An Improved QoE Estimation Method based on QoS and Affective Computing

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***Abstract*—With the massive uses of the video over the world in the last decade, the user perception, commonly called Quality of Experience (QoE) metric; has become the one of the most important topics for the Network services Providers (NsP) and Content service Providers (CsP). In this paper, we present a new QoE estimation method on the client side using Machine Learning methods (ML) based on subjective assessment in a controlled-laboratory environment. The major novel contribution of this study is the combination of Quality of Service (QoS) parameters and Affective Computing (facial expression) to estimate the Mean Opinion Score (MOS) for HTTP YouTube content. An evaluation using a collected subjective dataset indicates that combining QoS and Affective computing provides better prediction performance.**

***Index Terms*—QoS, QoE, Affective Computing, Emotions detection, Video service, Machine learning.**

I. Introduction

To ensure the best perceived quality from a user, the Network service Provider (NsP) and Content service Provider (CsP) try to anticipate user perceived quality by estimating their experience commonly called Quality of Experience (QoE) metric. The added value of the QoE-based strategies consists on the integration of many others QoE Influence Factors (QoE IFs), in addition to the traditional ones (QoS parameters), in the network management. For example, new factors such as device indicators (player information, device characteristics, etc.) and user's factors (user's feedback, user's emotions, etc.) can be added to avoid bad QoE that can lead to customer churn and eventually alters revenues related to a service.

To assess user's QoE, several rating scores like MOS (Mean Opinion Score) or Differential MOS (see ITU-T P.910 or P.913) are used to presents the perceived user's quality. Based on the estimation of these scores, CsP and NsP can achieve predicted QoE-models that they will use in the network management.

In this work, we focus on estimating MOS score to assess the user's QoE. However, many works use this score, it isn't always easy to estimate it due to the complexity of performing subjective test campaign in addition to customer involvement issue.

To avoid this issue, we thought about using Affective Computing (AC) to anticipate the user's point-view (QoE) using a camera. This is only possible thanks to the capacity of the devices to acquire the ability to express and recognize the human emotions [1]. So, the user's QoE can be evaluated by including the emotional factors (user-level) in addition to the QoS parameters (network and application level) in the estimation process. Since, we present in this paper a QoE management framework that we call : VAAF (Video Affective Analysis Framework), which aims to estimate user's QoE using both traditional QoS parameters and AC factors (facial expression) in order to predict the QoE for HTTP YouTube content. This framework is composed by four modules.

- QoS monitoring module to manage the QoS parameters.
- User emotion module used for video affective assessment where the facial expressions are analyzed.
- QoE estimation module that is based on Machine Learning (ML) methods. This module is established in two steps: selection of the best QoE IFs and calculation of the best user's QoE in term of MOS.
- Dataset that aims to collect the MOS rating score from the user and a set of QoE IFs (QoS parameters and emotions factors).

Furthermore, an evaluation, using the collected subjective dataset, is performed to highlight the added value of using a combination of AC factors with QoS parameters in the user's QoE measurement. According to this evaluation, QoE estimation using just QoS parameters is improved by 30% with combining AC factors and QoS parameters.

This paper is organised as follows, we present in the next section the related work around QoE and user's emotions collecting. Then, we describe in the section III our proposed system for estimating QoE. In section IV, we describe the performed evaluation to assess our estimation system. In section V, we discuss the results and we present the experiment conclusions. Finally, we conclude our work and present the possible future directions.

II. Context and contributions of this work

A. Why QoE assessment ?

To ensure service delivery and user's satisfaction that increases operators (CsP, NsP) revenues, these operators used basically QoS-based strategies in the network level to ensure a good delivered quality. However, good quality does not necessarily imply user satisfaction, because it also depends on user's profile (demanding consumer) and on device characteristics (not display HD or Full HD video quality). Since, these QoS-strategies don't consider user's satisfaction where it not take into account customer's perceived quality that can lead to customer churn (alters operator's revenues) when he is non-satisfied. This fact can be justified by two criteria : (i) subjectivity (viewpoint) of humans being and (ii) difference in user's context (device quality, network condition, Service Level Agrement(SLA), etc.). To avoid user's dissatisfaction, newer studies based on human centric approaches emerged to include user's perceived quality in the network management. In these approaches, operators used a new concept called: Quality of Experience (QoE)[2, 3] in order to find a deterministic relationship between factors that impact user's QoE (QoE IFs) and perceived quality (QoE) in terms of rating scores like MOS and DMOS. Based on these relationships, operators will initiate specific corrective actions following the arrival of unwanted events such as malfunctions of network elements, unsatisfactory QoS and negative experience feedback.

