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Automatic Quality of Experience Measuring for Video Conference in Real-Time

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Abstract— *In recent years, especially with COVID-19, video conference applications have become very important. Millions of peoples around the world have become to communicate with each other through using video conference applications. The most critical factor in the performance success of video conference applications is the user's perception of the quality of the experience. In this work, an Extreme Learning Machine (ELM) model was proposed for predicting video quality of experience. The proposed system extracts several features from videos that have a significant impact on the quality of the experience. The model performance was validated with unseen data. Spearman's Rank Correlation Coefficient (SRCC), Root Mean Square Error (RMSE), Pearson's Linear Correlation Coefficient (PLCC) metrics have been used to measure the accuracy of the model and correlation. The results demonstrate that the proposed model had better performance than models used by the previous researchers that were used for predicting video QoE in terms of precision, correlation, and running time.*

Index Terms— *Extreme Learning Machine***,** *Quality of Experience, Quality of Service, Video Streaming.*

I. INTRODUCTION

In recent years video conference becomes increasingly significant especially with COVID-19, millions of people in several countries are in quarantine and the only way that we can contact others, study, or work is through the internet. Millions of people are starting to use Zoom, Webex, or Google Hangouts Meet, employees at several companies are holding daily work meetings through video conferencing, also play an important role in E-learning by allow students to take their lectures through the internet. This leads to the massive demand for video conferences.

According to TrustRadius, during the first four months of the COVID-19 outbreak, search impressions for video conference software increased by 500%. Video meetings have been used 50% more in 2020 than they did prior to COVID-19. According to Upwork in the next five years, the number of remote employees is predicted to nearly double from pre-COVID-19 levels: by 2025, 36.2 million Americans will be working remotely, up 16.8 million from pre-pandemic levels [1]. For video conferencing customers, quality of experience is critical since they rely on real-time, live video and audio with no delays, jitters, or freezes, similar to what consumers anticipate from streaming videos they watch online. So become very important to create an automatic quality of experience(QoE) prediction system [2]. QoE reflects the level of end-user satisfaction by considering all of the factors that influence it. QoE is a significant metric for network operators and service providers to use in measuring their performance by taking into account all of the factors that affect it [3]. There are two methods used to measure QoE: subjective and objectives

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measurements in the subjective method number of viewers to judge on video quality [4]. The most popular type of subjective measurement is the Mean Opinion Score (MOS) used to assess the video quality level, scoring range between (1-5), as following each value represent the degree of satisfaction user on video quality: 1-worst,2-poor,3-fair,4-good,5-excelent [5]. The objective assessment approach utilizes a mathematical tool and is mostly depended on reference-based [6]. Most learning machine algorithms and feed-forward neural networks that have been used to predicate video QoE in real-time are suffered from slow training time. The learning velocity of feed-forward neural networks is overall has a huge bottleneck in the system because far slower than required in their application for the past many years. Video QoE assessment in real-time requires velocity so we propose to use the ELM model. The convolutional learning algorithms are normally much more slowly than required. It isn't unexpected to see that it might require a few hours, a few days, as well as more opportunities to train neural networks via utilizing the conventional approach [7].

ELM model is the most type of feed-forward neural network appropriate for predicting video QoE in real-time. This paper proposes using the ELM model for predicting QoE in real-time. The proposed model is implemented on three types of datasets. Many features that have a significant impact on the QoE are extracted. The proposed model is validated by using unseen data.

This paper is organized as follows: In Section2 we discuss the literature review. Section3 in this section explains the theoretical background that deals with the ELM model. Section4 presents the methodology that has been followed to build the proposed system. Section5 provides the results for the proposed system and its discussions. Lastly, the conclusion is present in Section 6.

