

# Intelligent Video QoE Prediction Model for Error-prone Networks

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## Abstract

**Objective:** Quantifying the quality of video transmitted over diversified networks is becoming critical in the frontiers of digital video Communication. The exponential growth of video-driven applications in wireless domain have created plethora of research issues to be explored in real time. Estimation of video quality in wireless environment requires the conception of better framework and methodologies to improve users' Quality of Experience (QoE). This paper depicts a novel QoE prediction model that uses machine learning algorithms in predicting video quality over an error prone environment with better prediction accuracy. **Methods:** The work deploys Pseudo Subjective Quality Assessment (PSQA) method that involves a hybrid technique in assessing the multimedia quality using WEKA machine learning workbench. **Findings:** The proposed model provides a comparative study of well-known Artificial Intelligence (AI) techniques in predicting the perceived quality of multimedia and the efficiency is analyzed using performance indicators such as Root Mean Squared Error, Correlation Coefficient and Mean Absolute Error. The results of the proposed method underline the effective and inherent advantage in using machine learning methods for video quality prediction. **Application:** The evaluation results exemplify the importance of applying machine learning paradigms in broad areas of visual quality assessment. The output of various error measures and error variation analysis of the model shows the superiority of Multilayer perceptron based AI technique over other methods.

**Keywords:** Machine Learning, Neural Network, Pseudo Subjective Quality Assessment, Quality of Experience, Video Quality Prediction

## 1. Introduction

Quality of Experience (QoE) is defined by the International Telecommunication Union (ITU) as "the overall acceptability of an application or service as perceived by the end user"<sup>1</sup>. In Multimedia Communication, accurate envisioning of end users' expectations can be critical for any service provider's success. The paradigm shift from technology oriented services to user oriented services in today's world have made QoE, an indispensable phenomenon and its crucial impact have triggered the exploration of various QoE modeling and evaluation schemes.

QoE assessment can be done in three different

ways: Subjective, Objective and Hybrid methods. The Subjective Video Quality Assessment scheme is the most fundamental and reliable way of assessing the perceived video quality. Human subjects are involved in assessing the video contents in a controlled environment. The most preferred scheme of subjective QoE evaluation is by Mean Opinion Scores (MOS), which provides an average human rating (say 1 to 5 scale) of the multimedia content viewed. Various subjective video quality methods are standardized by ITU-Rec B.T 500-11<sup>2</sup> and ITU-T Rec.P.910<sup>3</sup>. The methods such as Double Stimulus Impairment Scale (DSIS), Double Stimulus Continuous Quality Scale (DSCQS), Single Stimulus Continuous Quality Evaluation (SSCQE), Absolute Category

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Rating (ACR) and Stimulus Comparison (SC) are used extensively in Subjective testing. MOS method deploys tedious computations that warrant non-repeatable and non-scalable properties. Hence subjective methodologies hardly adapt to real time environments<sup>4</sup>.

Objective QoE metrics estimate the quality level of video through certain mathematical models. Objective methods such as PSNR (data metrics) provide swift computation and easy implementation. But these methods are inconsistent with Human Visual System (HVS) perception. Vision modeling and Engineering approach are the two picture-based Objective metrics. Moving Picture Quality Metric (MPQM), Motion based Video Integrity Evaluation (MOVIE), Perceptual Quality Index (PQI) are few important vision modeling approaches that adopts HVS properties. Structural Similarity Index (SSIM) and Video Quality Metric (VQM) are widely used as Objective metrics based on engineering approach. More extensive review on objective VQA methods can be found in<sup>5,6</sup>.

In general, till date there is no single accurate Objective Video Quality Method has been developed with consideration of all contributing factors such as terminal type, content and user expectations<sup>7</sup>. Hybrid video QoE approach such as Pseudo Subjective Quality Assessment (PSQA) provides better accuracy in predicting QoE and moreover the method works in real time. The hybrid nature is due to the involvement of both subjective and objective approaches with the properties of Random Neural Network<sup>8</sup>.

The tremendous increase of mobile data traffic is due to the exponential evolution of wireless multimedia in the applications such as video streaming, social networking and online gaming. The increased usage of smart phones and advancements in 4G wireless networks viz WiMax, LTE have made video-driven applications to keep track on perceptual qualities of mobile video. In the coming years, newly emerging visual signals based on scalable and mobile videos, 3D video quality assessment have enormous research potential<sup>9</sup>. QoE-aware wireless multimedia have gained greater significance in addressing broad areas such as architectures and protocols for QoE driven media streaming, optimization techniques based on QoE and online/offline QoE measurement from wireless networks. Predicting, modeling and measuring QoE is a crucial step in determining the outcome of multimedia quality, thereby enhancing the service providers' response in a greater scale.