B. QoE studies

In this part, we describe a few studies proposed to assess user's QoE.

In [4], authors use ML methods to estimate QoE from network-level parameters. To find this QoE-QoE IFs relationship, testbeds are achieved using MOS rating procedure for the video-on-demand (VoD) and VoIP services. The found results indicate that the accuracy is more than 80% compared to domain experts on smart phones. However, this approach can estimate (anticipate) video stalls and MOS score, but it has not undertaken any subjective parameters of user satisfaction.

In [5], a video quality tool called QoM framework is presented. In this tool, the evaluation uses various QoE IFs like qualitative ones (gender, profession and place of evaluation) and quantitative ones like: average delay, jitter and MOS score. The QoM framework performs functions of monitoring data, analyzing it and reporting it to the administrator. These functions help to anticipate the user's dissatisfaction by sending alert messages to the administrator based on some policy rules. However, capture service is not launched automatically where the user must activate manually the capture service at the beginning, and after that, the service will work well.

Another framework to assess user's QoE on Android client-side in a mobile environment is presented in [6]. This framework is called : YoMoApp (YouTube Performance Monitoring Application). It uses key performance indicators (KPIs) like player state/events, buffer, and video quality level (e.g. $240p$, $360p$, $480p$ and $720p$) of YouTube adaptive video streaming. To develop this framework, a real QoE subjective test is realized to monitor the performance of YouTube video streaming sessions under different network conditions (e.g. bandwidth : 1 Mo, 2 Mo and 4 Mo). In tests, 52 testers watched YouTube videos in smart-phones instrumented with the YoMoApp tool and rated resulting experience in terms of MOS score. The authors explain that the measured total stalling lengths and time on each quality layer could explain the subjective ratings, which indicates that the application works as expected.

In [7], authors proposed a study whose main objective is to identify QoS indicators in order to predict the QoE for HTTP YouTube content on mobile networks. Network operator parameters (throughput of a TCP connection, loss rate of packets and the Round Trip Time (RTT)) are used in addition to the VLC player indicators like: input video bitrate, lost picture, lost audio and buffering account. Results in this study indicate that the proposed indicator is easy to implement in order to predict QoE in real time (i.e on the fly during the session) and at the network scale (i.e for all users).

C. Why video affective content analysis ?

With the technological advancements, computer systems are more and more efficient and are increasingly capable of reading and responding to human emotions. According to Picard (one of the pioneers of AC) : *Emotions fulfill numerous functions which are related to humans, including the communication function when interacting with other people*[1]. Thus, the field of AC seeks to study the interaction between technology and humans feelings (users emotions)[8]. In literature, the AC domain try to provide machines with the ability to establish the communication between technology and humans feelings. In fact, it evaluates the emotions of a user (input) and display an emotional reaction either by using expressive avatars or continuous values of classes of feelings[9]. In the Human Computer Interaction (HCI), the feeling of multimedia customers regarding the service quality can be evaluated by one of the three elements : facial, vocal or gestural behavior[10]. Based on these elements, many works like[11, 12] are introduced in recent years. In this paper, we focus on the facial factors detection (emotions factors) to evaluate the user's satisfaction of the YouTube streaming video.

D. Why facial detection ?

Recently, a new domain search called video affective content analysis is appeared evaluate video service using AC. This domain tries to help the CsP and NsP to personalize the content delivery, movie recommendation and video summarizing. In another words, it helps to select the best target population for their videos based on the affective content. To attempt this objective, the emotions of users are observed and evaluated. These emotions can be : head motion, pupil gaze, eye gaze and facial expression. In [13], a state-of-the-art methods using these emotions, in video affective content analysis domain, is presented.

In this paper, we opted to use the facial expression detection from the existing of different methods for facial expression recognition like eMotion (a facial expression recognition software). This choice is justified by the fact that facial expression (e.g. anger, guilt, happiness, fear, sadness, etc.) can be presented with numerical values.

