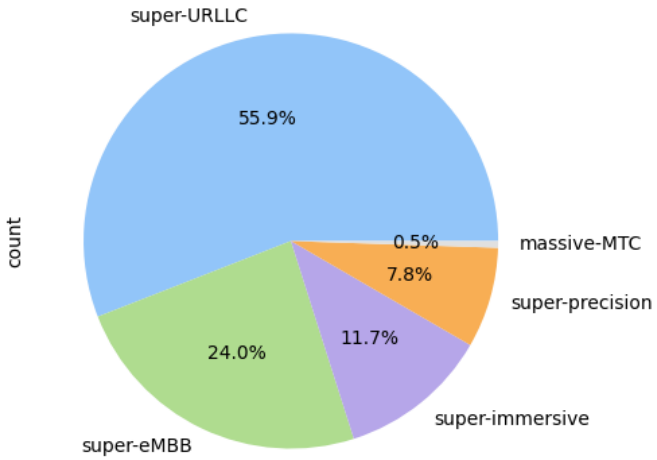


Fig. 1. Sample count distributions by label information

2) Feature Selection: In this study, feature selection is performed using a hybrid approach combining PSO and Random Forest algorithm. Each particle in the swarm represents a potential feature subset, and its position in the search space is encoded as a binary vector, where each dimension indicates whether a particular feature is selected or not. The fitness function is designed according to the classification accuracy of the Random Forest algorithm. The parameters used for PSO are given in Table I.

TABLE I.
PSO Algorithm Parameters

Params	**Values**
Population Size	10
Number of Iterations	30
Fitness Function	Random Forest Model Prediction
Fitness	(1-accuracy)
Normalization Range	[0,1]
PSO Inertia Weight (w)	Adaptive
PSO Cognitive Coefficient (c1)	2
PSO Social Coefficient (c2)	2
Number of experiment repetitions	5

This hybrid approach results in an optimized feature set that improves model performance minimize overfitting and improves generalization ability. The proposed method reduces the feature size of the dataset from 76 to 37. Thus, creating more efficient and accurate models in the high-dimensional data structures brought by 6G becomes possible.

3) Performance evaluation: Feature selection using PSO and Random Forest resulted in an overall improvement in model performance. The results are given in Table II. The Random Forest model showed a significant increase in accuracy and F1-score, from 0.91 to 0.95 and from 0.90 to 0.93, respectively. The XGBoost model remained stable with a slight increase, while the KNN algorithm showed a significant improvement in the F1-score (from 0.67 to 0.74), although

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the accuracy remained stable at 0.75. However, the AdaBoost model showed small fluctuations in performance and, in general, showed lower performance than the other models. These results suggest that PSO-based feature selection can improve model performance and provide more accurate predictions, mainly combined with ensemble methods.

TABLE II.
ACCURACY VALUES OF MODELS BEFORE AND AFTER FEATURE SELECTION

Dataset	Model	Accuracy	F1-score[c]
BFS[a]	Random Forest	0.91	0.90
	AdaBoost	0.70	0.65
	XGBoost	0.91	0.89
	KNN	0.75	0.67
AFS[b]	Random Forest	0.95	0.93
	AdaBoost	0.68	0.68
	XGBoost	0.91	0.90
	KNN	0.75	0.74

[a]BFS means that Before Feature Selection
[b]AFS means that After Feature Selection
[c]weighted average

IV. EXPERIMENTAL RESULTS

After feature selection, the model developed with Random Forest was analyzed in detail with LIME. The analysis results for each tag are given in Figures 2,3,4,5,6. When the figures are analyzed in detail, IP addresses (Source.IP and Destination.IP) stand out as important determinants in all classes. Protocol information plays a decisive role, especially in URLLC and immersive traffic types that require low latency and high reliability. Flag Counts are important for reliability and link management and contribute to the model's decisions, especially for URLLC and precision traffic. Packet length and timing variables are discriminative for eMBB and immersive traffic types, while more sensitive variables come to the fore for precision traffic. The model's predominant use of variables such as Source.IP and Destination.IP shows that certain address ranges in the network are associated with different types of traffic. When the source and destination IP addresses exceed certain thresholds, it affects especially super-immersive and super-precision predictions. In contrast, high forward time intervals (Fwd.IAT.Min and Fwd.IAT.Mean) significantly affect super-eMBB and super-immersive predictions. Furthermore, zero TCP flags (RST.Flag.Count and Fwd.PSH.Flags) cause the model to exclude some classes, while the network metrics of flow duration (Flow.Duration) and packet length (Min.Packet.Length) play a critical role in determining the massive-MTC and super-URLLC classes.