This paper explains the need for better QoE prediction models in error-prone networks and the work elucidates the working of PSQA based video quality prediction model to estimate QoE with the usage of Machine learning techniques.

The paper is organized as follows: Section 2 briefly explains the QoE concepts and its implications. Section 3 depicts the impact of various QoE measurement models in multimedia community. Section 4 describes the need and scope of Artificial Intelligence and Machine learning approaches in Video quality prediction. A novel wireless Video QoE prediction model using machine learning approach is proposed in section 5. Section 6 discusses the experimental evaluation of the proposed model and analysis of the results. Finally concluding remarks are pointed out in Section 7.

## 2. QoE Concepts

To quantify QoE, translation of user perception of video content in to statistical and interpretable values is required. Subjective QoE can be classified as Qualitative and Quantitative approach. Qualitative method provides verbal behavior of human perception through surveys and interviews. CCA (Catalog, Categorize, and Analyze) framework is used for such measurement. Quantitative Subjective measurement provides results in the form of numbers and statistics. ITU-T Rec.910 is one such model used extensively nowadays. Objective QoE assessment is of two types namely technology centric and human physiological /cognitive based methods. The former approach widely performs QoE prediction from QoS data and the latter is an application of cognitive science using certain neuro imaging techniques<sup>10</sup>.

Relationship between QoS and QoE, subsequent modeling of QoS/QoE relation is gaining greater importance in Multimedia Community. Logarithmic and exponential relationships are widely used to highlight the dependency of QoE on QoS levels. Logarithmic relation of QoS/QoE applied in web browsing and VoIP applications. Exponential relationship is based on IQX hypothesis that acts as generic exponential function<sup>11</sup>.

In general, Linear mapping function for mapping objective quality into predicted subjective scores is hardly productive and hence non-linear mapping based on logistic, cubic, exponential, logarithmic and power functions are applied in variety of applications<sup>12</sup>.

QoE is a multidimensional approach based on user-centric and holistic properties. QoE depends on broad influence factors viz context, user and system parameters. Henceforth, Quality of Service (QoS) stays as major factor in determining QoE. Network level QoS such as Packet Loss, delay, jitter, bit rate and application level QoS such as frame rate, resolution may have substantial impact on QoE<sup>11</sup>.

With respect to the availability of reference information, Objective Video Quality Metrics can also be classified as Full Reference (entire reference signal needed), Reduced reference (partial reference information needed), No-reference (no prior information of reference signal). Typical Full Reference (FR) metrics are PSNR, SSIM and MPQM. VQM metric belongs to Reduced Reference (RR) approach and V-Factor works by No-Reference (NR) method. ITU has formulated five models for QoE calculation. They are Media Layer, Packet Layer, Parametric Planning, Bit stream Layer Model and Hybrid Model<sup>13</sup>. The Quality degradation may depend on network related parameters such as loss, delay and network independent factors such as encoding and compression. Hence, the need for non-intrusive QoE framework that considers all the above parameters to work on real time is imperative and calls for decimation of problem space in to practical solutions.

### 3. QoE Models and Measurements

QoE framework may include broader areas of QoE modeling, QoE measurement and QoE-aware management and control. There are quite large methods of QoE models developed tilldate according to certain dimensions and criteria. Here, few of them are outlined.

#### 3.1 QoE Models based on Applications

Various QoE models are developed for specific applications such as web browsing, audio/video services, online gaming and telepresence. Web browsing QoE model shows the impact of session time and temporal correlations for determining the final QoE in browsing the web pages. For audio applications, PESQ (Perceptual Evaluation of Speech Quality) is proposed by ITU-T Rec.p.862 using Full reference method to assess speech quality. E-model (ITU- T G.107) considers delay, echo for determining speech quality. Typical video quality

estimators such as PSNR, MSE are used in video applications. VQM model (ITU-T G.1070) finds video quality based on codec type, video frame and packet loss. QoE model for HTTP based video streaming system and scalable video coded streaming is proposed and improvement strategies are in steady progress. QoE for online multiplayer gaming depends on quality factors such as interactivity and consistency. Online gaming and its QoE estimation is trending as it is one of the killer application in today's multimedia world. Telepresence application and determining QoE of telepresence through factors such as interactivity, consistency and vividness is swiftly gaining momentum for further deliberations<sup>14</sup>.