E. Affective computing (AC) related works

In this part, we describe a few studies proposed to assess QoE using AC.

In [14], Mitra et al. focused on QoE measurement depending on the context of use. They introduced the use of metrics from AC and HCI (Human-Computer Interaction) measuring blood pressure and heart rate to model the context-dependent factors then they are able to predict them in a real use case.

In [15], Bhattacharya et al. used emotions detected through a voice over IP (VoIP) communication to predict the quality of experience. The work used many classification procedures such as Support Vector Machines (SVM) and k-Nearest Neighbor (kNN) and suggested the consideration of emotions capturing in modeling user experience. Chen et al. [16] proposed the use of emotions and AC metrics to evaluate and maximize the quality of experience for Internet of Things (IoT) use.

In [17], Samsung used unobtrusive emotion detection system to detect users emotions. In this system, the rhythm of typing patterns (speed, use of symbols) and shaking the phone is analyzed to detect the emotional state. Similar works used mobile phone sensors also to detect the emotional state as a base for experimental social psychology research like EmotionSense [18]. Microsoft has recently released an emotion API able to detect the same set of emotions as affectiva with an added neutral state [1].

III. Proposal

The main objective of the work presented here is combining AC factors (facial emotions) with QoS parameters (e.g : bandwidth, video resolution and beginning time) in order to estimate user's perceived quality (QoE) in terms of MOS score. To attempt this objective, we implement a QoE management framework, called *Video Affective Analysis Framework (VAAF)*, for HTTP streaming videos. This framework is composed by four modules as explained below.

- QoS Monitoring : For monitoring the used network QoS parameters, we emulate via NetEm network emulator[19] the network bandwidth and (ii) we upload 8 short videos on YouTube (under Creative Common license) with several resolutions.
- User emotions : For gathering user's emotions (face expressions), the Clmtracker open source library and the Affectiva SDK[20] are used. The Clmtracker library provides information based on [21] returning 4 basic emotions, where the Affectiva SDK[20] uses the Viola-Jones face detection algorithm as introduced previously.
- Data set : For storing the collected QoE IFs (QoS parameters and emotional factors), a data base is created in the MySql relational database management system (RDBMS). The collected QoE IFs are sended to this data base using $XMLHttpRequest$.
- QoE estimation : Based on the collected dataset, QoE estimation model is achieved using a supervised learning. This model is implemented in the QoE estimation module in order to provide instantaneous user's perceived quality in terms of predicted MOS score.

The originality of our approach stems from the fact that our system is capable of taking into account the actual dynamics of the network and the detected facial expression by a camera to estimate the instantaneous user's viewpoint. This end-to-end approach requires user collaboration but works with every content, every protocol, encrypted or not. In contrast to the existing works, we further present a performance evaluation of our proposed using a set of ML methods (a classic, a bagging and a boosting-based). The obtained results (root mean square error and correlation rate) demonstrate the superiority of our approach in terms of prediction performance using both QoS and user's emotional factors.

A. User emotion module

The implemented "user emotion module" consists on a developed platform that is is able to provide users with several kinds of video, with different qualities, and to collect their emotions. To develop our proposed platform, we have created a $Node.js$ web server to provide a central mechanism to serve the YouTube video while adding more Javascript code to detect user emotions and record them. The main page contains the video player, and many buttons to select (i) the video type, (ii) test duration and (iii) validate the given Mean Opinion Score (MOS). In addition, the detected emotional factors (e.g. Disgust, Fear, Surprise, Smile,...etc.) by the web-camera are stored in a JavaScript object and then sent back to a server using an $XMLHttpRequest$.

To collect user's facial emotions, an automatic gathering process is achieved by Affectiva SDK[20] that uses Viola-Jones face detection algorithm to detect the face then extracts a Histogram of Oriented Gradient (HOG) features which are used in a Support Vector Machine model (SVM). This model detects user's face actions that presents user's emotions like: Anger, Disgust, Fear, Joy, Sadness, Surprise and Contempt.

Our demo setup view is presented in[22]. This demo consists on one tester that see a video sequence during 30 seconds and gives his MOS score value ate the end.

