Computers, Materials & Continua
DOI: 10.32604/cmc.2023.036013
Article

Machine Learning Based Classifiers for QoE Prediction Framework in Video Streaming over 5G Wireless Networks

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Received: 13 September 2022; Accepted: 04 November 2022

Abstract: Recently, the combination of video services and 5G networks have been gaining attention in the wireless communication realm. With the brisk advancement in 5G network usage and the massive popularity of three-dimensional video streaming, the quality of experience (QoE) of video in 5G systems has been receiving overwhelming significance from both customers and service provider ends. Therefore, effectively categorizing QoE-aware video streaming is imperative for achieving greater client satisfaction. This work makes the following contribution: First, a simulation platform based on NS-3 is introduced to analyze and improve the performance of video services. The simulation is formulated to offer real-time measurements, saving the expensive expenses associated with real-world equipment. Second, A valuable framework for QoE-aware video streaming categorization is introduced in 5G networks based on machine learning (ML) by incorporating the hyperparameter tuning (HPT) principle. It implements an enhanced hyperparameter tuning (EHPT) ensemble and decision tree (DT) classifier for video streaming categorization. The performance of the ML approach is assessed by considering precision, accuracy, recall, and computation time metrics for manifesting the superiority of these classifiers regarding video streaming categorization. This paper demonstrates that our ML classifiers achieve QoE prediction accuracy of 92.59% for (EHPT) ensemble and 87.037% for decision tree (DT) classifiers.

Keywords: QoE-aware; video streaming; 5G networks; wireless networks; ensemble method

1 Introduction

Recently, the augmented exploitation of video streaming facilities has abruptly enhanced bandwidth requisites via the internet. Generally, video streaming allows viewers to watch videos over the internet without the necessity of downloading them. Specifically, a chief portion of web/internet traffic, owing to live streaming, arrives from cardinal video sites like Netflix and YouTube [1]. In addition, video traffic involves video archives shared over the internet, video conferencing, internet video, and online games [2]. Slow web access is witnessed during peak periods like daytime when several customers are streaming videos simultaneously. This is likely to be extremely frustrating, particularly to those engaged in tasks that need an uninterrupted and rapid internet connection. Utilization of a major percentage of web traffic by video streaming services has raised heterogeneous concerns in the modern fast-pacing world. Several multimedia services like synergistic video gaming and HD video need high-speed connectivity, so the notion of fifth-generation (5G) ameliorates the end clients' experience in handling these services. 5G technology is anticipated to provide innovative features compared to 4G by offering ultra-reliable, low-latency, and ubiquitous connectivity 'anytime' and 'anywhere' [3]. High-reliability and low-latency wireless communication methods are anticipated to become the chief attributes of these wireless networks [4]. With 5G networks, many services and applications can be accessible to remote clients/users. Consequently, clients expect improved network quality of service (QoS) with a greater quality standard [5]. Table 1 shows the different 5G ranges supported by 5G small cell types [6].

Table 1: 5G small cell types

5G small cell types	Deployment	Number of concurrent users	Power range	Distance coverage
Femtocell	It is primarily used in residences and enterprises	4 to 8 users (residence) and 16 to 32 users (enterprise)	10 to 100 mW (Indoor) 0.2 to 1 Watt (Outdoor)	10 s of meters
Pico cell	Public areas such as indoors, outdoors, airports, malls, train stations	64 to128 users	100 to 250 mW (Indoor) 1 to 5 Watt (Outdoor)	10 s of meters
Microcell	Urban areas to fill macro coverage gaps	128 to 256 users	5 to 10 Watt (Outdoor)	Few 100 s of meters
Metro cell	Urban areas to provide additional capacity	>250 users	10 to 20 Watt (Outdoor)	100 s of meters

The difficulties with QoE management in networks are outlined in Fig. 1. In the world of 5G networking, QoE has recently drawn a lot of attention. The crucial goal of QoE is to maintain end users for accurately estimating the perceived standard of service, as well as to consider and evaluate the network's QoS.

In fact, providing a great user experience while utilizing fewer network resources is the primary objective of network service providers. Furthermore, because the success of their business agreements heavily depends on the satisfaction of their customers, it is essential for these service providers to consider the impact of every network element on customer perception. In order to meet the tight QoE requirements of current video streaming systems, network operators typically implement a variety of network management strategies. But classifying video streaming that is QoE aware has become incredibly laborious. Therefore, creating better frameworks capable of achieving this objective has become essential. This article creates a QoE-aware framework for video streaming categorization in 5G systems in order to address this difficulty. This paper has integrated the HPT decision tree and the EHPT ensemble in the ML approach, with the EHPT ensemble having a higher accuracy due to its meticulous optimization of the gradient boosting methodology. The entire boosting procedure greatly enhances training time. This work trains a number of models on various subsets of the training dataset instead of building the best model feasible directly on the data and voting for the model that performs the best. EHPT ensemble XGBoost is frequently superior to conventional gradient boosting techniques. A large number of core parameters are accessible in the Python implementation, allowing for fine-tuning for increased precision and accuracy.

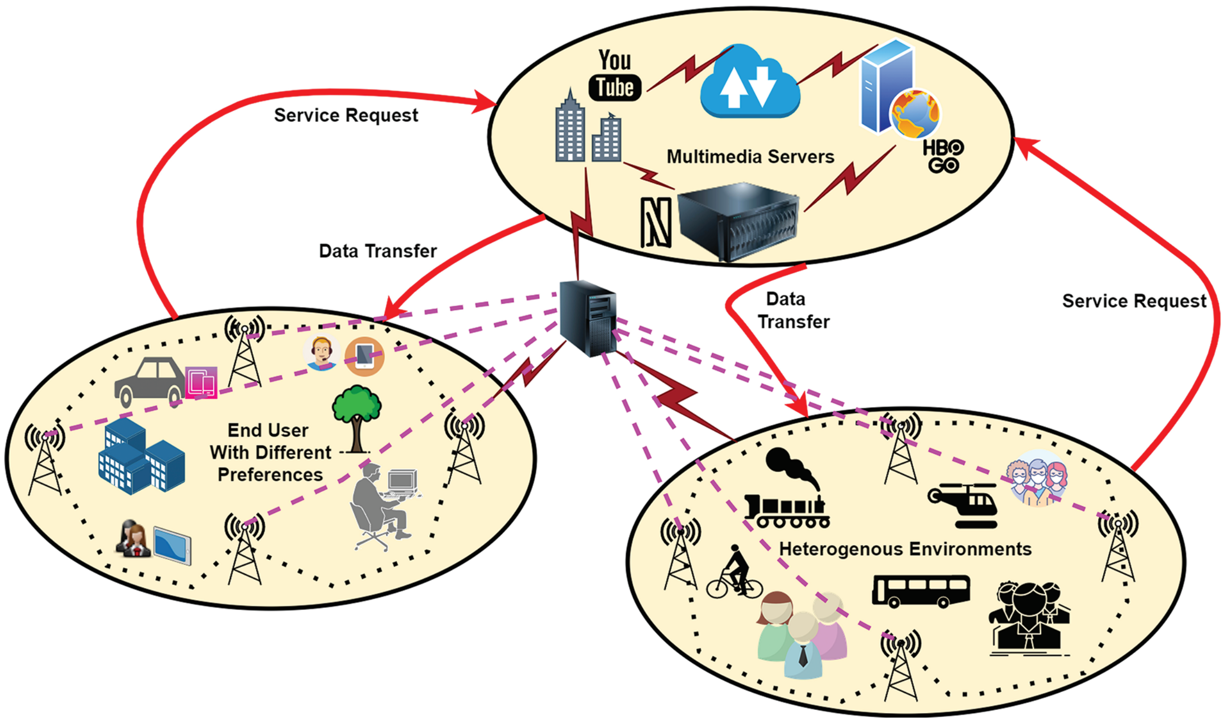

Figure 1: QoE management challenges in networks

1.1 Paper Organization

The rest of this paper is arranged as follows: Section 2 reviews the related works. Section 3 provides the problem statement. Section 4 presents the methodology exploited for video streaming categorization. Section 5 provides a discussion of the achieved results. Finally, Section 6 concludes the paper.