#### 3.2 Generic QoE Models

Various QoE Models are proposed for determining video quality based on different viable schemes. Gong et al.<sup>15</sup> proposed a five scale model for QoE calculation. Integrity, retainability, availability, usability and instantaneousness are the factors contributing to the pentagram model. Perkis et al.<sup>16</sup> describes a QoE model with technology and user related factors. Assuming strict independence of chosen parameters makes this scheme less effective. Laghari et al.<sup>17</sup> proposed a QoE scheme based on multiple domains of communication eco-system, yet the method fares poorly in real time.

Involvement of discriminate functions is used in statistical analysis method to determine the output of video prediction<sup>18</sup>. YouTube QoE model is proposed in<sup>19</sup> using crowd sourcing approach that has greater influence of video stalling events. QoE Model based on resource arbitration system is studied in <sup>20</sup>. Here QoE factor is formulated as a function of application QoS and network QoS. QoE models based on machine learning methods have shown greater significance in recent years. Naive Bays, K-Nearest Neighbor, Random forest methods are used for prediction of QoE and compared with Decision trees/SVM methods in<sup>21</sup>.

Artificial Neural Networks based Adaptive Neural Fuzzy Interference System (ANFIS) method is used in certain works for video quality prediction<sup>22</sup>. Hence supervised and unsupervised machine learning methods are effectively adopted to predict Video QoE in video applications.

QoE measurement process should take necessary values for the variables of QoE model. The complexity

in gathering all quality indicators and managing the interdependencies and counter-intuitive nature of QoE factors makes QoE prediction, a highly challenging task.

## 4. Towards Machine Learning Techniques in Video QoE Prediction

### 4.1 Machine Learning in Quality Assessment

Most of the traditional Objective Video Quality Assessment (OVQA) methods try to explicitly model the highly non-linear behavior of Human Visual System. Hence, such methods undergo intensive computations and results in relatively inaccurate results with high complexity. Machine learning based OVQA methods avoid explicit modeling of HVS and simply imitate the HVS interpretations to quality losses. Machine learning objective quality methods works by two steps. In the first step, feature based representation of video distortion is outlined. In the next step, ML based prediction system maps the feature vector in to resultant scores. Thus the method provides simple inexpensive model with the efficiency depending on the strictness of learning machine's training phase<sup>23</sup>. Such methods initially aim at reducing the dimension of original data space considerably and then single/multiple predictor phase outputs quality

scores through trained algorithms. Narwaria et al.<sup>24</sup> uses Singular Value Decomposition (SVD) as feature space with Support Vector Machines (SVM) as ML paradigm. Prediction of packet loss errors using SVM is highlighted in<sup>25</sup>. Le Callet et al.<sup>26</sup> proposed time delay Neural Network for video quality prediction. All the above methods use single mapping function to map feature to quality rating.

Albeit the wide applications of feed forward neural networks and Kernel machines in video quality prediction, novel method based on genetic programming supported symbolic regression<sup>27</sup> is conceived with considerable results. While applying machine learning approaches to multimedia quality prediction, better feature selection procedures and avoidance of 'Curse of Dimensionality' problem is mandatory to manipulate good results.

QoE prediction methods can be studied under three general ways. Regression based (linear and non-linear methods), correlation analysis methods and AI & Machine learning methods.

### 4.2 Regression and Correlation-analysis based Prediction Methods

Certain Regression and correlation analysis based QoE prediction methods are elucidated briefly in Table 1.

All the above schemes depend upon statistical QoE prediction methods. Calculation of variance and standard

**Table 1.** Description of Regression and correlation analysis based prediction methods

Method	Description
User Satisfaction Index (USI) method <sup>28</sup>	Prediction of Quality of Experience with respect to VoIP call session lengths is performed. The method is stamped inflexible as it neither provides support to mobile applications nor it considers substantial QoE parameters for assessment.
One Click <sup>29</sup>	Predicts QoE in various multimedia platforms such as VoIP, video streaming and gaming. Users' perception is studied using 'key-clicking' outcome on various network applications. The method is used in skype, MSN and henceforth ascertains its advantages such as application-independency and intuitiveness. But the need of validation with large user studies and poor handling of inter-parameter dependencies makes this method less productive.
GLZ(Generalized Linear Model) <sup>30</sup>	This method adopts linear regression and it is based on probability distribution. User ratings can be predicted with considerable accuracy yet the method needs improvement in handling multiple QoE factors.
QoE DIME model <sup>31</sup>	Provides conceptual framework of QoE in Distributed Interactive Multimedia Environments. Though QoE-QoS correlations is evaluated by multiple QoE parameters, the method lacks in applying cohesiveness of such parameters to fetch better efficiency.
QoS-QoE correlation model <sup>32</sup>	QoE prediction based on linear weighted QoS sum by considering critical QoS parameters such as delay, jitter and packet loss. The method can be hardly used in real time systems as it treats each QoS parameter independently and there is no provision to add new QoE parameter for investigation.

deviation, limitations of using ordinal scales ratings makes such methods less effective in most applications.