As seen in Figure 2, one of the most determining variables for the Massive-MTC class is the Destination IP and Source IP value. In addition, variables such as Protocol ($\leq$ 6.00) and RST.Flag.Count ($\leq$ 0.00) also drives the model. Variables related to packet size make a limited contribution. Since Massive-MTC is a type of traffic requiring low latency sensitivity and high link density, devices with specific IP ranges seem to be concentrated in this category.

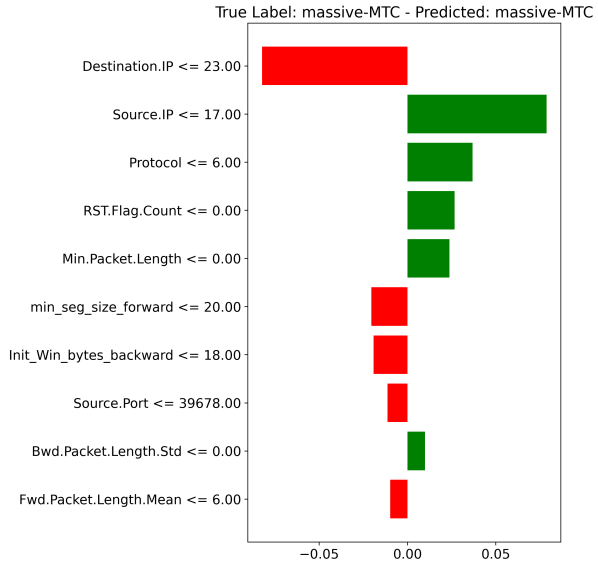


Fig. 2. LIME analysis for Massive-MTC class

Super-URLLC is a type of traffic that requires ultra-reliable and low-latency communication. Figure 3 shows that IP address-based variables are deterministic. This indicates that URLLC traffic is usually concentrated in a specific range of source and destination IPs. Flag values such as Protocol ($\leq$ 6.00), ECE.Flag.Count ($\leq$ 0.00) also makes significant contributions. In particular, variables such as Down. Up.Ratio ($\geq$ 1.00) and ACK.Flag.Count (0.00 $\leq$x $\leq$ 1.00) suggests that the routing mechanism has a specific directionality and is optimized to ensure reliability.

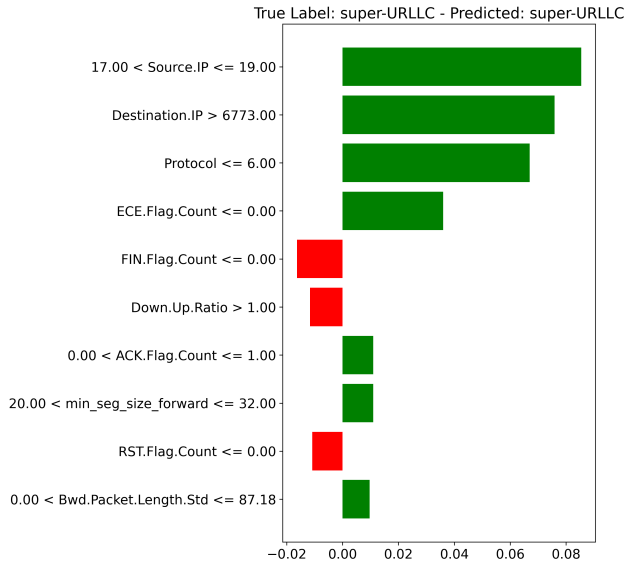


Fig. 3. LIME analysis for Super-URLLC class

Super-eMBB is a type of traffic with high bandwidth requirements. Figure 4 shows that specific IP ranges for this class are not associated with eMBB traffic by the model. Variables

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such as Protocol ($\leq$6.00) also have a negative effect, while variables such as Bwd.Packet.Length.Max (0.00$\leq$x$\leq$265.00) has a positive contribution. In addition, the contribution of variables such as Init_Win_bytes_backward ($\geq$ 513.00) and Fwd.IAT.Mean ($\geq$ 831176.00) shows that the size of data packets and transmission intervals are important for this traffic type. Considering that Super-eMBB is usually characterized by high-volume data flows, packet size, and timing variables are expected to be determinants.