1.2 Contributions of Work

The cardinal contributions of this work include the following:

- Development of a framework for QoE-aware video streaming categorization.
- The exploitation of an enhanced ML approach for optimizing the classification performance.
- Deployment of ML scheme for performing precise prediction of QoE-aware video streaming in 5G networks.

2 Related Work

In [7], personalized QoE management in 5G networks was described using a data-driven structure. The authors in this work used ML algorithms for establishing frameworks capable of predicting QoE using QoS network parameters like 5G-specific and wireless-specific parameters. Furthermore, a tool for assessing video QoE was adopted for gathering necessary QoE information for training prediction frameworks. This work utilized heterogeneous machine learning (ML) algorithms like neural networks (NNs), support vector machine (SVM), random forest (RF), and gradient-boosted (GB) trees for forecasting QoE. The impact of vital wireless-specific determinants was also explored in this work. Experimental outcomes clarified that among all employed ML schemes, the SVM approach performed better and achieved considerably low error. However, this work suggested that the use of wireless-specific determinants alone for QoE forecasting cannot offer the desired results. [8] described a QoE-aware video streaming using a deep reinforcement learning (DRL) scheme. The presented QoE framework used the data gathered during video playback. The DRL scheme was employed mainly for QoE optimization and viewport prediction. Furthermore, an LSTM framework was adopted for viewport and bandwidth prediction. It was identified from the experimental outputs that the presented framework exhibited improved performance than the previously introduced 3D video frameworks. Additionally, the presented system offered 10%–15% performance amelioration and could be adapted to every situation under distinct QoE targets.

In [9], an ML method was utilized for classifying streaming video. The authors utilized a Markov decision process and NNs for identifying the class and source of video streams. This work precisely categorized similar sorts of streaming traffic into distinct services. The employed ML method considered packets gathered via a network interface and categorized the information stream into one of five video streaming services, including Amazon Prime, HBO, Netflix, YouTube tv, and YouTube. In [10], a video streaming assessment was conducted using the QoE framework in LTE systems. This work compared the QoE outputs from two distinct test benches, emulated and real and TCP-dependent video transport protocols. Additionally, it tested diverse propagation frameworks in the emulated setting to determine the one best matching the real conditions depending on QoE. The findings of this study revealed that the presented framework provided QoE quantification in a low-complexity and cost-effective manner. In [11], a supervised ML scheme was presented for forecasting video QoE in 5G systems. This work considered dynamic adaptive streaming over HTTP video application in a practical emulation environment acquired from practical 5G traces in mobility and static scenarios for assessing QoE performance. In [12,13], Dynamic adaptive streaming over HTTP(DASH) has been governing network traffic in the recent era. DASH supplies layouts to deliver the best quality video streaming service on the internet. Dash adheres to ABS standards. The adaptive bit rate streaming (ABS) algorithms aim to detect a favourable quality of video streaming. ABS algorithms decide the quality of the segments to be downloaded based on the network's available resources. The choice of the ABS algorithm plays a significant role in end-user satisfaction. It works on the principle of dividing a larger video file into a number of minuscule segments of equal intervals. Every segment is encrypted in varying bitrates and resolutions, and the illustration of individual segments is defined in the media presentation description (MPD) file. Based on the current network scenario, the user determines the video segments which can be played; the user chooses the segment with the most efficient bitrate feasible, which can be downloaded in that duration without causing any interruption. DASH users can swap between various video qualities to enhance the viewing experience based on the available network. Thus, it is necessary to know the network conditions for enhanced video distribution. Furthermore, an ML scheme was adopted for forecasting user satisfaction by considering network metrics like the sum of packets, throughput, and round-trip time. Simulations manifested that the ML scheme offered 87.63% QoE forecasting accuracy and 79% accuracy for mobility and static scenarios.

In [14], a framework for optimizing QoS-aware video streaming over wireless systems was presented. The presented structure fuses a media-conscious proxy for monitoring chief performance factors from multiple layers, distinct entities, and an ML-dependent decision engine for modelling sensed video quality. The presented architecture was completely integrated with LTE-reinforced packet core systems. This work also explored the ML-oriented schemes for providing a target QoE framework depending on the network, data link, and physical layer parameters. Statistical analysis and extensive experiments indicated that this framework could accurately model the effect of network stultifications on the 3D video user's perception quality. In [15], an artificial intelligence-dependent scheme was presented for video stream categorization. The authors exploited video attributes of distinct time scales for analysis. Initially, video frame sequences of distinct time scales were input to the 3D system for attribute extraction, and then the attributes of distinct time scales were weighted and combined. Furthermore, after combining several sequential frameworks, the combined 3D deep learning (DL) framework was constructed. Simulations revealed that this framework offered 90.6% categorization accuracy and 2.9% performance amelioration. In [16], an ML-oriented approach for categorizing YouTube QoE was presented. This approach aimed at classifying end-users QoE while watching videos depending on the statistical characteristics of network traffic. This work utilized the ML approach for categorizing QoE depending on the traffic attributes computed for every video session. For categorization, this work employed 1060 distinct videos streamed across distinct bandwidth scenarios. It was viewed from simulations that the adopted ML-oriented approach offered 84% categorization accuracy regarding three ternary classifications (QoE classes involving high, medium, and low) and 91% accuracy regarding binary classification (QoE classes involving high and low).

An ML-dependent analysis and computation of video QoE were presented in [17]. The authors adopted a random forest scheme for video QoE analysis. The employed random forest framework was trained on estimated video quality measures using the baseline/reference videos. Results ascertained that this scheme offered 94% categorization accuracy. However, this work was not explored much in terms of video streaming categorization. In [18], a system for categorizing live video streaming was presented. The authors initially preprocessed the live video traffic packets purely depending on the statistical characteristics of network traffic packet flow. Here, traffic intensity was employed as a chief traffic form descriptor with certain additional transforms. This work investigated the categorization accuracy depending on diversified factors like traffic preprocessing type, traffic window length, and sampling time of traffic intensity. Findings declared that the traffic intensity samples offered 94% accuracy without auxiliary transforms. In [19], the prominence of QoE in 5G networks was discussed. The chief challenges, like an augmented quantity of information generation by advanced applications, the necessity for better quality services, and a large number of devices for connecting distinct radio access methods, were identified as crucial 5G challenges regarding QoE. The authors also presented a neural network-oriented approach for QoE computation. This work clarified that owing to NN's capability to completely analyze the causal link between QoS network parameters and the resultant QoE; they are extremely suitable for achieving QoE self-optimization in 5G.

In [20], another methodology for video streaming categorization was presented. The authors in this work gathered a group of video traffic information from a realistic network. Furthermore, this information was preprocessed for choosing the desired attributes for classifying video traffic. The presented methodology offered 99.3% overall accuracy in categorizing video traffic. In [21], an ML approach was described for QoE-aware networks. This work aimed at exploiting ML schemes for modelling the correlation of distinct network and QoS parameters of the application layer to QoE.

An empirical investigation depending on the ML scheme was provided in [22] for assessing QoE/QoS correlation. This work explored how distinct determinants contributed to QoE in a video streaming context. It described that the cardinal parameters influencing the QoE involved network parameters, terminal characteristics, video characteristics, and various customer profiles. ML classifiers were further employed for categorizing a QoE database. This work adopted six distinct ML schemes: SVM, DT, Naive Bayes, neural network, four-nearest neighbour, and RF. An instance categorization test was performed to choose the appropriate framework. It was explicitly observed from the outputs that DT and RF displayed better performance compared to the remaining ML schemes. Simulations indicated DT offered 74.8% precision, 74.5% f-measure, and 74.3% recall, while RF offered 75.2% precision, 75.2% f-measure, and 75.3% recall. Furthermore, a statistical investigation of classification was also presented to explore the effectiveness of RF and DT schemes. Statistical analysis outputs clearly manifested that the RF classifier superseded the DT approach. This work thus illustrated the appropriateness of ML techniques for the QoE/QoS correlation task.