### 4.3 ML based QoE Prediction Methods

In recent years, prediction of QoE based on AI/ML methods has shown tremendous scope in multimedia industry. Various methods such as Decision trees, Random Neural Network, Hidden Markov Model, Bayesian Network and Dynamic Bayesian Network are deployed to predict QoE. ML based methods provide better mathematical models and are more flexible than parametric statistical models. Moreover various online QoE prediction models are proposed and the implementation is based on viewers' feedback and caters the needs of dynamically changing environments. Online methods such as Hoeffding trees, Hoeffding option trees, oza bagging methods are reviewed extensively in<sup>7</sup>.

Some of the prediction methods for QoE based on Artificial Intelligence methods are highlighted in Table 2. given below:

**Table 2.** Description of Artificial Intelligence based QoE methods

Author(s)	Description
Rubino et al. <sup>33</sup>	Pseudo Subjective Quality Assessment method provides automatic quality prediction with better accuracy. The subjective study result is used in training a neural network process (Random Neural network) to extract prediction result in real time. The need for effective datasets and MOS dependent nature of PSQA has to be considered while deployed in critical applications.
Menkovski et al. <sup>34</sup>	This model is based on different ML classifiers viz. Bayesian Networks, Decision trees and SVM. The comparative study shows that Decision trees are better than other contemporaries. Yet, the method hardly takes the advantage of multiple QoE parameters to predict the final QoE.
Mitra et al. <sup>35</sup>	This method elucidates the usage of generative and discriminative Bayesian networks in predicting QoE with higher accuracies.
Liu et al. <sup>36</sup>	QoE prediction based on pervasive computing point of view. The method uses Rough set Theory and it has its own limitations due to rule based assumptions.
Mitra et al. <sup>37</sup>	CaQoEM (Context-aware, decision theoretic approach for QoE Measurement and prediction). The Scheme deploys Bayesian Network, Utility theory and bipolar scale. The method can efficiently map different QoE parameters and context factors to output the final QoE. The overall accuracy of the method is very encouraging and the validation of the method using elaborated experimental studies underline its application suitability in wireless environment.
Hossfeld et al. <sup>38</sup>	It is a web QoE model and insists on the importance of QoE prediction varying over time. This scheme uses Hidden Markov Model with single QoE-QoS parameter setup.
Mitra et al. <sup>39</sup>	QoE measurement and prediction method over time using Dynamic Bayesian Networks.
Lau et al. <sup>40</sup>	Video quality prediction over 4G wireless networks is presented. Regression based approaches such as K-nearest neighbor, SVM, NN are used for quality prediction. Fivefold cross validation is deployed for evaluation with Root mean squared error (RMSE) and Coefficient of determination ( $R^2$ ) as performance indicators.
Zheng et al. <sup>41</sup>	A novel PSQA based Neural Network scheme by considering various 3G LTE parameters is studied. Particle swarm optimization (PSO) is used in this scheme to balance the model's Mean Squared error and thereby enhancing the efficiency of the system.

## 5. Proposed Video QoE Prediction Model

The work depicts a novel video quality prediction model using Machine learning approach that could be used effectively in wireless domain. The proposed approach can be organized in to three stages 1 Exploration of PSQA-based QoE assessment procedure 2 Implementation of the proposed QoE Model 3 Interpretation of results. The first two stages are explained in this section and the interpretation of results will be discussed in Section 6.

### 5.1 Exploration of PSQA-based QoE Assessment Procedure (Stage 1)

Pseudo Subjective Quality Assessment (PSQA) is a hybrid video quality assessment method that aims at predicting QoE of video much closer to human perception in real time.

A general PSQA strategy for automatic estimation of perceived multimedia quality has the following steps:

**Step 1:** Choose finite set of parameters that significantly make impact on video quality. Let  $S_p = \{p_1, p_2, \dots, p_n\}$  be the Quality Affecting Parameters (QAF) selected for the study. Such parameters can be network and application dependant.

**Step 2 :** For each parameter, identify allowable range of discrete values in accordance with the system need i.e. for a parameter  $p_i$ , set of possible values  $\{v_{i1}, v_{i2}, \dots, v_{in}\}$  with  $v_{i1} < v_{i2} < \dots < v_{in}$  is considered.(termed as 'configuration')

**Step 3:** By applying different configurations of selected parameters, a distorted video database is created. Hence, for each video sample T and set of configuration C, a set  $D = \{T_1, T_2, \dots, T_C\}$  of the degraded video samples are observed.