II. LITRUTER REVIEW

In this section, the previous studies for measuring QoE are presented. Mohamed Alreshodi [8] proposed a FIS model for predicting video quality. The authors take into consideration the impacts of QoS parameters on QoE for various kinds of video content. They evaluated video quality as perceived from where MOS. The proposed system has been compared with the regression-based system, the FIS model produces more precision than the regression-based model. This research was restricted to 3G networks and was focused on the database generated by [9]. These few features are insufficient to meet the diverse network specifications of 4G technologies (LTE). Bao and et. Al [10] proposed a fuzzy clustering heuristic algorithm for video QoE evaluation. Some information and QoS parameters were collected on the server side and saved in a large database. To predict user score, the contents in a database used in the heuristic rules model, this procedure called fuzzy clustering analysis and produces a service quality of experience score that will be fed back to clients. O. Falah and R. Ghani, [6] suggested a no-reference objective approach for evaluating video stream quality of experience, and this achieved by applying machine learning algorithms (c.45, multilayer perception ANN, Random forest, AdaBoost), to contrast performance and choose the best option for working with, balancing time and accuracy . To predicate MOS they used bitrate with pixel mode features. The AdaBoost decision tree has the best real-time and accuracy performance. AdaBoost needs a sufficient number of iterations to produce good accuracy, this may lead to increase time complexity. A. Sufiuh and et. al. [11] purpose an ANN model for predicting video streaming quality of experience. The authors extracted seven features and used them as input for training data. The extracted features were: freezing, Spatial perceptual Information (SPI), luminance, an

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average of luminance difference, blocking, blurring, Temporal perceptual Information. The result demonstrates the best correlation between measured QoE and predicted QoE.

III. THEORITICAL BACKGROUND

In contrast to traditional implementations for predicting video QoE, this paper proposes using an extreme learning machine (ELM) for predicting video QoE in real-time. The model includes the multi-level process.

A. The Proposed System

ELM is a single hidden layer feed-forward neural network (SLFNS) which arbitrarily selects hidden nodes as well as analytically decides the output weights of SLFNsm [5]. Therefore, it requires one iteration process [12] and it doesn't have to learn in an iterative manner such as the conventional neural networks.

Calculating the generalized inverse of the output of the hidden layer yields its output weights. This operation significantly improves the network construction of the ELM [13]. This algorithm will in general give great generalization execution at a very quick learning speed. ELM can learn a huge number of times quicker than ordinary well-known learning algorithms for feed-forward neural networks. ELM will in general arrive at the smallest output weight norms as well as the training error [14].

While applying ML for predicting video QoE assessment displaying purposes, training data is utilized to make a prediction. This prediction ought to generalize well on new data on which there is no ground truth [15].

IV. METHODOLOGY

The methodology consists of six sections: datasets, features extraction, feature selection, normalization and unnormalization, model steps. *Fig. 1* shows the proposed system stages.

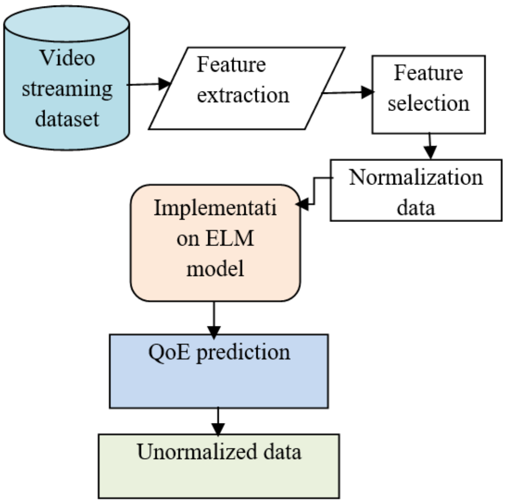

FIG. 1. THE PROPOSED SYSTEM DIAGRAM.

1. Dataset

In this work, we used three types of datasets; the INRS dataset, the Waterloo dataset, and the ReTRiEVED dataset. All datasets explained as following:

1.1 INRS Audiovisual Quality Database

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Made by "Instate National de la Research Scientifique" configure 160 separate videos were extracted from a single unique video that was feigned to fit real-time communications conditions, in reality, H.264/AVC used to encoded the original video, H. AMR WB by Gstream open-source (O/S) platform used for coded audio of the video to generate 32 3gp videos as a unique reference with various quality, quantization parameter(QP), and frame rate(FR), that has a high effect on the compression rate in H.264.The packet loos created network emulator initiated just when the primary second had been transmitting to acquire more practical results. Audiovisual file name embedded in the dataset, also its includes mean opinion score computed, some parameters extracted from broadcasted videos, the resolution of videos720p [16].

