Empirical Study based on Machine Learning Approach to Assess the QoS/QoE Correlation

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***Abstract*— The appearance of new emerging multimedia services have created new challenges for cloud service providers, which have to react quickly to end-users experience and offer a better Quality of Service (QoS). Cloud service providers should use such an intelligent system that can classify, analyze, and adapt to the collected information in an efficient way to satisfy end-users' experience. This paper investigates how different factors contributing the Quality of Experience (QoE), in the context of video streaming delivery over cloud networks. Important parameters which influence the QoE are: network parameters, characteristics of videos, terminal characteristics and types of users' profiles. We describe different methods that are often used to collect QoE datasets in the form of a Mean Opinion Score (MOS). Machine Learning (ML) methods are then used to classify a preliminary QoE dataset collected using these methods. We evaluate six classifiers and determine the most suitable one for the task of QoS/QoE correlation.**

***Index Terms*—QoE, QoS, Machine Learning, Data classification models.**

I. INTRODUCTION

MULTIMEDIA services over the Internet are growing in such a way that they have become dominant in the global Internet traffic. Many new multimedia services (like High Definition (HD) video, interactive video gaming) require more processing power, so the concept of Cloud Computing improves end users' experience by managing these services at remote data centers. Because of this trend, a large number of remote data centers have emerged, which is made possible by the availability of fast and reliable internet networks. In Cloud Computing, many applications and services are available to users remotely. As a consequence, users expect better network Quality of Service (QoS) with a high quality standard [1].

The concept of Quality of Experience (QoE) has recently gained greater attention in Cloud Computing networks. Its main objective is not only to consider and evaluate the network QoS, but also to keep it nearest to end users in order to better estimate the perceived quality of services. In fact, the aim of network service providers is to provide a good user experience with the usage of minimum network resources. It is also essential for network service providers to consider the impact of each network factors on user perception, because their businesses are highly dependent on users' satisfaction.

Video streaming services has now major shares of internet traffic. To meet the high expectation of users, it is necessary to analyze video streaming services thoroughly in order to find out the degree of influence of (technical and non-technical) parameters on user satisfaction. Among these factors, one can find network parameters, which represent the QoS. Delay, jitter and packet loss are the main parameters of QoS, and they have a strong influence on user (dis)satisfaction. In addition to network parameters, some other external environmental factors have a great impact on user perceived quality, such as video parameters, terminal types, and psychological factors.

To evaluate the quality of multimedia contents, researchers dispose of two methods: the subjective and the objective method. The *subjective* method is proposed by the International Telecommunication Union (ITU) and the Video Quality Expert Group (VQEG), and it consists of a group of people watching different video sequences under a specific controlled environment, and rating their quality. The Mean Opinion Score (MOS) is an example of a subjective measurement method in which users rate the video quality by giving five different point score from 5 to 1, where '5' is the best and '1' is the worst quality. On the other hand, *objective* method use different models of human expectations and try to estimate the performance of video streaming service in an automated manner, without involving human. For instance, a number of methods depend on video signal distortions due to the encoding process and packet delivery delays.

This paper analyses the influence of QoS and other parameters on the QoE of video streaming services. We propose a testbed for subjective measurements, in order to collect QoE datasets in the form of a MOS score and evaluate the impact of different parameters (*delay, jitter, packet loss, video types, users' profile and terminal characteristics*) on perceived quality. Based on these datasets, we evaluate how Machine Learning (ML) methods can help in building an accurate and objective QoE model that correlates low-level parameters with (high-level) quality. ML methods successfully apply on this type of problem, as the main application of ML is data mining. The concept of data classification is significant in ML, and the following methods are widely used in this field: Naive Bayes (NB), Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Decision Tree (DT), Random Forest (RF) and Neural Networks (NNet). In our study, we use ML methods to classify original datasets, collected in the form of MOS scores. We analyze datasets on six classifiers, in search of the most suitable one for the task of QoS/QoE correlation. As QoE is purely related to end-users, we can

978-1-4673-0951-6/12/$31.00 ©2012 IEEE

analyze the effect of both core networks and cloud networks as a whole. Therefore, in this paper, we use the terms of “cloud service provider” and “network service provider” interchangeably.

The remaining of the paper is structured as follows: we discuss related works in Section II. Section III contains discussion about metrics affecting the QoE. Section IV gives a brief detail of ML data mining techniques and discusses six ML classification methods. Section V is dealing with the different environmental approaches for assessing video QoE. Section VI focuses on the testbed experiment setup and discusses experimental details. We present our results in Section VII, and conclude the paper in Section VIII.

