A Video Quality Prediction Model for the Elderly

Debajyoti Pal
IP Communications Laboratory, School of Information Technology, King Mongkut's University of Technology Thonburi, Bangkok
P.O. Box 10140, Thailand
debajyoti.pal@mail.kmutt.ac.th

Vajirasak Vanijja
IP Communications Laboratory, School of Information Technology, King Mongkut's University of Technology Thonburi, Bangkok
P.O. Box 10140, Thailand
vachee@sit.kmutt.ac.th

ABSTRACT

In the recent times there has been a lot of effort to use the various ICT technologies available to monitor and improve the lifestyle of the older generation. In most of the countries across the globe, these elderly people have to stay alone especially during the daytime, when other family members go out for work. Thus, monitoring their presence and activities remotely through audio/video communications is a widespread practice. However, this group of elderly people generally suffers from various types of vision impairments. Hence, mere installation of surveillance audio/video systems only will not solve the problem, as they need to interact with the system and hear/watch the audio/video communications for their well-being.

In this work, we carry out a subjective test on a sample population of 59 people belonging to different age groups and record their Mean Opinion Scores (MOS). Thereafter, we run the VQM algorithm over the same set of videos and observe that the scores obtained are somewhat different for the elderly people compared to the rest. Therefore, we propose a video quality prediction model based upon the Artificial Neural Networks (ANN) that gives a better prediction for our target age group. For this model, we take into consideration the network level Quality of Service (QoS) parameters only as they have a greater impact on the perceived video quality compared to other QoS factors.

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics • **Networks** → Network reliability

KEYWORDS

Quality of Service, Quality of Experience; Mean Opinion Score; VQM; ANN

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1 INTRODUCTION

Use of Information and Communication Technologies (ICT) by the older generation people has been on the rise in the recent times [1]. There has been a positive psychological effect of ICT use in the well-being of seniors [2, 3]. In most of the countries across the world, this group of people has to stay alone generally during the daytime as other family members go out for work. Hence, monitoring and interacting with them through audiovisual communication means is a commonly employed practice [4]. However, these people generally suffer from some form of vision impairments like cataract, glaucoma, diabetic retinopathy just to name a few. Hence, it is very important to test their perception towards the video quality that they see during these sessions and judge if they are suitable for being monitored by using such remote audiovisual systems.

With the proliferation of high speed Internet services there has been a rapid increase in multimedia traffic over the Internet. A lot of work has been done in estimating the quality of videos being transmitted over the Internet by different subjective and objective techniques or methods involving combination of both [5, 6 and 7]. The subjective tests that have been conducted till date generally employ people in the age range of 18-36 years. To the best of our knowledge, still today there has been no video quality prediction model targeted towards the elderly people as they have special requirements. Similarly, the different objective techniques that are generally used for video quality prediction like Peak Signal to Noise Ratio (PSNR), Video Quality Metric (VQM), ITU-T G.1070 Model, etc. have also not been validated for the elderly people. This provides the motivation for this research where we establish a video quality prediction model for the elderly people.

Quality of Experience (QoE) and Quality of Service (QoS) are the two most common ways of expressing the perceived video quality, although there is a clear cut distinction between the two. QoS is defined as "the ability of the network to provide a service with an assured service quality level", while QoE as "how a user perceives the usability of a service i.e. how satisfied he/she is with the service" [8]. Thus, QoS is a purely technical concept best expressed in terms of the network and various network elements; while QoE measures the overall user experience. We must have proper techniques that map the QoS to the QoE.

There are a large number of QoS metrics that can be related to the QoE of a video streaming service [9, 10]. These QoS metrics can come from the video compression and encoding technology being used, type of the video being streamed and those which are induced by the network layer. In this paper, we consider only the network level QoS as they are the greatest predictors of the video QoE [11, 12]. We use the H.265/HEVC and VP9 codec for generating the distorted videos as they are representative of the modern day streaming scenario.