1.2 The ReTRiEVED Video Database

This database has eight separate videos, each with its own set of colors, content, and action. The eight were subjected to a variety of distortions as a result of a video transmission that led to acquiring of 184 altered videos. Each video is encoded by H.264 with frame rates of 25, 30, and 60 frames per second. Each film was judge by a panel of 41 people [17].

1.3 Waterloo Video QoE Database

The database includes 20 origin of HD high-quality reference movies and 450 manufactured streaming videos of various content in an average period of 13 seconds. Its contents including plants, human's natural scenes, architectures, computer-synthesized sceneries screen content. The H.264 was used for encoded each video with a frame rate of [24,25,30 and 60 frame per second]. Streaming sessions were created using 6 adaptive streaming algorithms and a diverse set of bandwidth constraints.34 subjective used for recorded and estimated. Each video sequences quality subjects score is based on a 0-100 numerical quality scale [18].

2. Features Extraction

To enhance the accuracy performance of the prediction model, the number of features was extracted. The extracted feature has a strong linkage to the Human Visual System (HVS) which affects video streaming service users. The features extracted in this work are:

2.1 Blocking Feature

To extract blocking feature the Kirsch compass masks have been applied by rolling one mask to eight common compass orientations: W, SW, N, NW, S, SE, NE, and E. *Fig. 2* shows Kirsch masks directions [19].

$$G_1 = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} G_2 = \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} G_3 = \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} G_4 = \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

$$G_5 = \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} G_6 = \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} G_7 = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} G_8 = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

FIG. 2. KIRCH MASK DIRECTION.

2.2 Blurring Feature

Is an essential and complicated feature, because of the way it is implemented. The Laplacian operator was implemented to calculate a blur value. The Laplacian highlights areas of a picture that have a lot of changes in intensity. The image convolved with 3×3 Laplacian operator, the variance is returned by using Laplacian kernel for every frame after that the bluer average finds for video frames, as display in *Fig. 3* [20].

0	1	0
1	-4	1
0	1	0

FIG. 3. LAPLACIAN KERNEL.

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2.3 Natural Sences Statistics (NSS)

This feature has a significant effect on the end-user of video stream service because it has a strong linkage on the Human Visual System (HVS). The NSS extracted features are: (N_H Shape, N_H Variance, N_Shape, N_V Shape, N_Shape, N_Variance), Blind/reference less image spatial quality evaluator (BRISQUE) The model's parameters were used to quantify naturalness using normalized luminance coefficients [21].

2.4 Freezing Feature

Is a significant kind of packet loss. It occurs because the frames were dropped but that frame was as yet shown while the following right frame is gotten. So the freezes frame video sequence influenced the video quality [18].

Algorithm 1 presents the freezing operation to calculate two frames' resemblance and return a percentage value (0-100). In the testing operation, the results present an inverse relationship between the QoE and freezing, and the freezing feature has a considerable impact on QoE [11].

Algorithm 1:Feature of Extraction Freezing

Input: Set of video frames;
Output: Extracting freezing value;

```
Begin
For i=1 to number of video frames
{
Compare (frame1,frame2,frame.diff matrix)" if there relation between pixels (frame1,frame2); set=1 else set=0"
Similarity metric=count non zero(frame.diff matrix)
Similarity Metric[i]=Similarity metric/(frame1.Height* frame2.Width)*100
}
For i= 1 to i < Simalirity Metric[index]
    {
    If Similarity Metrics [i]>95.0
        {
        Frame freeze count++
        }
    }
Freeze percentage =Frame freeze count / actual frame count*100
Save the video freeze percentage value in a file
End
```