**Step 4:** By using pure subjective evaluation criteria, the received degraded samples are rated through MOS measure. Each sequence gets MOS quality rating value  $Q_{mos}$  and stored properly.

**Step 5:** The subjective data (including MOS results) obtained in the previous step is trained using a suitable machine learning method to generate a prediction model and it is validated by reliable means i.e. for any video sample belonging to set D, the trained machine learning model is seen as a function  $fx()$  that maps any viable parameters in to quality score. The validation process is justified by closer proximity values between trained model's quality score and actual MOS values.

The hybrid approach was first proposed by Rubino et al.<sup>8</sup> and it considers Random neural networks for implementation.

Our proposed method considers application layer parameters namely Content Type (CT), Sender Bit Rate (SBR) and Frame Rate (FR). Also, physical layer factors such as Mean Burst Length and Block Error rate (BLER) are taken as quality affecting parameters since the critical usage of these parameters in video quality evaluation for UMTS networks is lucidly documented in<sup>42</sup>.

Original video input of Akiyo, Foreman, Stefan, Suzie, Carphone and Football sequences ranging from slow moving to fast moving videos is considered. Typical values of SBR ranges between 48 and 130 kbps. BLR assigns values in the range of 1% to 20% content type is mapped to certain discrete values by cluster analysis and frame rate is assigned numeric values endorsed for mobile video applications. Total of 135 distorted videos are created and ITU recommended subjective study provides MOS outputted database.

Henceforth, this standard subjective database<sup>42</sup> is used

in our work to test the proposed video quality prediction model.

## 5.2 Implementation of the Proposed QoE Model (Stage 2)

Implementation Steps:

**Input:** Aforementioned Subjective dataset as explained in Stage 1.

**Tool:** Weka Machine learning workbench<sup>43</sup>

- The dataset is divided in to learning set and validation set using cross validation method.
- The video quality prediction model is generated for the given input using learning dataset (Training phase).
- Validation data set is given as source to the prediction model. The validation process checks for the closeness of quality rating (QoE) between trained model's MOS and actual MOS.
- The properly validated QoE prediction model henceforth provides hybrid video QoE evaluation for the users.

**Output:** The final QoE prediction model that works automatically for any input in real time without human intervention.

The algorithms considered for analysis of our prediction model includes Linear Regression (LR), Simple Linear Regression (SLR), Multilayer Perceptron (MLP), SMOreg, Gaussian Process (GP), K Nearest classifier (KN classifier), K\* Instance Based Classifier (K\* IBC) and Locally Weighted Learning(LWL)<sup>44</sup>. Linear regression applies Akaike criterion and prediction is done with weighted instances. Simple Linear regression learns by choosing attribute with minimum squared error. Multi Layer Perceptron is a feed forward Artificial Neural Network that uses back propagation for training the network. SMOreg implements Support vector machine for regression and it uses Alex Smola and Bernhard Scholkopf's sequential minimal optimization algorithm for training. Gaussian process belongs to the class of probability distribution which shows prior distribution over non linear function with respect to Bayesian inference. K Nearest Neighbor classifier is instance based learning scheme with lazy approach. K\* and Locally Weighted Learning uses entropy based distance function and limited weight assumption respectively.

## 6. Experimental Evaluation

The final stage of the proposed model is the evaluation of experiments and interpretation of results using the aforesaid machine learning algorithms. WEKA tool has been used for evaluation since it is an effective open source toolkit for performing Data preprocessing, Clustering, Classification and Regression<sup>45</sup>. The prediction efficiency of the model is analyzed using various error measures. Performance indicators such as RMSE (Root Mean Squared Error), CC (Correlation Coefficient), MAE (Mean Absolute Error), Relative Absolute Error (RAE) and Root Relative Squared Error (RRSE) are used.

### 6.1 Effect of RMSE and CC

RMSE measures the average magnitude of the error and it is one of the important error measure used to assess the accuracy of the prediction model. Figure 1. Shows the plot of RMSE values against all the selected machine learning algorithms. In general, lower the RMSE, better the prediction accuracy. From the graph, Multilayer perceptron method outperforms all the other methods with least RMSE value of 0.1273. Linear regression and SMOreg shows considerable accuracy in terms of RMSE. Locally Weighted Learning shows poor performance of the lot.