II. RELATED WORK

A large number of research works have been achieved to correlate QoS with QoE in search of capturing the degree of user entertainment. Some other techniques are also developed to evaluate and predict the users’ QoE, in order to deliver a better quality of service to end-users. To do so, many testbed studies have been undertaken, involving different tools, equipments and methods. In [5], a testbed experiment is proposed, to explore how network QoS affects the QoE of HTTP video streaming. In [6], a testbed is implemented to collect data with the help of ten participants, correlating stream state data with video quality ratings. These datasets were used to develop self-healing networks, i.e., having the ability to detect the degradation of video streaming QoE, react and troubleshoot network issues. The correlation of QoE-QoS is studied in [7] by controlling QoS parameters (packet loss, jitter, delay) of networks.

Because subjective campaigns are, by nature, quite limited in size and number of participants, it is impossible to cover all possible configurations and parameter values. However, a QoE prediction model is proposed in [8], for the unseen cases based on primarily limited subjective tests. This model reduces the need of cumbersome subjective tests, to the price of a reduced accuracy. To overcome the weakness of [8], a Learning-based prediction model is proposed in [9]. In [10], a machine learning technique is proposed using a subjective quality feedback. This technique is used to model dependencies of different QoS parameters related to network and application layer to the QoE of the network services and summarized as an accurate QoE prediction model.

III. METRICS AFFECTING THE QOE

QoE is very subjective by nature, because of its relationship with user’s point of view and its own concept of a “good quality”. However, it is very important to devise an automated strategy to measure it as realistically as possible. The ability to measure QoE would give network operators some sense of the contribution of the network’s performance to the overall customer satisfaction, in terms of reliability, availability, scalability, speed, accuracy and efficiency. As a starting point, it is necessary to precisely identify the factors that affect QoE, and then try to define methods to measure these factors. We categorize these factors in four types, as follows.

A. Network Parameters

QoE is influenced by QoS parameters, which highly depend on network elements. Key factors are packets loss, jitter and delay. The impact of each individual or combined factors lead to blockings, blurriness or even blackouts with different levels of quality degradation of video streaming.

Packet losses have a direct effect on the quality of video presented to end users. Packets losses are occurring due to the congestion in the networks and late arrival of packets at application buffers. If packet loss is occurring, then it becomes difficult for the video decoder to properly decode the video streaming. This results in the degradation of video quality.

Jitter is another important QoS parameter which has a great impact on video quality. It is defined as the variance of packet arrival times at the end-user buffer. It occurs when packets travel on different network paths to reach the same destination. It causes jerkiness and frozen video screens.

However, the effects of jitter can be nullified or reduced to some extent, by adding a large receiving buffer at the end user and delay the playout time of the video. By adding a larger buffer, the tolerance level of network jitter will be high but there is still a playout limitation to tolerate its effects. When packets arrive out of order, after the expiration of a buffering time this packet is discarded by the application. In this context, jitter has the same influence as packet loss [2].

Delay is defined as the amount of time taken by the packet to travel from its source until its reception at the final destination. Delay has a direct influence on user perception while watching the video. If the delay exceeds a certain threshold, then its effect is a freeze and lost blocks of video. The threshold of delay values varies according to the nature of the multimedia service.

B. Video Characteristics

The characteristics of video have a direct influence on QoE. The characteristics of video are defined in terms of frame and resolution rate, codec and types of content. Network service providers reduce the bit rate of video streaming services according to the available bandwidth, which strongly influences perceived quality. The impact of these two factors is presented in [3]. This work shows that these two parameters also have high impact on the users’ satisfaction while using the video streaming services.

The video content types can also influence users’ opinions. In case of “interesting” video contents, a user will be more tolerant, and low quality will not influence user’s experience as much as in case of a boring content. In [4], authors found that if users show enough interests in the video content, then they can accept even an extremely low frame rate. In this study, a group of participants interested in soccer were selected. Participants gave a very high acceptable rate (80%), although they watched a video with only 6 frames per second. This result clearly shows that if there is a sufficient interest in the topics, then the human visual system can tolerate the relatively gross interruptions and users can tolerate a very low quality video streaming.