2.5 Average Bit Frame

We extracted this feature from coding parameters to increase the accuracy of prediction performance. The relationship between bitrate and frame rate is important and has a significant impact and is correlated to the quality of experience of the end-user. The average bite frame is calculated by Eq. (1), which represents the average number of bits used to represent a single pixel. The video resolution is represented by the height and width [6].

$$AVGBF = BR / Height \times Width \times Fr \quad (1)$$

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3. Features Selection

To select the best features that have the highest and least impact on the video QoE, the information gain method was used. The features for the INRS dataset in this work focused on the video Packet Loss Rate (PLR), quantization parameter, bitrate, blur, NSS. Waterloo dataset in this work focused on frame bitrate, bitrate, average Bf, blockness, blur, freeze, NSS. *Fig. 4* shows the correlation between features and QoE in INRS dataset, video frame rate, and NR are ignoring because it does not have impacts on the QoE, and packet loss rate has the most significant impact on the QoE. In *Fig. 5* the frame rate has no impact on QoE, so it is ignored. ReTRiEVED database in this paper includes several features such as jitter, delay, packet loos rate, throught and NSS feature. In *Fig. 6* present the jitter feature has most significant effect on the QoE and the PLR does not have any impact on the QoE therefore it is ignored.

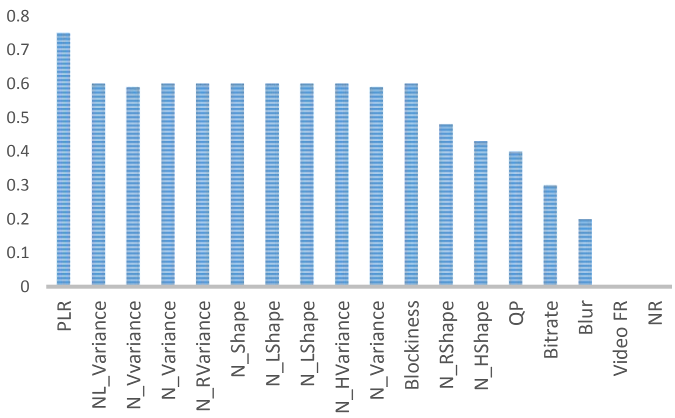

FIG. 4. IMPACT FEATURES ON QoE in INRS DATASET.

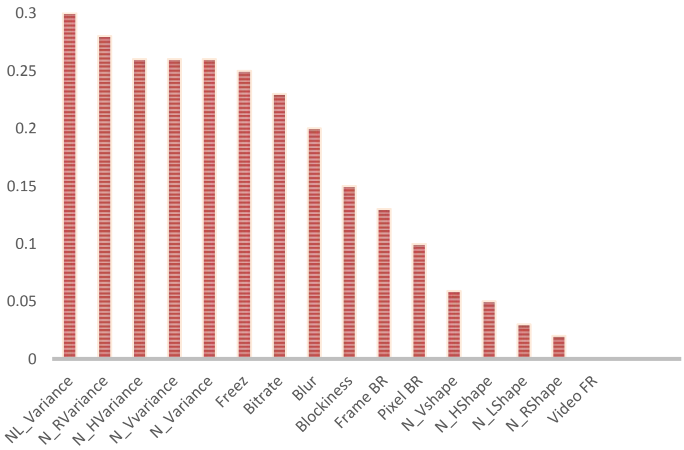

FIG. 5. IMPACT FEATURES on QoE in WATERLOO DATASET.