Subjective methods that evaluate the video QoE in terms of the Mean Opinion Score (MOS) are considered to be the most accurate ones for QoS to QoE mapping [13]. However, they are generally not preferred as they are expensive and time consuming to be carried out. This makes them unsuitable for real time applications like video streaming. Objective methods on the other hand, use some algorithms or mathematical formulae to evaluate the video QoE from the QoS factors. PSNR, VQM, ITU-T G.1070 model are some of the examples of such a method [14, 15, 16]. VQM is considered to be a very accurate objective measurement algorithm as it takes into consideration the effect of the human visual system (HVS) [17]. However, it is a full reference method which requires the source signal to be present for the comparison purpose. In general all these methods should faithfully reproduce the individual QoS factors to the overall QoE score.

Use of artificial intelligence and machine learning in predicting the video QoE is being attempted by several researchers recently. Different techniques based upon Artificial Neural Networks (ANN), regression based analysis and Fuzzy Inference Systems (FIS) are being commonly employed [18]. Researchers in [19 and 20] proposed two learning models to predict the quality in terms of the PSNR mapped into MOS. Their models were based upon the Adaptive Neural Fuzzy Inference System (ANFIS) and non-linear regression analysis method. The models show a fairly high accuracy rate, but the work has not been validated against subjective testing. Also, low video resolution of 176×144 pixels have been taken into consideration. Similar types of studies were conducted by authors in [21 and 22]. In their work they took both the QoS and QoE parameters as an input parameter to estimate the overall QoE of the user as an output. However, real time QoE estimation was not studied. A real time estimation was proposed by Aguiar et al. in [23] which used the Multiple Artificial Neural Network (MANN) as the prediction engine. However, they considered only certain application level QoS factors like group of pictures (GoP) size, spatial resolution, etc. Joscowicz et al. in [24] proposed a parametric model that uses a random packet loss factor only. They do not consider other network factors and also do not provide any type of model validation.

All the existing research has focused on videos encoded with older generation codecs like H.264 and MPEG-2. Also, in most of the objective methods the output has not been validated by carrying out complementary subjective tests. Standalone subjective tests that have been carried out do not include the elderly population that we want to target in this paper. All these facts motivated us to do this research. Here, at first we perform a subjective test comprising of people in the age group of 18-70 years. The test videos that have been used for the purpose are encoded with H.265/HEVC and VP9 codecs and impaired by several network QoS factors only. Apart from taking packet loss, jitter and throughput as the primary network QoS factors, we also introduce variable initial delay, buffering delay and auto scale resolution as three additional secondary factors while evaluating the overall QoE. Details about the parameters have been given later. Due to the excellent performance of the VQM algorithm, next we evaluate the quality of the same set of videos by using VQM as the objective algorithm. After mapping the VQM values to corresponding MOS values, we find a noticeable difference between the VQM generated MOS and the subjective MOS obtained from our experiment for the elderly population. Hence, we propose a multi-layer perceptron based artificial neural network model for predicting the video quality as perceived by the elderly.

Rest of the paper is organized as follows. Section 2 describes our research methodology. In Section 3 we provide the result analysis. Finally, Section 4 concludes the work and provides the scope of future work.

2 RESEARCH METHODOLOGY

2.1 Subjective Test

At first we carried out a subjective test based upon the ITU-T Recommendation P.910 [13]. The total number of subjects involved was 59. A breakdown of the participants' age has been shown in Fig. 1.

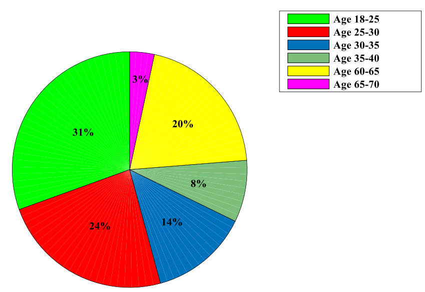

Figure 1: Breakdown of Participant Ages

Out of the 59 subjects involved, 14 belonged to the age group of 60-70 years which is considered to be the elderly population in this study. For the remaining population, the age varied from 18 to 40 years (non-elderly group). The test has been carried out in a controlled environment. All the elderly subjects who were chosen had some form of visual disability. As for the remaining ones; they did not suffer from any sort of visual defects, specifically color blindness and myopia.