Uncompressed video requires a large amount of storage and bandwidth, to be streamed over a network. Therefore, a large number of video codecs were developed (H.262, H.263, H.264, WVID, WMV3, etc) to compress the video in an effective and efficient way, so that acceptable quality of videos can be maintained. Each codec has its own standard way to compress the video contents, providing various video quality levels. The quality levels of video codecs explain the important impact of codecs on users' perceptions.

C. Terminal Types

Consumers' electronic devices expand largely with the rapid growth of new advancement in telecommunication industries, and they offer a large number of products available for modern multimedia services. These new-generation devices are available in different sizes, processing powers, advanced functionalities, usage and so many other aspects. We can classify these devices into three categories: Personal Computers, Mobile devices, and Television (TV). All these terminal devices influence user satisfaction while using video streaming services. For example, it is pointless to send HD video streaming on a low processing terminal equipped with a small screen.

IV. Machine Learning Classification Methods

Machine Learning (ML) is concerned with the design and development of programs and algorithms which have the capability to automatically improve their performance either on the basis of their own experience over time, or earlier data provided by other programs. The general functions provided by ML are training, recognition, generalisation, adaptation, improvement and intelligibility. There are two types of ML, i.e. unsupervised and supervised learning. Unsupervised refers to find the hidden structure in unlabelled data in order to classify it into meaningful categories, while Supervised Learning assumes that the category structure or hierarchy of the database is already known. They require a set of labelled classes and return a function that maps the database to the pre-defined class labels. In other words, it is the search for algorithms that reason from externally supplied instances to produce general hypotheses. It makes predictions about future instances in order to build a concise model that represents the data distribution. In our case we are considering Supervised Learning, and we are interested in classification methods because of the discrete nature of our datasets. We have applied six ML data classification methods on our datasets, which are Naive Bayes (NB), Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Decision Tree (DT), Random Forest (RF) and Neural Networks (NNet).

1 Naive Bayes

The Naive Bayes (NB) classifier is a probabilistic model that uses the joint probabilities of terms and categories to estimate the probabilities of categories given in a test document. The naive part of the classifier comes from the simplifying assumption that all terms are conditionally independent of each other in a given category. Because of this independence assumption, the parameters for each term can be learned separately, and as a result this simplifies and speeds up the computation operations [12].

2 Support Vector Machines

Support Vector Machines (SVM) are a very powerful classification method, used to solve the two-class-pattern recognition problem. It analyzes the data and tries to identify patterns so that a classification can be done. The idea here is to find the optimal separating hyperplane between two classes, by maximizing the margin between the closest points of these two classes.

The SVM classifies data which have the possibility to be linearly separable in their origin domain or not. The simple linear SVM can be used if the data is linearly separable. When the data is non-separable in their original domain through the hyperplane, then it can be projected in an higher order dimensional Hibert space. By using a kernel function, it is possible to linearly separate the data in a higher dimensional space [14].

3 K-Nearest Neighbors

The k-Nearest Neighbours (k-NN) method is an instance-based ML method and it is considered a very simple method as compared to all other ML classification methods.

In supervised statistical pattern recognition, the k-NN method often performs better than other methods. There is no need of prior supposition of distribution, when the training sample is drawn. It works in a very simple and straightforward way: to classify any new test sample, it compares the new test sample with all other samples in the training set. The category labels of these neighbours are used to estimate the category of the test sample. In other words, it calculates the distance of the new test sample with the nearest training sample, and then at this point finds out the classification of the sample [15].

4 Decision Tree

Decision Tree (DT) is a method used to create a model to predict the value of a target variable based on several input variables. The structure of DT consists of the following elements: (1) internal nodes, that tests an attribute; (2) branches, corresponding to attribute values, and (3) leaf nodes, which assign a classification.

Instances are classified by starting at the root node, and based on the feature values, the tree is sorted down to some leaf node. It is a simple classifier which can efficiently classify new data and compactly store them. It has the capability of reducing complexity and automatically features selection. The information about the prediction of classification can be easily interpreted, thanks to its tree structure. Finally, the accuracy of DT is less affected by user-defined factors as compares to the k-NN classifier [16].

5 Random Forest

Random Forest (RF) is an ensemble classifier, that uses multiple models of several DTs to obtain a better prediction performance. It builds on many classification trees and a bootstrapped sample technique is used to train each tree on the set of training data. This method only searches for a random subset of variables in order to find out a split at each node. For the classification, the input vector is submitted to each tree in the RF, and each tree votes for a class. Finally, RF chooses the class which with the highest number of votes. It has the ability to handle larger input data sets than other methods [17].