In [23], practical video QoE monitoring was discussed. The authors introduced an ML-oriented approach for monitoring QoE measures for encoded video traffic. The transport and network layer data were employed as attributes for training ML classifiers necessary for deducing video QoE measures like rebuffering events and startup delay. Experimental assessments declared that the exploited ML-oriented approach offered 90% accuracy. In [24], the quality assessment of video streaming was discussed. The authors analyzed and compared distinct variations of target QoE assessment frameworks with and without ML schemes for video streaming. Performance analysis clarified that the hybrid frameworks performed better than QoS-initiated QoE approaches. Prior works on video QoE estimation have shown that network-level performances directly impact QoE. This motivates the use of machine learning to link the 5G network level measurements to QoE. Hence, in this article, video streaming is considered where prediction models are built by controlled experimentation that allows both the forecasting and monitoring of Video QoE using 5G network metrics. This study clarified that the ML-dependent framework slightly outperformed the framework without ML in the case of the same setting. Additionally, the findings of this work indicated that the available video QoE assessment frameworks still exhibit limited performance, thereby making it tedious to be applicable in realistic communication networks. Table 2 represents the comparison between ML-based QoE prediction models for video services with our proposed model.

Table 2: Machine learning-based QoE prediction model for video services

Reference	ML technique	Influencing factors	Assessment metrics	Prediction accuracy (%)	Application
[25]	DTR, multi-linear regression, RFR	Round trip time (RTT), throughput, number of packets per video segment, rate-based, buffer-based, and hybrid ABS algorithms, number of stalls	MOS, ACR	91	DASH video streaming
[26]	LR, KNN, DT, Gaussian naive Bayes, SVM	Bitrate, FPS, Resolution	ACR	73.5–86	HAS video streaming
[27]	DL [CNN & LSTM]	Text, video, categorical information, continuous information, sequence data	MOS	88.74	HAS video streaming

(Continued)

Table 2: Continued

Reference	ML technique	Influencing factors	Assessment metrics	Prediction accuracy (%)	Application
[28]	SVM	Brightness, colour information, FPS, initial buffering delay	MOS	91.3	HTTP video streaming
[29]	DT	Average quantization parameters, average bits in interframes	MOS, SSIM, VQM	88.9–90.5	H.264 AVC video streaming
[30]	Multiclass incremental SVM	Delay, packet loss, FPS, video type, mean bitrate	MOS	89	Mobile video streaming
[31]	RF	RSSI, RSRP, RSRQ, CQI, frame delay	MOS, PSNR	75–85	Mobile video streaming
[32]	DT	Immersion and presence, reality judgement	MOS	91	VR 360-degree video
Proposed work	HPT DT, EHPT ensemble	The bitrate of video packets, traffic flow, simulation time	MOS	87.037–92.59	Adaptive Bitrate streaming (ABS)

The comparison between the proposed EHPT ensemble method and the existing ML algorithms attained prediction accuracies (%) is highlighted in Fig. 2.

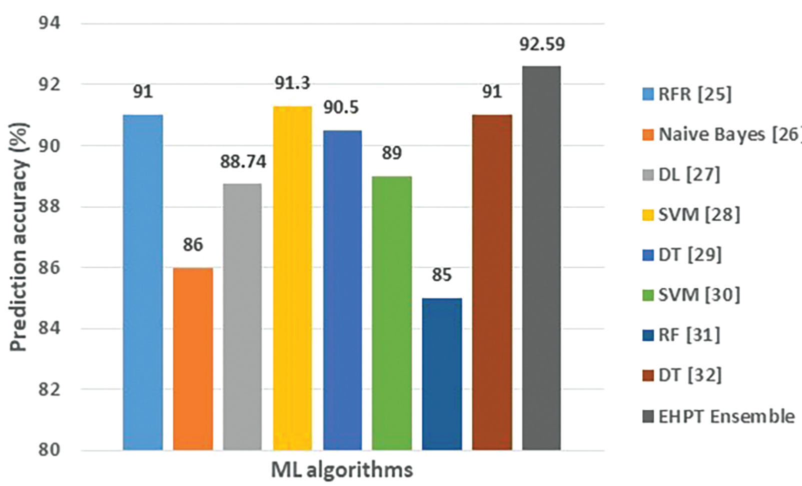

Figure 2: Comparison of existing ML algorithms with the proposed EHPT ensemble method

3 Problem Statement

The use of multimedia information is inescapable in daily life and is anticipated to grow rapidly in the next years. Greater throughput is made possible by 5G technology, which also greatly facilitates multimedia content streaming in a variety of applications like YouTube, Facebook, etc. The main goal of any video streaming technology is to provide the best possible quality of service (QoS) and quality of experience (QoE). Although it is predicted that the 5G system would provide better QoE, the challenge of balancing operator provisioning and meeting customer expectations remains a crucial concern. Numerous studies have recently been carried out to address this barrier and develop a QoE-aware network. ML frameworks have gained popularity recently for providing precise answers to complex problems and are widely used in a variety of fields. It has been demonstrated that ML approaches work well for a variety of classification problems. Therefore, the purpose of this work is to utilize an ML technique for classifying streaming video. Studies that have already been published employed ML techniques to predict video QoE in 5G systems. These studies assessed the quality of experience (QoE) of streaming approaches and used ML classifiers to predict the degree of user satisfaction. However, it was noted in these works that there was still a sizable area for improvement with reference to the accuracy measures. This work aims to optimize existing ML schemes by including the hyperparameter tuning concept and building enhanced ML classifiers for efficient QoE-aware video streaming categorization because employing the right tuning of ML schemes to achieve the necessary classification accuracy is laborious. Fig. 3 shows a comparison of the current worldwide data usage with mobile video use in various streams [33].

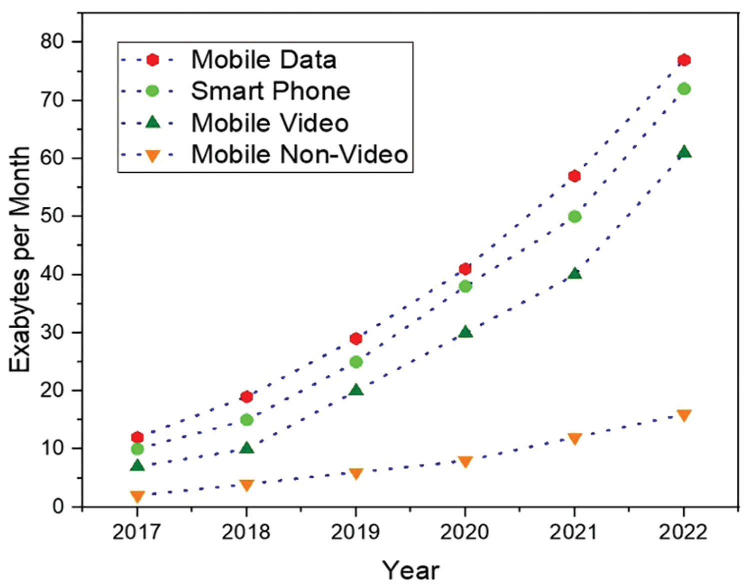

Figure 3: Global mobile data traffic forecast

4 Proposed Methodology

This methodology involves the network configuration and network construction, video packet streaming, ML-directed video streaming classification, and finally, performance evaluation of the developed ML approach. The block diagram of the proposed methodology is depicted in Fig. 4.

4.1 Network Construction and Configuration

Initially, a 5G network is constructed and configured using 100 nodes for transmitting video streaming. Here, all nodes are placed, and every node is identified as n1, n2, n3 . . . n100. For network construction and configuration, the distinct network parameters considered in this work include transmission range, base station, number of nodes, traffic model, mobility model, bandwidth, carrier frequency, mmWave maximum physical rate, packet size and frame size. The values of these network parameters are enumerated in Table 3.