B. Dataset build

To build a subjective "dataset" of the VAAF framework, we perform a testbed using Absolute Category Rating (ACR) method[23]. The testbed demonstration consists on a subjective QoE assessment in a dedicated controlled-laboratory testbed where we provide a network emulation node to modify network conditions using NeteM[19] as shown in Figure 1.

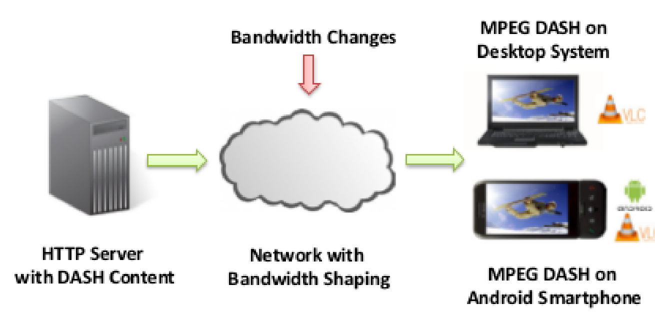

Fig. 1. Description of network management.

[1]https ://www.microsoft.com/cognitive-services

In this testbed, the ITU-T-P.910 recommendations[23] is followed as below:

- The evaluation concerns the video service where the MOS score is collected for each sample.
- A replication of video sequences is done. The same video sequences with the same parameters selected were shown to the subjects. This is important for results validation.
- 16 testers (4 women and 12 men) participated in the subjective campaign. In this campaign all the participants are students or researchers from different disciplines aged 24 to 34 years with more/less experience of this kind of evaluation. All the participants in this testbed spent at least 5 minutes on watching a set of videos.

Table I summarizes the overall tested conditions.

Parameters	**Description**
Video	**-2 Types** : Movie and Cartoon. **-Duration** : 30 seconds **-Resolution** : $144p$, $240p$, $360p$, $480p$, $720p$, $1080p$
Dell	**CPU** : i7 **RAM** : 8 Go
Emulation	**Emulator** : Linux Netem **Bandwidth** : 256, 512, 1024, 1536, 2048 Kbs

TABLE I
OVERALL TESTED CONDITIONS.

Finally, the database contains 19 parameters : 15 emotional factors, 3 QoS parameters (bandwidth, video resolution and delay) and the user's MOS score. The video demo presented in[22] illustrates all collected QoE IFs. Table II summarizes a part of the these QoE IFs.

QoE IF	**Symbol**	**Source**	**Description**
Link Bandwidth	f_{bwd}	Integer	256, .., 2048 Kbs
Time begin	$f_{timeBegin}$	Integer	Integer in ms.
Codec	$f_{resolution}$	Integer	Video resolution ($144p$ to $1080p$)
Disgust	$f_{disgust}$	Integer	$[1, 100]$
Contempt	$f_{contempt}$	Integer	$[1, 100]$
Fear	f_{fear}	Integer	$[1, 100]$
Mouth open	f_{mouth}	Integer	$1, 2, 3, \ldots$
MOS	mos	Integer	$\{1, 2, 3, 4, 5\}$

TABLE II
OVERALL TESTED CONDITIONS.

C. QoE estimation module

Several kinds of ML methods can be used to build QoE estimation model in the literature[24]. These methods can be divided on three types. The first one presents the traditional ML method such as : SVM, RNN (Random Neural Network), DT (Decision Tree), etc. The second one is the bagging-based methods such as : Random Forest. The third one presents the boosting-based method like Blackboost (boosting based on Decision Tree)[25]. In our case, we test several of them to choose the best one according to our collected dataset.

So, to build our QoE estimation module, two stages are defined as described in figure (2) below.

$-$**First stage** (**QoE IFs selection**). A set of candidates factors which is a subset of all the available QoE IFs is selected using specific method. In this work, we opted to use our proposed heuristic in [26] that is based on correlation matrix.