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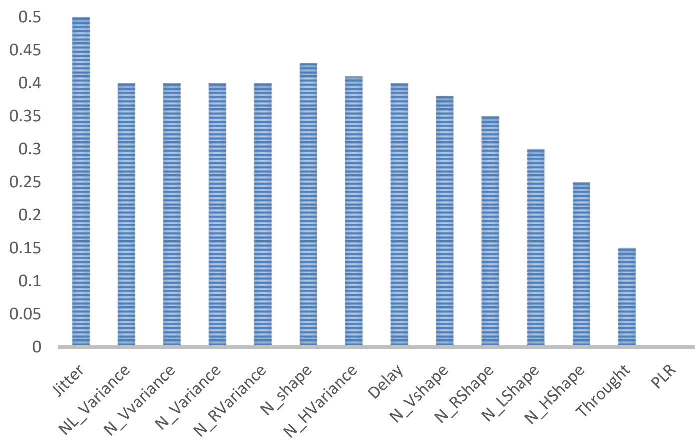

FIG. 6. IMPACT FEATURES on QoE in ReTRiEVED DATASET.

4. Normalization and unnormalization

To transform each input variables and output variable into the range (0-1) we used the MinMax scaler. Normalization and unnormalization can be explained as the following:

$Xn_{pi}=(X_{pi}-\min(X_{pi})/(\max(X_{pi})-\min(X_{pi}))$, i=1,2..n, p=1,2..n (2)

$Yn_p=(Y_p-\min(Y_p)/\max(Y_p)-\min(Y_p))$, p=1,2…n (3)

To transform data back into unnormalized unites is given as the following:

$Xun_{pi}=Xn_{pi}*(\max(X_{pi})-\min(X_{pi})+\min(X_{pi})$, i=1,2,3..n ,p=1,2..n (4)

$Yun_p=Yn_p*(\max(Y_p)-\min(Y_p))+\min(Y_p)$, p=1,2..n (5)

To choose the minimum and maximum values from the dataset, the min (.) and max (.) operators in equations (2) to (5) are used.

5. Extreme Learning Machine Steps

The essential algorithm steps of ELM is as per the following:

Input: Training Sample$\{x_i, t_i\}_{i=1}^{N} \subset R^n \times R^m$, testing sample set $\{y_i\}_{i=1}^{M} \subset R^n$, number of hidden layer node L, and g(.)activation function.

Step1: In the hidden layer output matrix H has been calculated by using equation (6):

$$H(c_1,.,c_L;b_1..b_L;x_1..x_n)=\begin{bmatrix} g(c_1,b_1,x_1) & g(c_L,b_L,x_1) \\ \vdots & \vdots \\ g(c_1,b_1,x_N) & g(c_L,b_L,x_N) \end{bmatrix}_{N\times L} \quad (6)$$

(c_i,b_i) i=1,2,3,……L arbitrarily created hidden node parameters, is the input weights represented by c_i of ith hidden layer node, ith hidden layer node deviation represented by b_i.

Step2: The output weight matrix β in the hidden layer computed as following:

Eq. (7) has been for computed output weight when H is nonsingular.

$$\beta = H^+ T \quad (7)$$

Where T is in demand output, but H^+ is the Moore-Penrose generalize reverse matrix of the hidden node output matrix H. In the situation when the hidden layer output is complete rank, $H^+ = (H^T H)^{-1} H^T$.

$$\beta=\begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L\times m} \quad T=\begin{bmatrix} T_1^T \\ \vdots \\ T_N^T \end{bmatrix}_{N\times m}$$

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Output: output weight matrix b.

The proposed system works as a regression system by using a supervised technique for predicting video QoE by utilizing the training dataset. The dataset is separated into 70% for training data and allocated 30% for testing data. The ELM model is composed of three layers: layer one used 15 features as input for the INRS dataset. 16 features were used as input for layer one for the Waterloo video dataset and 13 features were used as input to layer one for ReTRiEVED dataset. The hidden layer contains some neurons are equal to the number of inputs for each dataset. The third layer includes one neuron as output that represents the predicates video QoE. The activation function used in this system was Rectified Linear Unit (ReLu). This work was achieved by Python language, version 3.8.