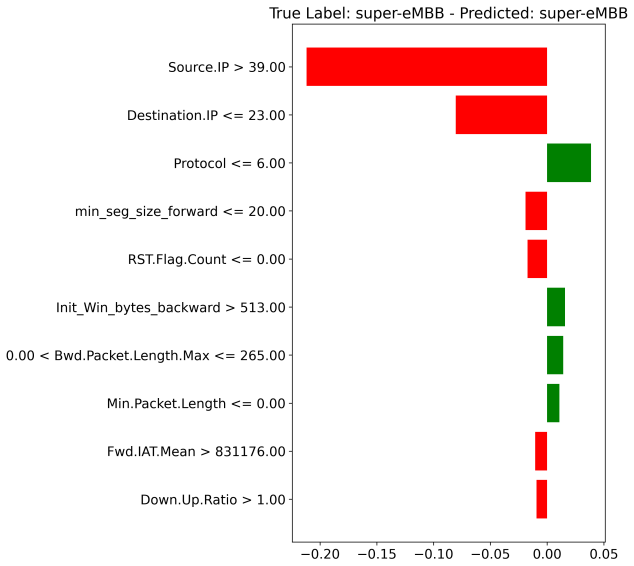


Fig. 4. LIME analysis for Super-eMBB class

Super-immersive traffic covers applications that require low latency and high bandwidth, such as augmented reality (AR) and virtual reality (VR). As shown in Figure 5, in particular, variables such as Protocol ($\leq$ 6.00) and Min.Packet.Length ($\leq$ 0.00) have a positive effect. On the other hand, variables such as flow a re u sed. D uration $\geq$ 2 0345951.00) and RST.Flag.Count ($\leq$ 0.00) have a negative effect. This suggests that immersive traffic i s t ransmitted w ithin a s pecific source IP range and usually in small packets, but long-lasting flows are not counted as such. Variables such as Max.Packet.Length ($\leq$ 6.00) also has an effect, suggesting that immersive traffic is typically associated with low latency and continuous data flows.

Super-precision traffic i s o ptimized f or p recision industrial control systems and critical applications. As shown in Figure 6, the positive contribution of variables such as Min_seg_size_forward ($\leq$ 20.00 $\leq$ x $\leq$ 32.00) indicates that the forward segment size is important for the model. The negative contribution of the variable Fwd.IAT. Mean ($\geq$ 831176.00) indicates that large transmission intervals in super-precision control systems are not considered by the model as belonging to this class. This supports the idea that super-precision traffic requires low latency and continuous data transmission.

Figure 7 can be examined for a detailed analysis of the model created in the study. The confusion matrix is used to