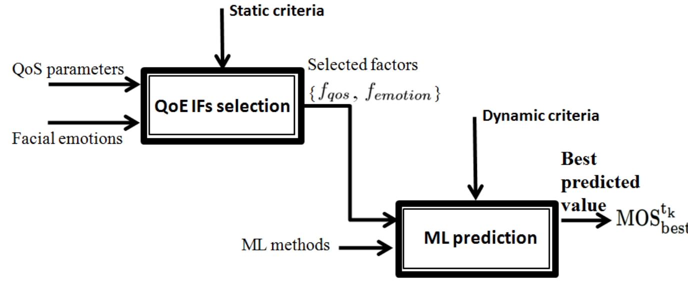

Fig. 2. QoE prediction BF-based system.

$-$**Second stage** (**Machine Learning calculation**). The QoE IFs selected in the first stage are used as input in the ML-prediction process where different ML methods are tested. Each ML method calculates its candidate value ($\mathbf{MOS^{t_k}_{pred_i}}$). To achieve best ML method, all the ML methods are compared in terms of Root-mean-square deviation (RMSE). The method that gives the closest value ($\mathbf{MOS^{t_k}_{pred_i}}$) to the user's MOS score ($\mathbf{MOS^{t_k}_{real}}$) is selected.

IV. EVALUATION

A. QoE estimation module implementation

- Stage 01 (QoE IFs selection)

In the first stage, our objective is to select, from all emotions factors (15 factors), the best emotions factors ($f_{emotions}$) that we will use to estimate the nearest user's QoE value. To this end, we opted to use our proposed heuristic in [26] to select 9 facial expressions.

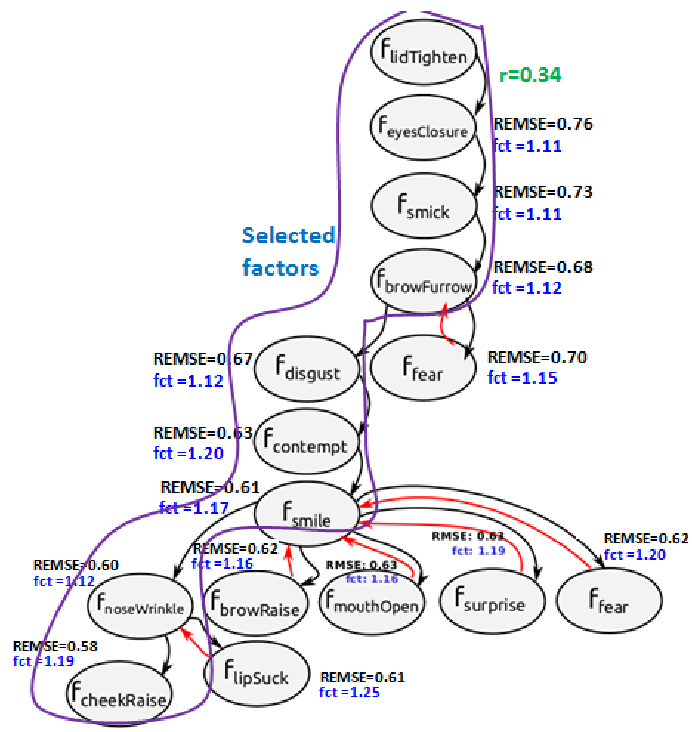

Fig. 3. Heuristic execution.