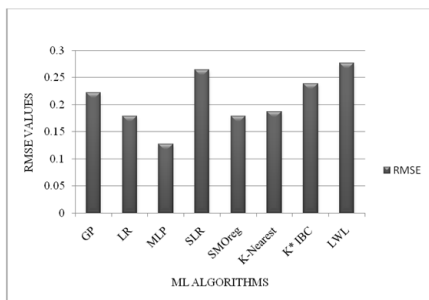


Figure 1. Interpretation of RMSE values.

Correlation Coefficient (CC) tries to portray the relationship between predicted and actual values. It should ideally take maximum possible value to show accuracy in quality prediction. From Figure 2., it is apparent that Multilayer perceptron takes the maximum value of CC with 0.9704 followed by k\* IBC and SMOreg with values of

0.954 and 0.9396 respectively. Here again locally weighted learning method runs with less prediction accuracy.

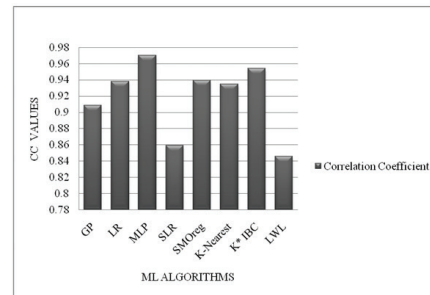


Figure 2. Interpretation of Correlation Coefficient values.

### 6.2 Error Variation Analysis of RMSE and MAE

In prediction analysis, MAE and RMSE can be used together to determine the error variations. RMSE values will always be greater than or equal to MAE. Difference between RMSE and MAE should be least and hence this error variation of the two measures is depicted in Figure 3. Out of all the algorithms compared, MLP shows the least difference between RMSE and MAE and hence underlines its superiority. Also individually MAE value is minimum for MLP, which augurs good prediction accuracy.

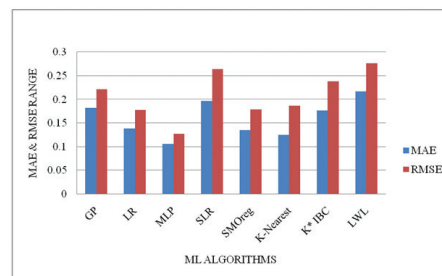


Figure 3. Error variation analysis of MAE and RMSE.

### 6.3 Impact of RAE and RRSE

Relative Absolute Error and Root Relative Squared Error provide percentage values as error measures with both measures reaching zero in ideal case. The usage of RAE and RRSE is elucidated in<sup>46</sup>. Table 3 shows the performance of our method with respect to RAE and RRSE.

The minimum percentage values of both the measures

Table 3. Comparison of RAE and RRSE

	LR	SLR	MLP	SMOreg	GP	KNN	K*	LWL
RAE (%)	31.476	44.7312	24.0474	30.547	41.3077	28.3573	40.1249	49.1078
RRSE (%)	34.2092	50.5873	24.3948	34.3233	42.5622	35.8647	45.7217	52.9675

will justify the efficient working of the model. The interpretation of the results confirms that MLP can be best preferred as it shows lowest RAE and RRSE values, whereas other methods can be used sparingly in real time.

## 7. Conclusion

The multimedia quality assessment methods of newly emerging visual signals have gained greater significance since the advent of advanced wireless networks. The phenomenal use of killer video applications in error prone and energy constrained networks have underlined the importance of conceiving viable video quality evaluation methods. Better handling of non-linear relationship between various quality affecting parameters and deft usage of cross validation technique makes machine learning based Video QoE predictions, a potential game changer in the broader areas of multimedia quality evaluation. This paper depicts the working of an Intelligent video quality prediction model that incorporates several machine learning algorithms through PSQA approach. The analysis of results using various performance indicators suggests that Multilayer perceptron based AI technique shows good prediction accuracy than the other supervised machine learning algorithms and henceforth can be adapted for non-intrusive Video QoE evaluations. In today's Multimedia era, the unpredictability of wireless domain still needs further exploration of wide array of quality affecting parameters tested with extended empirical dataset to reach pinnacle in perceived video QoE evaluation.