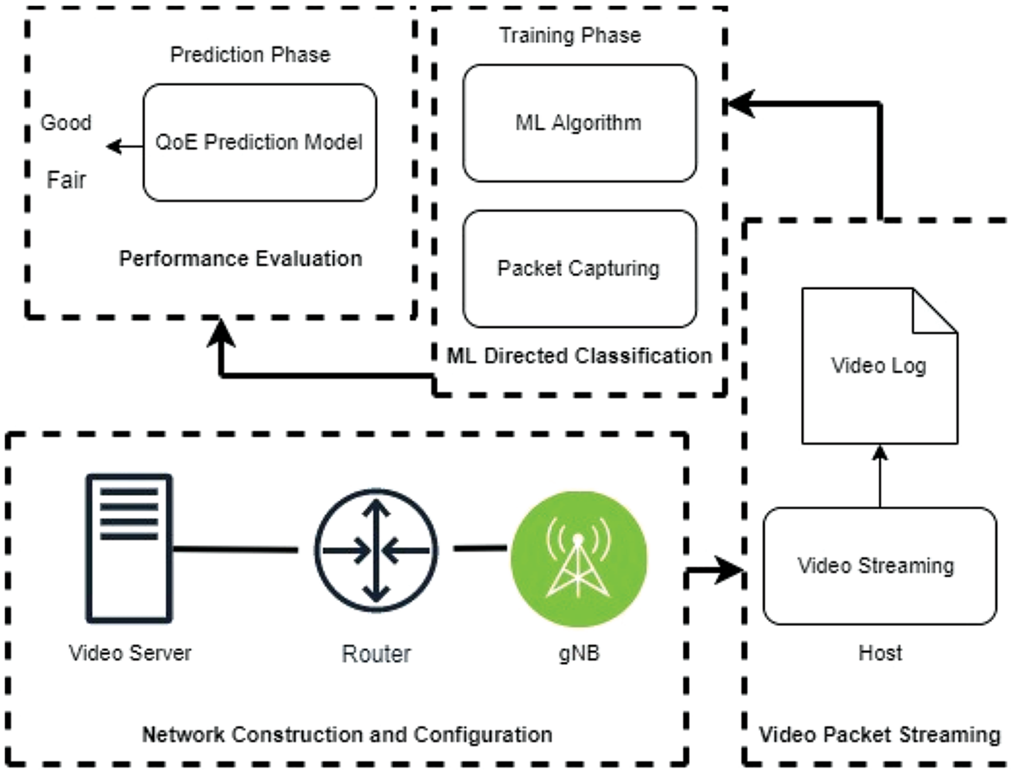

Figure 4: Schematic diagram of QoE improvisation in 5G Wireless Networks

Table 3: Network configuration parameters

Sl. No.	Network parameter	Value
1	Transmission range	1000 ∗ 1000
2	Number of nodes	100
3	Base station	gNodeB
4	Mobility model	Static-Constant Position Mobility Model, Dynamic-Random Walk 2D Mobility Model
5	Traffic model	ON/OFF Adaptive Bitrate Streaming (ABS)
6	mmWave max phy rate	3.2 Gbit/s
7	Bandwidth	1 GHz
8	Carrier frequency	28 GHz
9	Packet size	1400 bytes

4.2 Video Packet Streaming

For video packet streaming, initially, a request for connection establishment between the nodes is sent by the 5G users. Once the connection is established, the video packet is transferred between the nodes through the bitstream segment. Thus, through this communication, the data pertinent to video packets are received, and further, this data is input to the ML classifier for categorizing the video streaming.

In this work, video packet streaming is performed using the adaptive bitrate streaming (ABS) method, illustrated in Fig. 5. ABS adapt the video quality depending on network conditions for ameliorating video streaming across HTTP networks. It is basically a technology devised for delivering video in an extremely effective manner and in a usable quality for the device and every specific user. ABS begins mainly at the video encoding phase. For ABS to work, distinct video files which support distinct bit rates are created. In ABS, source content encoding is performed at diverse bit rates. Each of the distinct bit rate (BR) streams are partitioned into diminutive multi-second components. Initially, a manifest file is downloaded, which describes the existing stream segments and their corresponding bit rates. During stream initiation, the segments with the minimum BR stream are typically requested. If the network throughput is higher than the downloaded segment's bit rate, then a higher BR segment is requested. However, if the network throughput deteriorates, a lower BR segment is requested. The ABS technique thus aids in deciding which BR segments to be downloaded, depending on the network's current state.

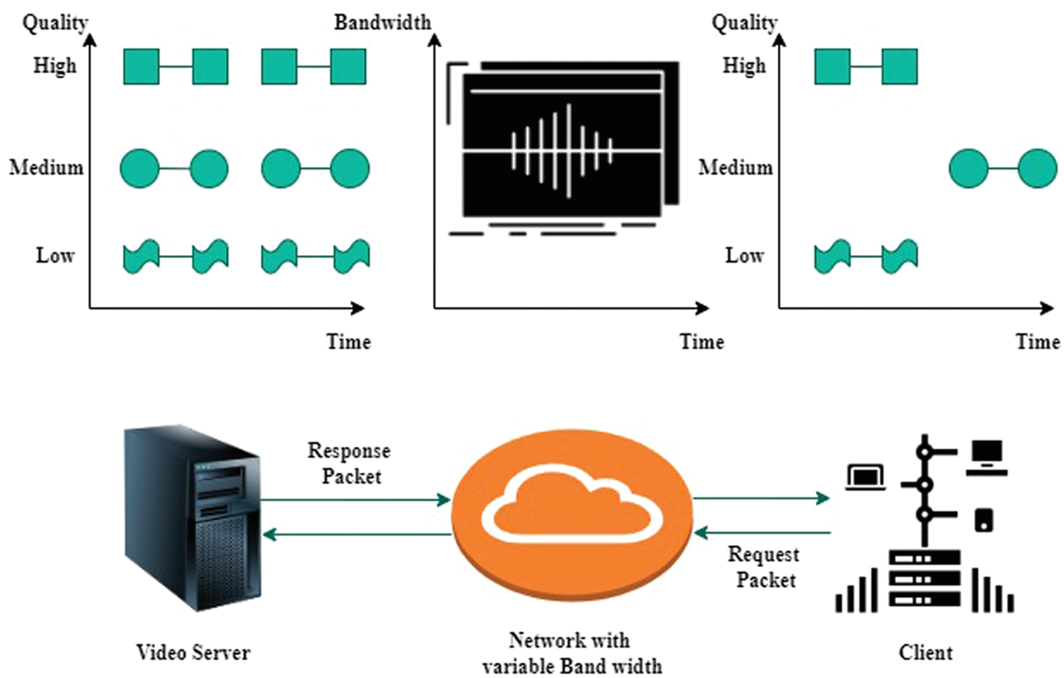

Figure 5: Adaptive bitrate streaming according to network conditions

4.3 Machine Learning-Based Classification

The final stage involves the classification of video streaming. This process is executed after performing video packet streaming. In the current paper, video streaming categorization is achieved using the ML approach. Two distinct ML approaches, namely, enhanced hyperparameter tuning (EHPT) ensemble classifier and hyperparameter tuning (HPT) decision tree (DT) classifier, are used.

4.3.1 XG Boost Ensemble with HPT

Extreme gradient boosting (XGBoost) is an improved distributed gradient boosting library that implements ML techniques under the gradient boosting model. In gradient boosting, the loss function is minimized by incorporating weak learners via a gradient descent maximization method. XGBoost is typically an extension of gradient-boosted decision trees specifically devised for ameliorating performance and speed. XGBoost precisely forecasts a target parameter by fusing estimates of a group of weaker frameworks. XGBoost decreases a regularized objective function which integrates a loss function depending on the discrepancy between the target and predicted outputs. Here, the training proceeds repetitively, adding neoteric trees which forecast the errors or residuals of previous trees, which are further fused with the preceding trees to make the ultimate prediction. In this work, an XGBoost ensemble is exploited, as ensemble learning involves a set of predictors (frameworks) for offering better forecasting accuracy. For achieving improved performance, hyperparameter tuning is done in the ensemble classifier. HPT is chiefly done to achieve the best fit. It functions by executing several trials in a solitary training job. Every trial comprehensively executes a training process with values selected for hyperparameters. HPT optimizes a solitary target variable known as the hyperparameter metric.