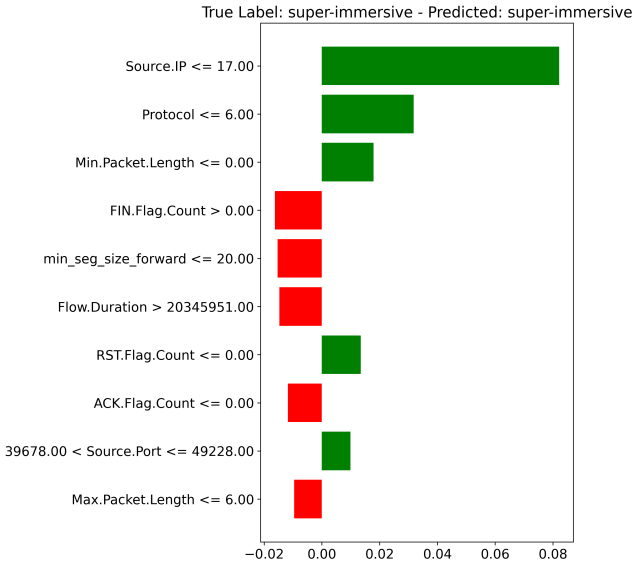


Fig. 5. LIME analysis for Super-Immersive class

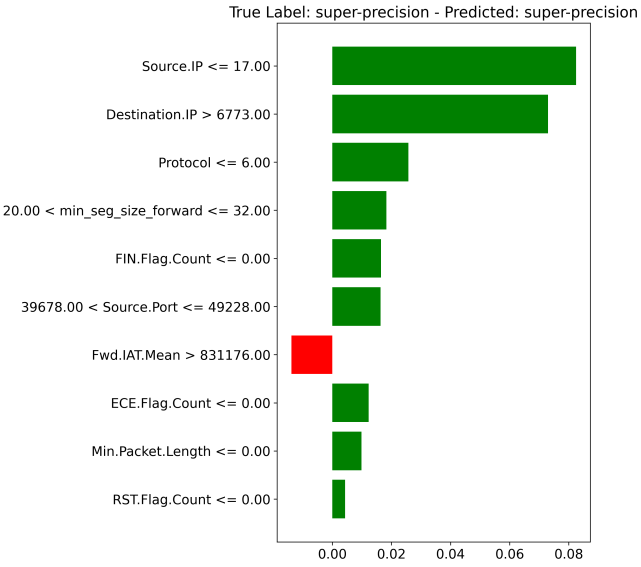


Fig. 6. LIME analysis for Super-Precision class

evaluate the performance of the 6G network slicing classification m odel. T he m odel p erformed e xceptionally w ell in the classes of super-URLLC (79,117 correct classifications) and super-eMBB (30,995 correct classifications). However, the super-eMBB class was misclassified a s s uper-URLLC in 3,033 instances, indicating that there are some similar features between these two classes. Although some misclassifications are also observed in the super-immersive and super-precision classes, overall, the model has a high accuracy rate. The error rate is relatively low in the Massive-MTC class, but the smaller number of samples may explain this compared to the other classes.

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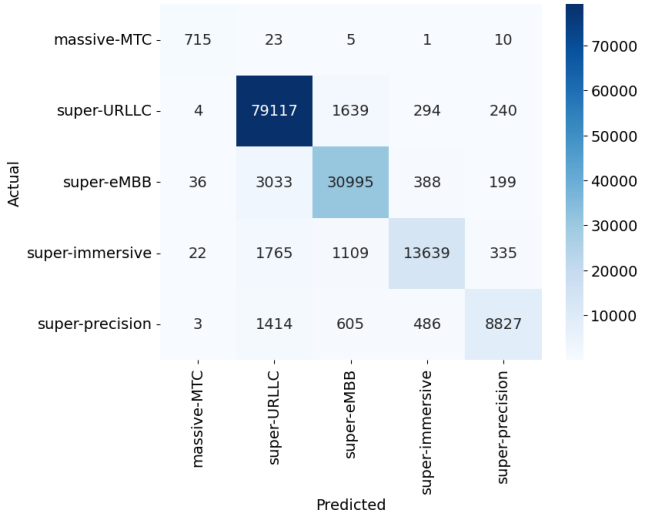


Fig. 7. Confusion Matrix

V. CONCLUSION

This study uses PSO-based feature selection and ensemble learning methods to solve the network slicing classification problem in 6G networks. Experimental results show that the features selected by PSO improve the classification performance, especially ensemble methods such as Random Forest and XGBoost, which provide high accuracy rates. Model performances are compared before and after feature selection, and it is observed that PSO reduces the computational cost by eliminating redundant features while increasing accuracy and F1-score.

Furthermore, the LIME method was used to analyze the interpretability of the model decisions for each slicing category. This analysis helped network managers make more informed and reliable decisions by explaining which features the model is based on. Accurate and reliable classification o f network slices in 6G networks is critical to optimize resource allocation, improve service quality, and ensure network security.

In conclusion, this study has demonstrated that PSO-assisted feature selection and ensemble learning provide a powerful approach to 6G network slicing classification p roblems. The LIME-based analysis helps to understand the decision mechanisms of the model and provides significant c ontributions in terms of reliability and explainability. These findings suggest developing more effective and interpretable artificial intelligence solutions for future autonomous 6G network management systems.

The findings of this study shed light on the development of more efficient a nd e xplainable a rtificial in telligence solutions for future autonomous 6G network management systems. Future work could focus on integrating different meta-heuristic optimization algorithms, examining the effectiveness of deep learning-based models in classification, and testing the system on real-time data streams. Furthermore, increasing reliability and transparency by applying explainability methods such as LIME to more complex AI models could also be an important research area. These directions will make 6G networks more intelligent, autonomous, and reliable.

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