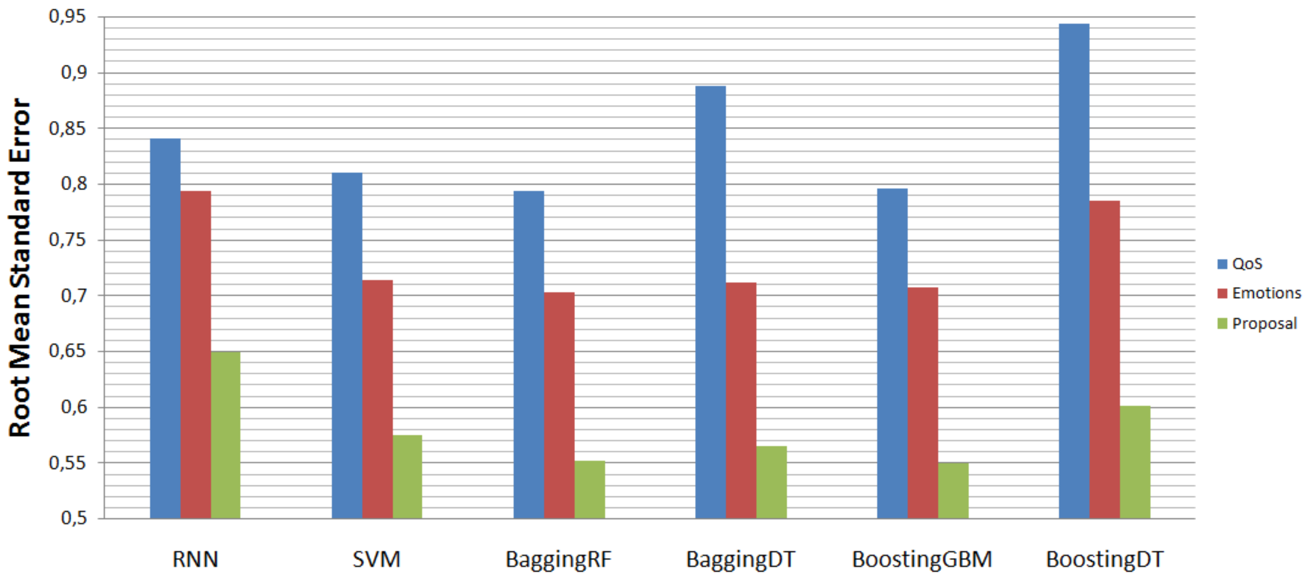

Fig. 4. Evaluation performance

This heuristic is based on the interactive/repulsive relation between the QoE IFs that we find in the Pearson "r" correlation matrix. The heuristic execution is presented in the figure (3).

- Stage 02 (ML prediction)

To estimate user's QoE in terms of MOS score in the second stage, several methods can be used[24]. Since, we opted to test here six ML methods (RNN, SVM, $RFbagging$, $DTbagging$, $GBMboost$, $BoostingDT$). In fact, the selected facial emotions (9 factors ($f_{emotions}$)) in the previous stage and QoS parameters (3 parameters (f_{qos})) are used as inputs to build each ML model. The second stage is summarized as follows :

- **Input:** 12 factors (9 emotions and 3 QoS).
- **Broker:** Six ML methods are evaluated (section $IV-B$).
- **Output:** Best estimated MOS value.

B. Machine Learning evaluation

In our evaluation, we use two methods in each kind of ML techniques (classic, boosting and bagging). The SVM and the RNN are implemented as classic methods, the Random Forest ($BaggingRF$) and the DT based-bagging ($BaggingDT$) are implemented as bagging methods. For the boosting methods, we used the Gradient boosting-based ($GBRboost$) and DT boosting-based ($DTboost$) methods. All the evaluations are performed in the R software[27] tool, where different configurations are tested for each ML method (BaggingRF (trees number), SVM (kernel type), RNN (hidden nodes), etc.) to minimize the error rate in terms of RMSE as presented in the equation (1).

$$RMSE = \sqrt{\frac{\sum_1^n (f_i - y_i)^2}{n}} \tag{1}$$

The best configuration is selected for each ML method and used in the final comparison (comparison between all ML methods). In fact, we use a cross-validation method with $k = 10$ folds to calculate the RMSE.

where : f_i is the prediction of MOS, y_i is the true value of the MOS and n is the total number of the considered samples.

C. Results

To achieve the best estimation ML method, we compare six ML methods to select the best one that we will use in the QoE estimation module of the proposed VAAF framework. The results of our comparison are presented in this section, where the tested ML methods are compared against.

Three cases are considered in our evaluation. In the first case (QoS in figure 4), just the QoS parameters (bandwidth, video resolution and beginning time) are used as input to build the QoE estimation model. In the second case ($Emotions$ in figure 4), just the selected emotions factors from user are considered. In the third case ($Proposal$ in figure 4), both QoS parameters and user's emotion factors are used as input. Figure 4 shows estimation performance in term of RMSE (y-axis) for the six ML-based methods (x-axis) in each case (QoS, $Emotions$, $Proposal$).

- **Case 01: QoE estimation using QoS parameters**

According to figure 4, we observe in the first case (QoS) that the bagging and boosting methods are more efficient that classic ML (RNN and SVM). This is can be justified by the fact that we test just a small number configuration for these methods. In fact, we show that RF method ($BaggingRF$) is the best estimation method with 0.792 of RMSE followed by the boosting gradient method ($GBRboost$) with 0.794 of RMSE.