In this case, the created ensemble framework is represented by Eq. (1) as a weighted sum of weak learners.

$$s_q(\cdot) = \sum_{q=1}^{Q} c_q \times w_q(\cdot) \tag{1}$$

$s_q(.)$ is the quality of the video, and Q stands for the number of decision trees, where c_q Stands for learning rate. The learning rate value ranges between 0 to 1 and is selected based on the HPT. The major goal of this work is to determine the classifier's accuracy on the validation set; nevertheless, it appears that a learning rate of 0.01 delivers excellent performance on both the validation and training sets. $w_q(\cdot)$ is the output given by the decision tree.

The issue is modelled as a gradient descent via gradient boosting. Eq. (2) represents the gradient descent method over the ensemble framework.

$$s_q(\cdot) = s_{q-1}(\cdot) - c_q \times grad_{s_{q-1}} E\left(s_{q-1}\right)(\cdot) \tag{2}$$

where c_q Represents the learning rate corresponding to step size, and E $(\cdot)$ characterizes the framework's fitting error.

Initially, a weak framework is trained and aggregated to the ensemble framework. Furthermore, pseudo-residuals (targets of weak learners) are updated considering the ensemble framework's predictions.

Algorithm 1: Implementation of XG Boost ensemble with HPT algorithm

Step 1: **Declaration of input and output parameter**
Input dataset: {simulation time, traffic flow, bit rate of video packets}
Output dataset: {status of video transfer: 0 and 1}

Step 2: **Splitting the dataset into training and testing**
X_Train, X_Test, Y_Train, Y_Test = train_test_split(x, y, test_size = 0.3, random_state = 0)

(Continued)

Algorithm 1: Continued

Step 3: **Importing preprocessing library**
def Preprocessing ( ):
begin
for (set i = 0 i < = data_limit; incr i}
begin
Resize the data using StandardScalar ( )
endfor
end Preprocessing ( );
Step 4: **Importing ensemble library**
def ensemble_HPT ( )
XGBoostClassifier (n_estimators = 1000, criterion = 'entropy', random_state = 0)
Step 5: **Classification report analysis**
classification_report(Y_test, Y_Pred)
Step 6: **Applying hyperparameter tuning**
HP_params = {
'n_estimators': [15, 25, 35],
max_depth': [15, 20, 30, 50],
"criterion": ['gini', 'entropy'] }
Step 7: **Confusion matrix and accuracy calculation**
cm = confusin_matrix (Y_Test, prediction)
accuracy = 100.0 ∗ accuracy_score(Y_Test, prediction)
end ensemble_HPT ( )

4.3.2 DT with HPT

DT is an imperative ML scheme involving a tree-like structure, signifying the predictions resulting from a chain of feature-dependent splits. It begins with a root (base) node and terminates with an appropriate decision. For ameliorating the video streaming categorization performance, in this study, the HPT process is executed with DT.

In a DT approach, the entire training set is treated as a root. Here, categorical attribute values are preferred. If the attribute values are found to be continuous, then firstly, they are discretized before constructing the DT framework. Depending on the attribute values, here, the records are recursively distributed. For arranging attributes as the internal node or root, statistical metrics are employed. In the proposed HPT DT approach, attribute selection is achieved using two well-known attribute selection metrics, namely, entropy and the Gini index.

Entropy indicates the measure of a random variable's uncertainty. It mainly describes the impurity of a random set of examples. Information gain is the average of all entropy. If the information gain is higher, then that particular split of DT will be taken. In Eq. (3), if A represents an attribute, C is the set of examples, Value (A) indicates a set of all plausible values of A, and C_z indicates the sample after a split, then

$$Gain\ (C,\ A) = Entropy\ \ (C) - \sum\nolimits_{Values\ (A)} \frac{C_z}{|C|} \cdot Entropy\ \ (C_z) \tag{3}$$

The Gini index is basically a metric employed for estimating how frequently a randomly selected element would be identified incorrectly. In simpler terms, an attribute possessing a lower Gini value must be considered. In this metric, some arbitrary values are chosen for categorizing every attribute. By Eq. (4) Gini index can be estimated as

$$GiniIndex = 1 - \sum_{z} p_z^2 \tag{4}$$

where p_z Indicates the percentage of positive value.

Thus, using entropy and Gini index metrics, attributes are selected. These attributes are then subjected to classification.

Algorithm 2: Implementation of HPT DT algorithm

Step 1: **Declaration of input and output parameter**
Input dataset: {simulation time, traffic flow, bit rate of video packets}
Output dataset: {status of video transfer}
Step 2: **Splitting the dataset into training and testing**
X_Train, X_Test, Y_Train, Y_Test = train_test_split(x, y, test_size = 0.3, random_state = 0)
Step 3: **Importing DT library**
defDecision_Tree_HPT ()
clf = tree. DecisionTreeClassifier ()
Step 4: **Classification report analysis**
classification_report(Y_test, Y_Pred)
Step 5: **Applying hyperparameter tuning**
'HP_params = {
'n_estimators': [15, 25, 35],
'max_depth': [15, 20, 30, 50],
"criterion": ['gini', 'entropy']
Step 6: **Confusion matrix and accuracy**
cm = confusion_matrix(Y_Test, prediction)
Accuracy = 100.0 * accuracy_score(Y_Test, prediction)
end Decision Tree_HPT ()

After receiving the video packet data, as explained in the previous phase, the data is categorized using HPT ensemble and DT schemes. Furthermore, the video streaming categorization performances of these schemes are compared to determine the effectiveness of each classifier.

4.4 Performance Evaluation

The video streaming QoE dataset comprises simulation time, traffic flow, video packets, and packet transfer status. Here, the packet transfer status is treated as a label. The dataset class label in this work is categorized as good, denoted as '1' and fair, denoted as '0'. Here, the category 'good' indicates successful video transfer without interference, and the category 'fair' indicates failure in video transfer owing to certain interference.

The confusion matrix values achieved for the EHPT ensemble classifier and HPT DT method are presented below.

$$\text{Confusion matrix of EHPT ensemble classifier} = \begin{bmatrix} 1 & 3 \\ 1 & 49 \end{bmatrix}$$

$$\text{Confusion matrix of HPT DT classifier} = \begin{bmatrix} 1 & 5 \\ 2 & 46 \end{bmatrix}$$

The confusion matrix plots of the EHPT ensemble and HPT DT classifier are depicted in Figs. 6 and 7.

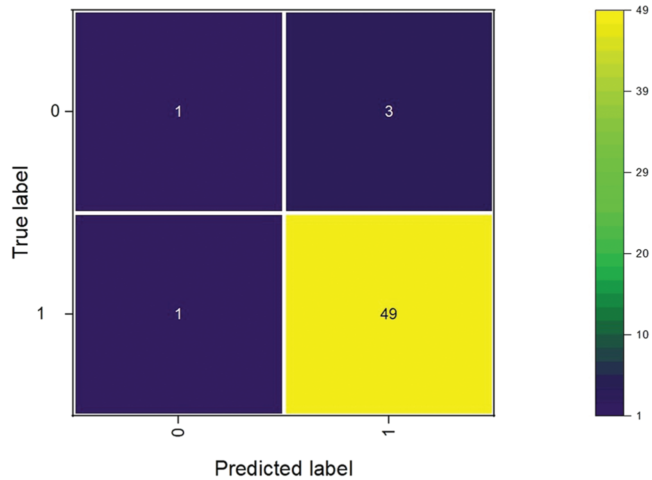

Figure 6: EHPT ensemble classifier

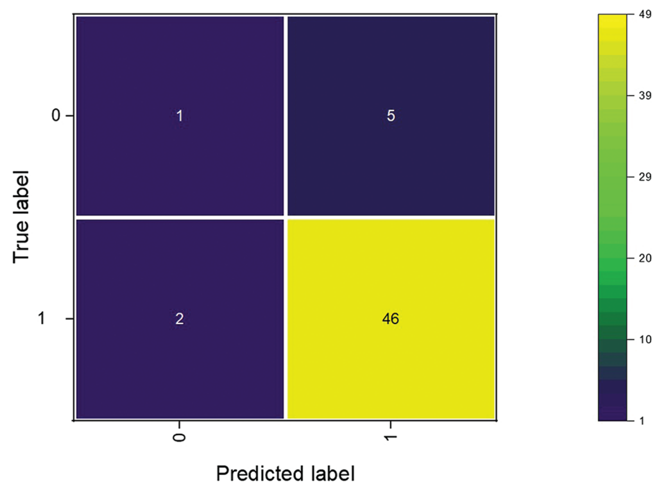

Figure 7: HPT DT classifier

The performance of the developed EHPT ensemble and HPT DT methods is evaluated using distinct metrics like precision, recall, accuracy, and computation time [34]. These metrics are calculated as follows:

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$Computation\ time = \frac{Time\ taken\ for\ computation}{Total\ time} \tag{8}$$

TN, TP, FP, and FN represent true negative, true positive, false positive, and false negative, respectively. The TN and TP indicate the number of negative and positive samples which are correctly classified, while FN and FP indicate the number of misclassified negative and positive samples, respectively.