## 8. References

1. ITU-T. P.10/G.100. Amendment 1 (01/07): New Appendix I. Definition of Quality of Experience (QoE). 2007.
2. ITU-R Recommendation BT.500-11. Methodology for the subjective assessment of the quality of television pictures. Geneva: ITU; 2002.
3. ITU-T Recommendation P.910. Subjective video quality assessment methods for multimedia applications. Geneva: ITU; 1999.
4. Venkataraman M, Chatterjee M, Siddhartha C. Evaluating Quality of Experience for streaming video in real time. IEEE Conference on Global Telecommunications (GLOBECOM 2009); 2009.
5. Chikkerur S, Sundaram V, Reisslein M, Karam LJ. Objective video quality assessment methods: a classification, review and performance comparison. IEEE Transactions on Broadcasting. 2011; 57:165–82.
6. Mario V, Snjezana R-D, Kresimir G. Review of objective video quality metrics and performance comparison using different databases. Signal processing: Image Communication. 2013; 28:01–19.
7. Menkovski V, Exarchakos G, Liotta A. Online QoE prediction. 2nd International Workshop on Quality of Multimedia Experience (QoMEX 2010); 2010. p. 18–23.
8. Mohamed S, Rubino G. A study of real-time packet video quality using random neural networks. IEEE Transactions on Circuits and Systems for Video Technology. 2002; 12(12): 1071–83.
9. Lin M, Chenwei D, King Ngi N, Lin W. Recent advances and challenges of visual signal quality assessment. IEEE Communications, China. 2013 May; 10:62–78.
10. ur Rehman Laghari K, Issa O, Speranza F, Falk TH. Quality-of-Experience perception for video streaming services: preliminary subjective and objective results. IEEE Signal & Information Processing Association Annual Summit and Conference (APSIPA ASC); 2012.
11. Schatz R, Hossfeld T, Janowski L, Egger S. From packets to people: quality of experience as a new measurement challenge. Data Traffic Monitoring and Analysis. 2013 Apr.
12. Mohammed A, John W. Survey on QoE/QoS correlation models for multimedia services. International Journal of Distributed and Parallel Systems (IJDPS). 2013 May; 4(3).
13. Takahashi A, Hands D, Barriac V. Standardization activities in the ITU for a QoE assessment of IPTV. IEEE Commun Mag. 2008 Feb; 46(1):78–84.
14. Siris VA, Balampekos K. Mobile quality of experience: recent advances and challenges. IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops); 2014.
15. Gong Y, Yang F, Huang L, Su S. Model-based approach to measuring quality of experience. 1st International Conference on emerging Network Intelligence; 2009. p. 29–32.
16. Perkis A, Munkeby S, Hillestad OI. A model for measuring Quality of Experience. 2006 Proceedings of the 7th Nordic Signal Processing Symposium ((NORSIG'2006); 2006 Jun. p. 198–201.
17. Laghari KUR, Connelly K. Toward total quality of experience: A QoE model in a communication ecosystem. Communications Magazine, IEEE. 2012 Apr; 50(4):58–65.
18. Agboma F, Liotta A. QoE-aware QoS management. Proceedings of the 6th International Conference on Advances in Mobile Computing and Multimedia; 2008. p. 111–16.
19. Hossfeld T, Schatz R, Seufert M, Hirth M, Zinner T, Tran-Gia P. Quantification of You Tube QoE via Crowdsourcing. IEEE International Workshop on Multimedia Quality of Experience - Modeling, Evaluation and Directions (MQoE); 2011; Dana Point, CA, USA
20. Siller M, Woods J. Improving Quality of Experience for Multimedia Services by QoS arbitration on a QoE Framework. IEEE Packet Video, Nantes. 2003.
21. Mushtaq MS, Augustin B, Mellouk A. Empirical study based on machine learning approach to assess the QoS/QoE correlation. 17th European Conference on Networks and Optical Communications (NOC); 2012. p. 1–7.