• Case 02: QoE estimation using emotions factors

In the second case ($Emotions$), figure 4 shows that estimation performance in term of RMSE using all 15 user's emotion expression factors. Since, we observe that estimation QoE model, using facial emotions as input, improves by an average 12% to 15% the prediction using the QoS parameters. Like the first study, the bagging and boosting methods are more efficient that classic ML methods (RNN and SVM). In this study, the RF using bagging ($BaggingRF$) is the best prediction method with 0.701 of mean error followed with the Gradient using boosting method with RMSE=0.7043. In fact, we observe also that the RNN is the least efficient ML method with 0.793 of mean error.

• Case 03: QoE estimation combining QoS parameters and emotions factors

According to figure 4, we show that combining QoS parameters and selected emotions factors in the QoE estimation model build decreases the RMSE error in all the tested ML methods. In fact, the prediction performances of Gradient boosting-base and RF based-bagging ($BaggingRF$) are better all the ML methods. In case of Gradient based boosting with 0.550 RMSE, the best ML method using just the QoS parameters (case 1) is improved by 30% of RMSE. Since, the best ML method using justthe emotions expression factors (case 2) is improved by 21.5% of RMSE.

This is justified by the performance of the boosting-based methods and bagging-based methods in which estimation calculation is improved by using ensemble-based methods. Therefore, we clearly see that our combining QoS parameters and user's emotions ($Proposal$) to build QoE estimation model offers better results in terms of RMSE according to our collected dataset that we must enrich to be more consistent.

D. Prediction performance with correlation rate

To confirm the results shown in the previous part concerning the ML methods comparison, we calculate as suggests in[28, 29] the correlation rate for the case 3, where both QoS parameters and emotion factors are considered. The figure 5 presents the correlation value for the used ML methods in in the broker.

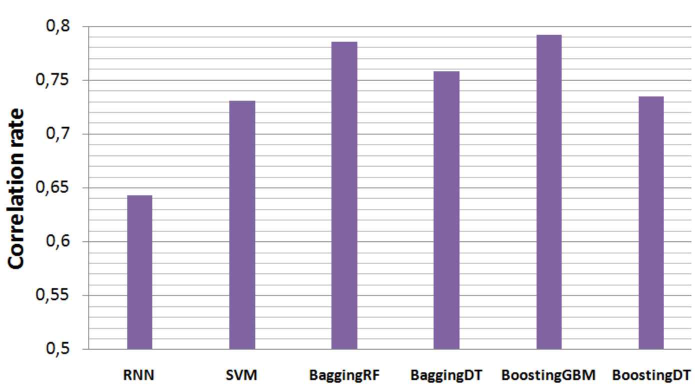

Fig. 5. Prediction performance in terms of correlation rate for the 6 used ML methods.

The x-axis represents the ML methods and the considered combination rules, while the y-axis represents the correlation rate.

In Figure 5, we show that two ML methods are more efficient than the others. The first one is Gradient based-boosting method with 0.79 of correlation rate. The second one is the Random Forest bagging based method with 0.785 correlation rate . This results confirms the first result where the Gradient using boosting and RF using bagging ($BaggingRF$) had the minimum RMSE. Since, the Random Neural Network gives the least prediction performance with 0.64 correlation rate.

V. Conclusion and future work

In this paper, we presented a novel framework that estimates users perceived quality in terms of MOS rating score using both Affective Computing factors (user emotions) and traditional QoS parameters. First of all, we implemented a platform for collecting these parameters at the client side. Then, we performed a subjective assessment in a controlled-laboratory environment using ACR method to build a subjective dataset. Based on this dataset, we predict user QoE in terms of MOS in real time using a set of ML-based methods. The evaluation results highlight that combining QoS and emotional parameters improves the QoE estimation efficiency compared to using only QoS parameters. As perspectives, we plan to introduce more affective computing factors like the user's skin impedance which can indicate the stress, or heartbeat rate. These two parameters can be easily collected using smart objects like smart watch. We will also try to apply this system to video communication platforms like those based on the WebRTC protocol.

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