5 Results and Discussion

Simulations are conducted in this work using the software NS-3-mmwave and Python 2.7. The configuration of the 5G network is portrayed in Fig. 8.

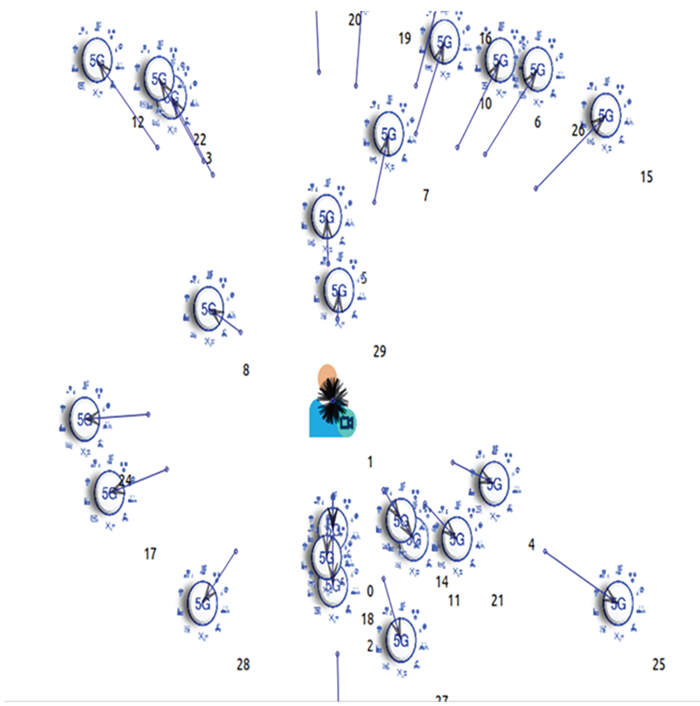

Figure 8: 5G Network configuration in NS-3

Furthermore, video stream communication data from NS-3 simulation is employed for analysis, and the performance of the enhanced tuning ensemble and DT classifiers is assessed by considering diverse performance measures like precision, accuracy, recall, and computation time. The achieved values and simulation results are presented below in Table 4.

Table 4: Performance results of tuning ensemble and DT classifier

Technique	Precision (%)	Accuracy (%)	Recall (%)	Computation time (ms)
EHPT ensemble classifier	94.23	92.59	98	0.0088
HPT DT classifier	85.18	87.037	95.83	1.6388

The simulation time (ms) for a 5G video stream (Mbits/s) is depicted, and the UDP packets of video communication are analyzed and displayed in Fig. 9. It could be viewed that for 10 ms, the video stream exhibits 1000 Mbits/s and for 15 ms also, the video stream exhibits 1000 Mbits/s. This is chiefly because the video transfer speed increases, reduce, and remains depending on the network traffic and the number of user access in the network.

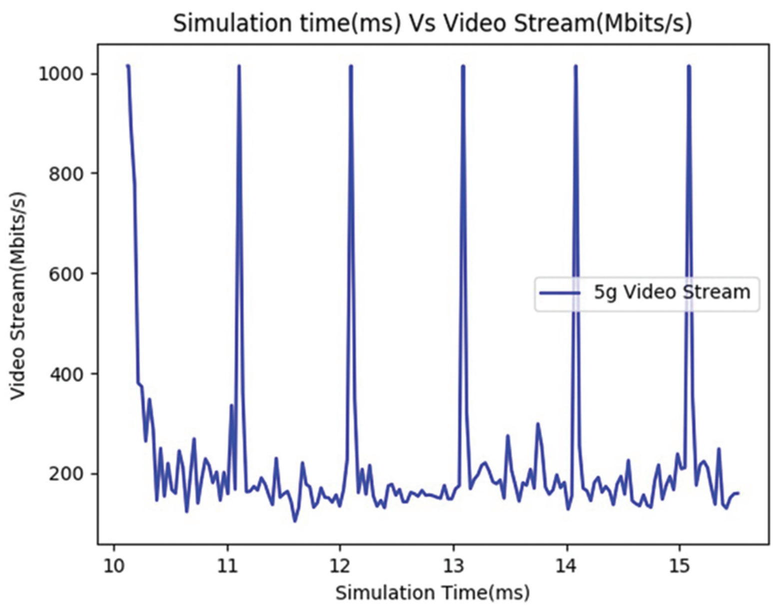

Figure 9: Simulation time *vs.* video stream

Fig. 10 depicts the precision achieved by the developed EHPT ensemble and HPT DT classifier for a distinct number of packet flows. In Fig. 10, it can be observed that the EHPT ensemble classifier offers a greater precision value of 94.23% and the HPT DT classifier provides a precision value of 85.18%. Simulation outputs reveal that for greater packet flows, the EHPT ensemble classifier offers a greater precision value than the HPT DT classifier. Thus, it could be viewed from the precision performance evaluation that the EHPT ensemble classifier outperforms the HPT DT classifier regarding precision.

Fig. 11 depicts the recall value achieved by the developed EHPT ensemble and HPT DT classifier for a distinct number of packet flows. In Fig. 11, it can be observed that the EHPT ensemble classifier provides the highest recall value of 98% while the HPT DT classifier provides the highest recall value of 95.83%. The attained results clarify that for greater packet flows, the EHPT ensemble classifier offers a greater recall value than the HPT DT classifier. Thus, the evaluation of the recall performance of the presented classifiers manifests that the EHPT ensemble classifier outperforms the HPT DT classifier in terms of recall.