22. Asiya K, Lingfen S, Emmanuel I. Content-Based video quality prediction for MPEG4 video streaming over wireless networks. *Journal of Multimedia*. 2009 Aug; 4(4).
23. Gastaldo P, Zunino R, Redi J. Supporting visual quality assessment with machine learning. *EURASIP Journal on Image and Video Processing*. 2013.
24. Narwaria M, Lin W. SVD-based quality metric for image and video using machine learning. *IEEE Trans on Systems, Man and Cybernetics, Part B Cybernetics*. 2012; 42(2):347–64.
25. Argyropoulos S, Raake A, Garcia MN, List P. No-reference video quality assessment of SD and HD H.264/AVC sequences based on continuous estimates of packet loss visibility. *Proceedings of the 3rd International Workshop Quality of Multimedia Experience (QoMEX)*; Mechelen, Piscataway: IEEE; 2011. p. 31.
26. Le Callet P, Viard-Gaudin C, Barba D. A convolutional neural network approach for objective video quality assessment. *IEEE Trans Neural Networks*. 2006; 17(5):1316–27.
27. Staelens N, Deschrijver D, Vladislavleva E, Vermeulen B, Dhaene T, Demeester P. Constructing a No-Reference H.264/AVC Bitstream-based Video Quality Metric using Genetic Programming-based Symbolic Regression. *IEEE Transactions on Circuits and Systems for Video Technology*. 2013 Aug; 23(8).
28. Chen KT, Huang CY, Huang P, Lei CL. Quantifying skype user satisfaction. *Proceedings of the 2006 Conference on Applications, Technologies, Architectures and Protocols for Computer Communications (SIGCOMM)*; 2006; ACM..
29. Chen K, Tu C, Xiao W. One click: A framework for measuring network quality of experience. *IEEE International Conference on Computer Communications (INFOCOM)*; 2009. p. 702–10.
30. Janowski L, Papir Z. Modeling subjective tests of quality of experience with a generalized linear model. *International Workshop on Quality of Multimedia Experience (QoMEX)*; 2009. p. 35–40.
31. Wu W, Arefin A, Rivas R, Nahrstedt K, Sheppard R, Yang Z. Quality of experience in distributed interactive multimedia environments: toward a theoretical framework. *Proceedings of the 17th ACM international conference on Multimedia (MM'09)*; 2009; New York, US. p. 481–90.
32. Kim HJ, Lee DH, Lee JM, Lee KH, Won L, Seong GC. The QoE Evaluation method through the QoS-QoE correlation model. *4th International Conference on Networked Computing and Advanced Information Management*. 2008 Sep; 2:719–25.
33. Rubino G, Tirilly P, Varela M. Evaluating user's satisfaction in packet networks using random neural networks. *Artificial Neural Networks, Lecture notes in Computer science (ICANN 2006)*. 2006; 4131:303–12.
34. Menkovski V, Oredope A, Liotta A, Sanchez AC. Predicting quality of experience in multimedia streaming. *Proceedings of the 7th International Conference on Advances in Mobile Computing and Multimedia (MoMM'09)*; 2009; New York, USA: ACM; p. 52–9.
35. Mitra K, Ahlund C, Zaslavsky A. Performance evaluation of a decision-theoretic approach for quality of experience measurement in mobile and pervasive computing scenarios. *Wireless Communications and Networking Conference (WCNC)*; 2012; IEEE. p. 2418–23.
36. Li-Yuan L, Zhou W, Song J. The research of quality of experience evaluation method in pervasive computing environment. *1st International Symposium on Pervasive Computing and Applications*; 2006. p. 178–82.
37. Mitra K, Zaslavsky A, Ahlund C. Context-aware qoe modelling, measurement and prediction in mobile computing systems. *IEEE Transactions on Mobile Computing*; 2014. p. 99.
38. Hossfeld T, Biedermann S, Schatz R, Platzer AR, Egger S, Fiedler M. The memory effect and its implications on web qoe modeling. *Proceedings of the 23rd International Teletraffic Congress (ITCP)*; 2011. p. 103–10.
39. Mitra K, Zaslavsky A, Ahlund C. Dynamic bayesian networks for sequential quality of experience modelling and measurement. *Smart Spaces and Next Generation Wired/Wireless Networking, Lecture notes in Computer science Springer*. 2011; 6869:135–46.
40. Lau CP, Zhang X, Shihada B. Video quality prediction over wireless 4G. *Advances in Knowledge Discovery and Data Mining, Lecture notes in Computer science*. 2013; 7819:414–25.
41. Zheng K, Zhang X, Zheng Q, Xiang W, Hanzo L. Quality-of-Experience Assessment and its Application to Video Services in LTE Networks. *IEEE Wireless Communications*. 2015 Feb; 22(1):70–78.
42. Asiya K, Sun L, Emmanuel I. QoE Prediction Model and its Application in Video Quality Adaptation over UMTS Networks. *IEEE Transactions on Multimedia*. 2012 Apr; 14(2):431–42.
43. Mark H, Eibe F, Geoffrey H, Bernhard PF, Peter R, Witten IH. The WEKA data mining software: an update. *SIGKDD Explorations*. 2009; 11(1).
44. Theofilis G-N. Weka Classifiers Summary [Internet]. 2013. Available from: [https://www.academia.edu/5167325/Weka\\_Classifiers\\_Summary](https://www.academia.edu/5167325/Weka_Classifiers_Summary)
45. Sudha M, Kumaravel A. Performance Comparison based on Attribute Selection Tools for Data Mining. *Indian Journal of Science and Technology*. 2014 Nov; 7(S7):61–5.
46. Gharehchopogh FS, Seyyed Reza K, Isa M. A new approach in bloggers classification with hybrid of k-nearest neighbor and artificial neural network algorithms. *Indian Journal of Science and Technology*. 2015 Feb; 8(3):237–46.