6 Neural Networks

A Neural Network (NN) is a structure of a large number of units (neurons) linked together in a pattern of connections. The interconnections are used to send signals from one neuron to the other. The calculation by neural networks is based on the spread of information between basic units of computation. The possibilities of each one are small, but their interconnection allows a complex overall calculation.

The behaviour of a neural network is determined by its architecture: number of cells, how they are connected and the weights assigned to each connection. Each connection between two neurons is characterized by its weight, that measures the degree of influence of the first neuron on the second one. The weight is updated during a training period.

This method has the ability to solve multivariate non-linear problems. Its performance is degraded when it is applied on a large number of training datasets [17].

V. Experimental Environment For QoE Assessment

QoE assessment is subjective by nature, because it tries to match the real perception of users while using a service. This section discusses two different approaches to collect QoE datasets: a crowd-sourced, and a controlled environment approach.

A. Crowd-sourcing Approach

In this part, we consider the crowd-sourcing approach, which helps in gathering a large amount of QoE tests. This approach allows a large number of users to participate remotely. In crowd-sourcing, one assigns the video testing task to a large number of anonymous users who can participate from different regions of the world. For this purpose, we can use the wide variety of video streaming services currently offered on the internet. In this study, we select YouTube, because it is considered as one of the most prominent video streaming website. According to [13], in May 2010, 14.6 billion videos were served per day.

In this context, we propose a framework for recording the degree of users' satisfaction, in the form of feedback while using the video services on the Internet. The framework detects the presence of a YouTube video on a Web page, and automatically adds a button on which the user is asked to click, whenever she is unhappy of the video she is viewing. The plugin also stores the QoE values, which, in terms, are used to build a large dataset of heterogeneous users, devices and situations. In future work, this dataset will be used for enhancing a QoS/QoE correlation model for video service. Fig. 1 shows the framework structure in which remote users participate via the IP network (Internet).

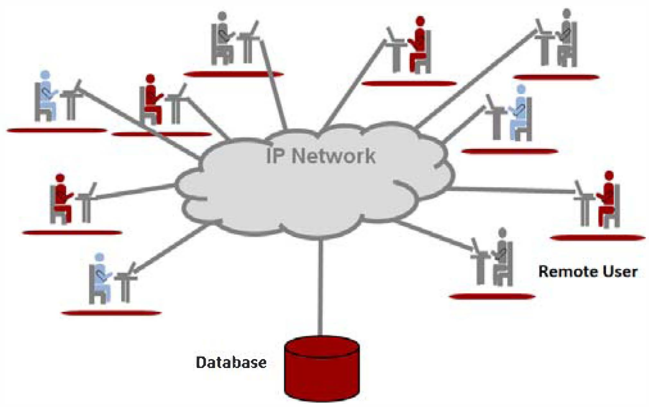

Figure 1 Framework

The framework setup contains the following items:

a. A Firefox plug-in is developed and installed on end users' devices to run the real-time experiment. In particular, the plug-in is able to detect the presence of a video in a Web page, and automatically adds a button, on which the user can click whenever user is unhappy of the video quality.

b. A large number of remote volunteers are invited to watch video sequences online, on their machines.

c. Each video can have different characteristics and experience various, realistic QoS parameters.

d. During the video, and in the end of it, users rate the quality of video (MOS) according to their perception.

e. All feedback information are stored in the database for the analysis of QoE parameters.

B. Controlled Environment Approach

In parallel to the crowd-source approach, we also take an orthogonal approach in which the environment is totally controlled. The ITU has provided guidelines to conduct such subjective tests in a controlled environment, including the selection of participants that represent the users of a service [11].

In order to analyze the impact of different parameters on user's perceived quality in video streaming, a subjective test is carried out with the participation of 45 persons. The participants watch the video streaming and rate the quality of the different videos. In the next sections, the relationship between MOS and the different low-level parameters will be analyzed.

In this testbed experiment, the QoS parameters (packet loss, jitter and delay) are varied in a fully controlled manner. Further, their influence on user perception is recorded in the form of a MOS. In addition, another parameter is taken under observation, the conditional loss. Conditional loss reflects the loss probability of the next packet, given that the current packet has already been lost. As most real-time applications exhibit a certain tolerance against occasional packet losses, this metric helps in concentrating losses on a single part of the sequence, which makes the losses occasional.

For our experiment, the relevant parameters and their selected values are given in Table 1.