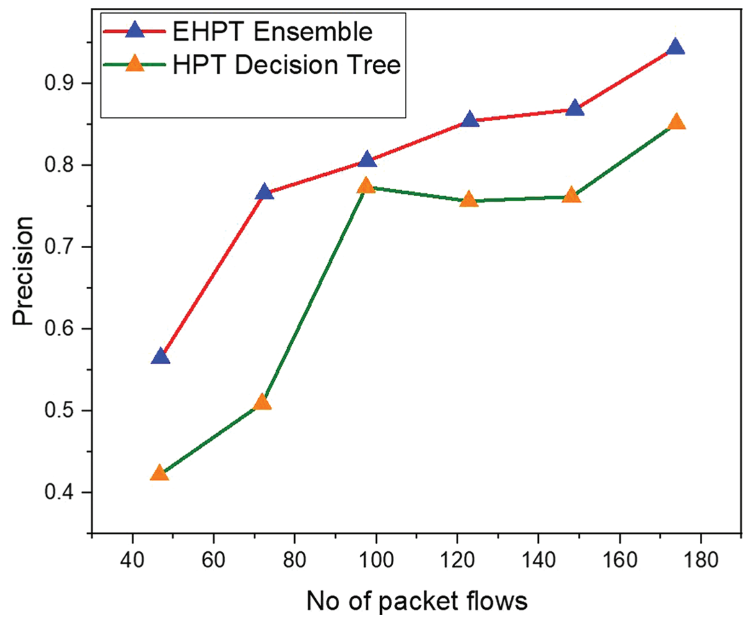

Figure 10: Performance of EHPT ensemble and HPT DT with regarding precision

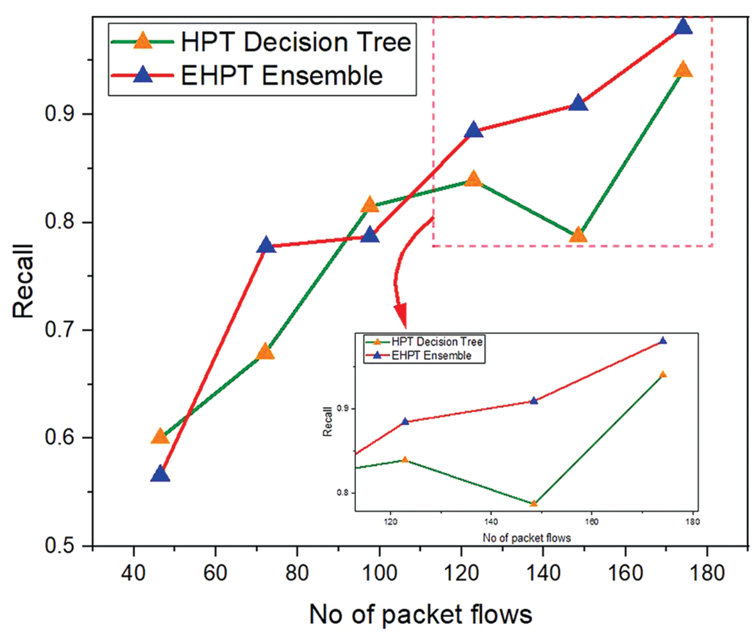

Figure 11: Performance of EHPT ensemble and HPT DT regarding the recall

Fig. 12 depicts the accuracy value achieved by the developed EHPT ensemble and HPT DT classifier for a distinct number of packet flows. In Fig. 12, it could be observed that the EHPT ensemble classifier provides the highest accuracy value of 92.59% while the HPT DT classifier provides the highest accuracy value of 87%. Simulation outputs reveal that for greater packet flows, the EHPT ensemble classifier offers a greater accuracy value than the HPT DT classifier. Five simulations ran for each transmission of 20 packets, and the average of various performance values are plotted. The EHPT ensemble classifier outperforms the HPT DT classifier, according to the accuracy performance of the provided classifiers. According to Figs. 10–12, the confusion matrix of the video transfer flow during 5G video streaming determines the increase and fall in precision, recall, and accuracy values. From this video transfer research work, the undertaken problem is a good fit for machine learning using ensemble classification. Here, Ensemble classification predicted high accuracy (92.59%) compared to Decision Tree classification (87.037%).

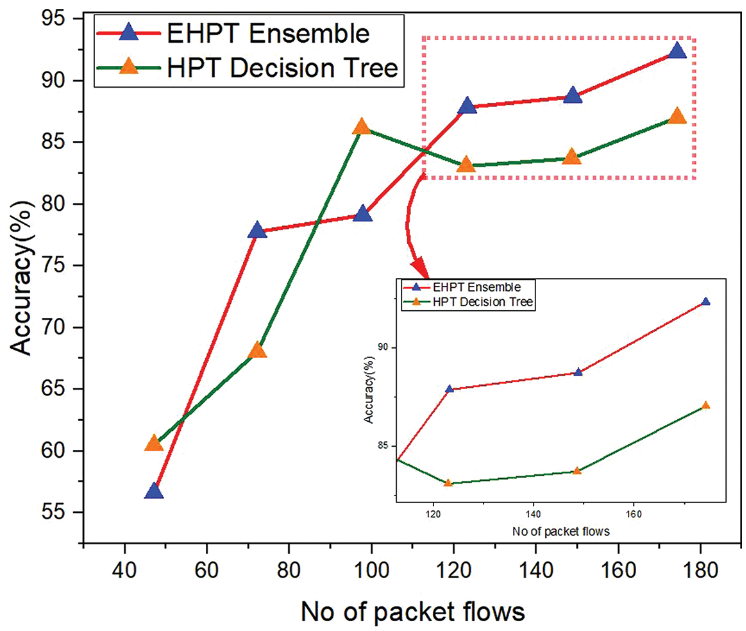

Figure 12: Performance of EHPT ensemble and HPT DT regarding accuracy

6 Conclusions

This work presented an effective framework for QoE-aware video streaming categorization. It exploited video stream communication information from NS-3 simulation for analysis. A 5G network was configured and developed for transmitting video streaming, and then video packets were transferred. The video packet information was then fed to ML classifiers. In this work, enhanced ML classifiers like EHPT ensemble and HPT DT were developed for video streaming categorization. The classification performance of these classifiers was assessed and compared using distinct performance validation metrics. Simulation outputs explicitly confirmed that the implemented EHPT ensemble classifier displayed greater precision, accuracy, and recall scores than the HPT DT classifier. Moreover, the EHPT ensemble classifier exhibited faster computation time than the HPT DT classifier. Thus, the achieved results greatly manifested that the EHPT ensemble classifier greatly outperformed the HPT DT method in video streaming classification. Additionally, the findings of this work substantiated the enhanced ML classifier efficacy regarding QoE-aware video streaming categorization. Future work could involve building datasets based on each time slot's ground truth and the properties of the temporal network layer in order to provide a more reliable machine-learning strategy for addressing anomalies.

Acknowledgement: The authors would like to acknowledge Vellore Institute of Technology, Chennai, India, for their valuable support.

Funding Statement: The authors received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

[1] P. Ameigeiras, J. J. Ramos-Munoz, J. Navarro-Ortiz and J. M. Lopez-Soler, "Analysis and modelling of YouTube traffic," *Transactions on Emerging Telecommunications Technologies*, vol. 23, no. 4, pp. 360–377, 2012. https://doi.org/10.1002/ett.2546.

[2] F. Loh, F. Poignée, F. Wamser, F. Leidinger and T. Hoßfeld, "Uplink vs. downlink: Machine learning-based quality prediction for http adaptive Video streaming," *Sensors*, vol. 21, no. 12, pp. 4172, 2021. https://doi.org/10.3390/s21124172.

[3] M. Agiwal, A. Roy and N. Saxena, "Next generation 5G wireless networks: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 3, pp. 1617–1655, 2016. https://doi.org/10.1109/COMST.2016.2532458.

[4] J. A. Adebusola, A. A. Ariyo, O. A. Elisha, A. M. Olubunmi and O. O. Julius, "An overview of 5G technology," in *2020 Int. Conf. in Mathematics, Computer Engineering and Computer Science (ICMCECS)*, Ayobo, Nigeria, IEEE, pp. 1–4, 2020. https://doi.org/10.1109/ICMCECS47690.2020.240853.

[5] M. Jarschel, D. Schlosser, S. Scheuring and T. Hoßfeld, "An evaluation of QoE in cloud gaming based on subjective tests," in *2011 Fifth Int. Conf. on Innovative Mobile and Internet Services in Ubiquitous Computing*, Seoul, Korea (South), IEEE, pp. 330–335, 2011. https://doi.org/10.1109/IMIS.2011.92.

[6] 5G speed vs 5G range-What is the value of 5G speed, 5G range, 2019 [Online]. Available: https://www.rfwireless-world.com/Terminology/5G-Speed-Vs-5G-Range.html.

[7] Z. qasim EL-ezzi, A. M. Al-Dulaimi and A. A. Ibrahim, "Personalized quality of experience (QOE) management using data driven architecture in 5G wireless networks," in *2020 4th Int. Symp. on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, Istanbul, Turkey, IEEE, pp. 1–10, 2020. https://doi.org/10.1109/ISMSIT50672.2020.9254863.

[8] P. Zhou, Y. Xie, B. Niu, L. Pu, Z. Xu *et al.,* "QoE-Aware 3D video streaming via deep reinforcement learning in software defined networking enabled mobile edge computing," *IEEE Transactions on Network Science and Engineering*, vol. 8, no. 1, pp. 419–433, 2020. https://doi.org/10.1109/TNSE.2020.3038998.

[9] A. Shaout and B. Crispin, "Streaming video classification using machine learning," *International Journal of Arab Information and Technology*, vol. 17, no. 4A, pp. 677–682, 2020. https://doi.org/10.34028/iajit/17/4A/13.