V. RESULTS and DISSCUTIONS

In this section, we display the performance results of the proposed ELM model for predicting video QoE in terms of accuracy, correlation, and running time. As we mentioned before, three types of databases have been chosen and each dataset has been separated into 70% for training data and 30% for testing data. The testing data have been used to validate the generalization ability model. The measured QoE results have been compared with the predicted QoE in the ELM model. Some metrics that have been used to validate the accuracy and correlation for the ELM model were Spearman's Rank Correlation Coefficient (SRCC), Root Mean Square Error (RMSE), and Pearson's Linear Correlation Coefficient (PLCC). When the ELM model has been applied, the results were as the following: In case Dataset1 (INRS), the RMSE scored 0.14. The prediction error rate was less in the case dataset (Waterloo); the RMSE scored 0.13. Lastly, in case dataset3 (RETrived); the RMSE scored 0.19, as shown in Table I The results have demonstrated that video content types in the Waterloo database have a high impact on the video QoE. As a result, an effective video QoE prediction model should take into account all types of content.

TABLE I. RESULT of PERFORMANCE ELM MODEL

Dataset Type	RMSE	SRCC	PLCC
INRS	0.14	0.87	0.89
Waterloo	0.13	0.83	0.71
ReTRiEVED	0.19	0.96	0.84
Average Correlation	0.15%	0.88%	0.81%

A. Performance Evaluation of The Proposed ELM Model

The proposed system was evaluated by comparing our results with other researchers. In [22], they used the INRS database in their system to predicate QoE and got an RMSE of 0.34-0.46 to measure the accuracy, but the proposed system achieved a better RMSE value of 0.14 In reference [6] the QoE prediction model was used the INRS and ReTRiEVED database, they implemented RMSE to measure the system performance and got 0.07. In [17] the researchers have used ReTRiEVED database and obtained a good correlation value by used SRCC and PLCC metrics. The proposed system performed better value for SRCC 0.83 compared to the result in reference [18]. The correlation value for SRCC was 0.95 in reference[11], but for the proposed system was 0.96. We can summarize that we have applied a suitable model for predicting QoE in real-time with the lowest prediction error rate, good correlation, and with the lowest running time. Table II displays different accuracy and correlation metrics with different researchers.

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TABLE II. COMPARISON BETWEEN ELM MODEL PERFRMANCES WITH OTHER RESEARCHERS

Model	Dataset Type	RMSE	SRCC	PLCC
Demirbilek[22]	INRS	0.340-0.469	-	-
Osama [6]	INRS	0.072	-	-
Paudyal[17]	ReTRiEVED	-	0.85	0.79
Zhengfang[18]	Waterloo	-	0.78	-
Amal- ANN[11]	ReTRiEVED	-	0.95	-
ELM_model	INRS,Waterloo, ReTRiEVED	0.15%	0.88%	0.81%

Table III present the time consumed for running the ELM model. The time is calculated in milliseconds and microseconds. In the case dataset Waterloo, the ELM model consumed time is higher than in the case dataset INRS and ReTRiEVED because Waterloo contains more data. The time consumed by ELM model is very suitable for predicting video QoE in real-time.

TABLE III. TIME- CONSUMING for RUNNING ELM MODEL

Type of Dataset	Time Consumed in Milliseconds	Time Consumed in Microseconds
INRS	16 M.S	41Microsecond
Waterloo	16 M.S	73 Microsecond
ReTRiEVED	16 M.S	04 Microsecond

VI. CONCLUSIONS

This paper proposed, a no-reference model to predicate video QoE in real-time. Several features that have the most significant impact on QoE have been extracted. The proposed system was built by using an extreme learning machine (ELM) algorithm. The proposed system was validated by testing the dataset (unseen data). The ELM model was evaluated by comparing its results with results for other researchers.

The obtained result indicates that the proposed model success in estimating video QoE. ELM model proves it is very suitable for predicting QoE in real-time because it needs one iteration process and it doesn't have to learn iteratively, this leads to a very quick learning speed. The proposed system result has the littlest training error and gives great generalization execution this is due to the structural nature of the algorithm. Finally, the results demonstrate that the proposed system had better performance than models used by previous researchers for predicting video QoE in terms of accuracy and running time.

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