Table 1 QoS metrics

Parameters	Values
Delay	0ms, 30ms, 60ms,100ms 120ms
Jitter	0ms, 4ms, 8ms, 16ms, 32ms
Loss	0% to 5% with a step of 0.5%
Conditional Loss	0%, 30%, 60%, 90%

In this experiment, we consider the users participation according to ITU-R Rec. BT.500-11. Indeed, to obtain a subjective notation according to this recommendation, participants should be non-experts, in the sense that they should not be directly concerned with image or video quality as part of their normal work. User characteristics are also stored for analysis purposes, which include user's participant profile like age, gender, familiarity with video streaming, and interest on video content. End-user devices are Dell desktops with Intel core duo processor, 2 GB of RAM, and a display size set to 1024 x 740. Mozilla Firefox is used as the Web navigator.

Table 2 User Characteristics

User Profile	Values
Age	18 to 30 years
Gender	Men, women
Familiarity with the video streaming	Rarely, weekly, daily
Interest on the content	Interested, not interested

25 HD and Non-HD video streams are selected for this experiment, with different motion complexities (high, alternating, and low). These videos have the same frame rate (25 frames per second) and video codec (H.264), and they are related to different fields of interests (e.g. politics, sports, news, social life, commercial ads, and animated cartoons). In our experimental analysis, we used NetEm as a network emulator to control QoS parameters. This tool has the ability to emulate the properties of wide area networks.

VI. Experiment Setup

The experimental setup consists of three important elements: a video streaming server, a video client, and the Network Emulator (NetEm), that emulates a core and cloud network. The traffic flows between the server and the client is forwarded via the network emulator. The emulator introduces artificial delay, jitter and packet loss within a dedicated connection. The client side is built on a Windows environment, while the streaming server and the shaper (NetEm) are configured on a Linux OS. The experimental setup is shown in Fig. 2.

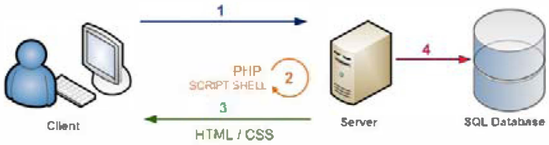

Figure 2 Experiment Setup

We have stored 25 videos at the server side and the client can reach them through a private Web site configured specially to stream those videos. During the session, when the client changes the video, QoS parameters settings are also randomly changed according to pre-defined values. Finally, a total of 25 videos were streamed at the client end, each time using a different combination of parameters.

At the client side, the user connects to the Web site to read the description of the experiment. Before the beginning of the video streaming procedure, the user also fills a form with her personal information (age, gender etc). Users are unaware of the QoS parameters settings on the videos, and they are asked to rate the perceived quality after watching each video. The rating is done by picking out one of the five quality levels of MOS, possibly adding different remarks: problems encountered during the visualisation, user's personal tolerance to the quality, and her personal interest on the video's topic.

In this experiment, a total of 45 users are participating in which 20 are female and 25 are male participants. Most of them belong to the age group ranging from 18 to 30 years old. We collected 25 * 45 = 1125 samples in our database, which means that we have 1125 different combinations of all settled parameters, associated with a MOS value to each combination. However, we reduced this number after a deeper look over on the dataset, to average repeated lines and try to eliminate parasite ones. This cleaning was necessary for the next phase, which consists on training the learning models and evaluated their accuracy.

VII. Results

Initially, datasets resulting from the controlled experiment were processed and cleaned from any parasite information. Therefore, we have a dataset that is ready to apply for data analysis. As an input to our ML tool, we are considering all nine parameters, which are gender, frequency of viewing, interest, delay, jitter, loss, conditional loss, motion complexity and resolution. In order to minimize biases, we perform 4-fold-cross-validation to estimate the error rate efficiently, using the following procedure: a single sub-sample is chosen as testing data, and the remaining 3 sub-samples are used as training data. This procedure is repeated 4 times, in which each of the 4 sub-samples is used exactly once as the testing data. All results are averaged and a single estimation is obtained. For the modelling process, we use the six classifying models for determining which one is best and offers the best model. Recall that these six classifying models are: Naives Bayes (NB), 4-Nearest Neighbour (4-NN), Support Vector Machine (SMV), Decision Tree (DT), Random Forest (RF) and Neural Network (NNT).