[10] H. F. Bermudez, J. M. Martinez-Caro, R. Sanchez-Iborra, J. L. Arciniegas and M. D. Cano, "Live video-streaming evaluation using the ITU-T P. 1203 QoE model in LTE networks," *Computer Networks*, vol. 165, pp. 106967, 2019. https://doi.org/10.1016/j.comnet.2019.106967.

[11] R. Ul Mustafa, S. Ferlin, C. Esteve Rothenberg, D. Raca and J. Quinlan, "A supervised machine learning approach for dash video QoE prediction in 5 G networks," in *Proc. of the 16th ACM Symp. on QoS and Security for Wireless and Mobile Networks*, Alicante, Spain, pp. 57–64, 2020. https://doi.org/10.1145/3416013.3426458.

[12] W. Zhou, X. Min, H. Li and Q. Jiang, "A brief survey on adaptive video streaming quality assessment," *Journal of Visual Communication and Image Representation*, vol. 86, pp. 103526, 2022. https://doi.org/10.1016/j.jvcir.2022.103526.

[13] N. Barman and M. G. Martini, "QoE modeling for HTTP adaptive video streaming–A survey and open challenges," *IEEE Access*, vol. 7, pp. 30831–30859, 2019. https://doi.org/10.1109/ACCESS.2019.2901778.

[14] I. Politis, A. Lykourgiotis and T. Dagiuklas, "A framework for QoE-aware 3D video streaming optimization over wireless networks," *Mobile Information Systems*, vol. 2016, pp. 1–18, 2016. https://doi.org/10.1155/2016/4913216.

[15] X. Luo, O. Ye and B. Zhou, "An modified video stream classification method which fuses three-dimensional convolutional neural network," in *2019 Int. Conf. on Machine Learning, Big Data and Business Intelligence (MLBDBI)*, Taiyuan, China, IEEE, pp. 105–108, 2019. https://doi.org/10.1109/MLBDBI48998.2019.00026.

[16] I. Orsolic, D. Pevec, M. Suznjevic and L. Skorin-Kapov, "A machine learning approach to classifying YouTube QoE based on encrypted network traffic," *Multimedia Tools and Applications*, vol. 76, no. 21, pp. 22267–22301, 2017. https://doi.org/10.1007/s11042-017-4728-4.

[17] M. Shahid Anwar, J. Wang, S. Ahmad, A. Ullah, W. Khan *et al.,* "Evaluating the factors affecting QoE of 360-Degree videos and cybersickness levels predictions in virtual reality," *Electronics*, vol. 9, pp. 1530, 2020. https://doi.org/10.3390/electronics9091530.

[18] E. Grabs, T. Chen, E. Petersons, D. Efrosinin, A. Ipatovs *et al.,* "Features extraction for live Streaming video classification with deep and convolutional neural networks," in *2021 IEEE Microwave Theory and Techniques in Wireless Communications (MTTW)*, Riga, Latvia: IEEE, pp. 58–63, 2021. https://doi.org/10.1109/MTTW53539.2021.9607153.

[19] L. Pierucci, "The quality of experience perspective toward 5G technology," *IEEE Wireless Communications*, vol. 22, no. 4, pp. 10–16, 2015. https://doi.org/10.1109/MWC.2015.7224722.

[20] M. Al Jameel, S. Turner, T. Kanakis, A. Al-Sherbaz and W. S. Bhaya, "Deep learning approach for real-time video streaming traffic classification," in *2022 Int. Conf. on Computer Science and Software Engineering (CSASE)*, Duhok, Iraq, IEEE, pp. 168–174, 2022. https://doi.org/10.1109/CSASE51777.2022.9759644.

[21] V. Menkovski, G. Exarchakos and A. Liotta, "Machine learning approach for quality of experience aware networks," in *2010 Int. Conf. on Intelligent Networking and Collaborative Systems*, Thessaloniki, Greece, IEEE, pp. 461–466, 2010. https://doi.org/10.1109/INCOS.2010.86.

[22] M. S. Mushtaq, B. Augustin and A. Mellouk, "Empirical study based on machine learning approach to assess the QoS/QoE correlation," in *2012 17th European Conf. on Networks and Optical Communications*, Vilanova i la Geltru, Spain, IEEE, pp. 1–7, 2012. https://doi.org/10.1109/NOC.2012.6249939.

[23] M. H. Mazhar and Z. Shafiq, "Real-time video quality of experience monitoring for https and Quic," in *IEEE INFOCOM 2018-IEEE Conf. on Computer Communications*, Honolulu, HI, USA, IEEE, pp. 1331–1339, 2018. https://doi.org/10.1109/INFOCOM.2018.8486321.

[24] R. U. Mustafa, D. Moura and C. E. Rothenberg, "Machine learning approach to estimate video QoE of encrypted dash traffic in 5 G networks," in *2021 IEEE Statistical Signal Processing Workshop (SSP)*, Rio de Janeiro, Brazil, IEEE, pp. 586–589, 2021. https://doi.org/10.1109/SSP49050.2021.9513804.

[25] R. U. Mustafa, M. T. Islam, C. Rothenberg, S. Ferlin, D. Raca *et al.,* "A supervised machine learning approach for dash video QoE prediction in 5 G networks," in *Proc. of the 16th ACM Symp. on QoS and Security for Wireless and Mobile Networks*, New York, NY, United States, pp. 57–64, 2020. https://doi.org/10.1145/3416013.3426458.

[26] R. Shalala, R. Dubin, O. Hadar and A. Dvir, "Video QoE prediction based on user profile," in *2018 Int. Conf. on Computing, Networking and Communications (ICNC)*, Maui, HI, USA, IEEE, pp. 588–592, 2018. https://doi.org/10.1109/ICCNC.2018.8390347.

[27] L. Liu, H. Hu, Y. Luo and Y. Wen, "When wireless video streaming meets AI: A deep learning approach," *IEEE Wireless Communications*, vol. 27, no. 2, pp. 127–133, 2019. https://doi.org/10.1109/MWC.001.1900220.

[28] L. Qian, H. Chen and L. Xie, "SVM-Based QoE estimation model for video streaming service over wireless networks," in *2015 Int. Conf. on Wireless Communications & Signal Processing (WCSP)*, Nanjing, China, IEEE, pp. 1–6, 2015. https://doi.org/10.1109/WCSP.2015.7341066.

[29] A. Hameed, R. Dai and B. Balas, "A decision-tree-based perceptual video quality prediction model and its application in FEC for wireless multimedia communications," *IEEE Transactions on Multimedia*, vol. 18, no. 4, pp. 764–774, 2016. https://doi.org/10.1109/TMM.2016.2525862.

[30] Y. B. Youssef, M. Afif, R. Ksantini and S. Tabbane, "A novel online QoE prediction model based on multiclass incremental support vector machine," in *2018 IEEE 32nd Int. Conf. on Advanced Information Networking and Applications (AINA)*, Krakow, Poland, IEEE, pp. 334–341, 2018. https://doi.org/10.1109/AINA.2018.00058.

[31] D. Minovski, C. Åhlund, K. Mitra and P. Johansson, "Analysis and estimation of video QoE in wireless cellular networks using machine learning," in *2019 Eleventh Int. Conf. on Quality of Multimedia Experience (QoMEX)*, Berlin, Germany, IEEE, pp. 1–6, 2019. https://doi.org/10.1109/QoMEX.2019.8743281.

[32] M. S. Anwar, J. Wang, S. Ahmad, W. Khan, A. Ullah *et al.,* "Impact of the impairment in 360-degree videos on users VR involvement and machine learning-based QoE predictions," *IEEE Access*, pp. 204585–204596, 2020. https://doi.org/10.1109/ACCESS.2020.3037253.

[33] CISCO Visual Networking Index, Global Mobile Data Traffic Forecast Update, 20172022 White Paper. Tech. rep.. CISCO, 2019. [Online]. Available: http://media.mediapost.com/uploads/CiscoForecast.pdf.

[34] S. K. Ray and S. Susan, "Performance evaluation using online machine learning packages for streaming data," in *2022 Int. Conf. on Computer Communication and Informatics (ICCCI)*, Coimbatore, India, pp. 1–6, 2022. https://doi.org/10.1109/ICCCI54379.2022.9741068.