We use the WEKA tool to run those different algorithms on the dataset. This tool gives information about the classification model that was generated, along with its performance and imperfection with detailed averaged statistics. We consider the mean absolute error rate to compare the error rate between the different models. The results are illustrated in Fig. 3. In terms of classification, this figure shows that DT has the minimum absolute error rate, with a value of 0.126, followed by the RF model with 0.136. SVM has the highest error rate with 0.26. The results clearly depicts that the DT model and RF model are the most reliable models on the current datasets.

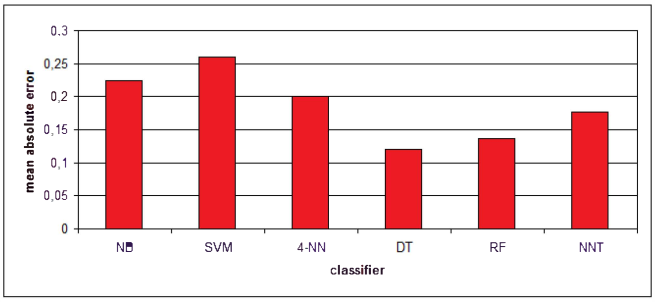

Figure 3 Mean absolute error rate for six classifiers

To choose the best model, we also perform an instance classification test on the six algorithms, in terms of the number of correctly classified instances. Fig. 4 shows that two methods correspond to the best classification: RF with 74.8% of correctly classified instances, followed by the DT model with 74% of correctly classified data. The worst model is 4-NN model with 49% of correctly classified instances. These results again clearly demonstrate that the DT and RF models are the best models, according to our datasets.

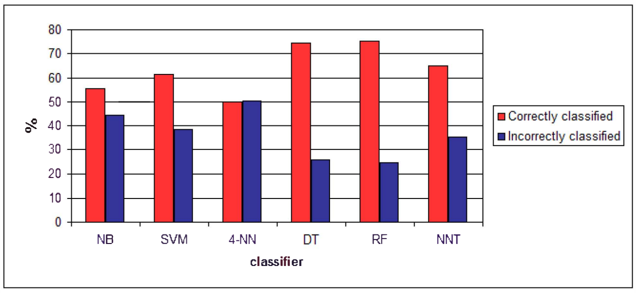

Figure 4 Instances classification

To find more details about the models and their classification errors, we compare the efficiency of DT and RF models. The efficiency of these models is evaluated by measuring the statistics analysis data about classification. Results are presented in Table 3.

Table 3 Average weighted for RF and DT models

Model	TP	FP	Precision	Recall	F-Measure
RF	0.753	0.078	0.752	0.753	0.752
DT	0.743	0.084	0.748	0.743	0.745

We consider five statistical metrics to compare the performance of DT and RF models, which are: True Positive (TP), False Positive (FP), Precision, Recall and F-measure.

1) *TP (True Positive)* occurs when a statistical test rejects a true hypothesis. The best value for this measure is 1.
2) *FP (False Positive)*: a false value means rejecting the hypothesis. Its value should be close to 0, which means the model works well.
3) *Precision* is the probability when a (randomly selected) retrieved result is relevant:

$$Precision = TP/\,(TP+FP)$$

4) *Recall* is the probability when a (randomly selected) relevant document is retrieved in a search:

$$Recall = TP/\,(TP+FN)$$

5) *F-measure* is a measure of a test accuracy, where an F1 score reaches its best value at 1 and in worst case its value is 0.

$$F\text{-}measure = 2 * (Precision * Recall) / (Precision + Recall)$$

The results of a classification can be negative or positive. If the results of the test correspond to reality, then one considers that a correct decision has been made. However, if the result of the test does not correspond to reality, then an error has occurred. According to these metrics, we conclude in Table 3 that RF is slightly more suitable than the DT model for QoS/QoE correlation.

VIII. Conclusion

In this paper, we have investigated the correlation between QoS and QoE in the perspective of video streaming services. ML classifiers are used to classify the collected dataset. In case of mean absolute error rate, it is observed that DT has a good performance as compared to all other algorithms. An instance classification test is also performed to select the best model, and results clearly show that performance of RF and DT are approximately at the same level. Finally, to evaluate the efficiency of DT and RF, a statistical analysis of classification is done, and results show that RF performs slightly better than DT.

Acknowledgments

This work was funded by the CELTIC European Project IPNQSIS. We specially thank our Master's Students, Emna Rekik and Mayssa Jemel, from SupCom School (Tunisia) for their great participation in this work.

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