Before conducting the actual subjective test, we carried out a demo session so as to familiarize them with the entire testing procedure. We used the 5 point Absolute Category rating (ACR) method described in [13], where after watching each video sequence, the subject rated it on a scale of 1 to 5 as shown in table 1. The assessments were recorded in a scoring sheet created for this purpose and afterwards entered into a computer for the purpose of data analysis.

An independent sample t-test was carried out in SPSS in order to compare the mean MOS scores between the elderly and the non-elderly group. We found a significant difference between the non-elderly (μ=3.055, σ=1.058) and the elderly (μ=2.062, σ=1.397) group with $t(174) = 5.316$ and $p < 0.05$ assuming a 95% confidence interval.

Table 1: MOS Scale Interpretation

MOS Scale	Meaning
1	Bad
2	Poor
3	Fair
4	Good
5	Excellent

2.2 Video Selection

We used the publicly available SVT High Definition multi format test set maintained by the Video Quality Experts Group for this research (VQEG) [25]. 4 reference videos; each having different levels of spatial and temporal information (SI and TI values) have been carefully chosen. The SI and TI values for the selected clips have been calculated as per the procedure give in [13] and shown in Fig. 2. The relevant video clips are presented in table 2. SI and TI values are a direct indication of the nature of video content. Since, perceived QoE depends heavily upon the type of video content as established by researchers in [26, 27]; hence we chose to use videos having a wide range of SI/TI values to cover the entire gamut possible. All the selected reference video sequences are approximately of 10 seconds duration and in the native YUV 4:2:0 format. Microsoft network emulator was used to simulate all the relevant network impairments for creating the degraded sequences. The overall process of creating the impaired videos and measuring the QoE/MOS has been shown in Fig. 3.

Table 2: **Details of Selected Video Sequences**

Sr. No	Name	Resolution	Frame Rate
1	CrowdRun	1920×1080	30 fps
2	DucksTakeOff	1920×1080	30 fps
3	OldTown	1920×1080	30 fps
4	ParkJoy	1920×1080	30 fps

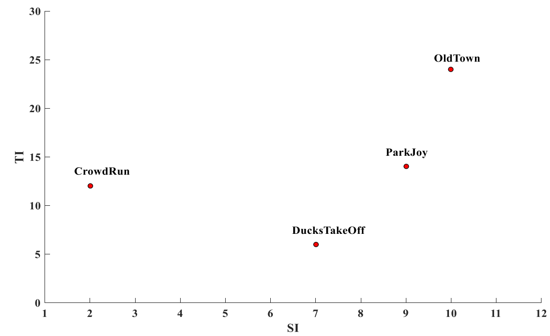

Figure 2: SI and TI values of selected video clips

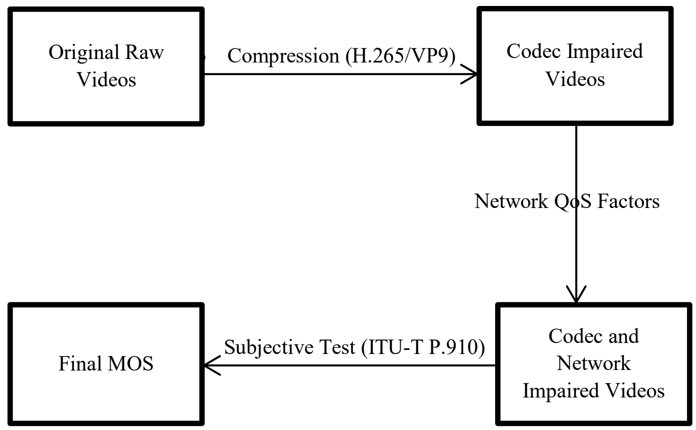

Figure 3: Process of measuring MOS

2.3 Network QoS Parameters

For this work we have taken 6 network QoS parameters. 3 out of the 6 parameters viz. packet loss (PL), jitter (J) and throughput (T) are considered to be the Key Performance Indicators (KPI's), while the remaining 3 viz. variable initial delay (VID), buffering delay (BD) and auto scale resolution (ASR) are secondary factors introduced by us. This has been shown in Fig. 4. An Analysis of Variance (ANOVA) is also carried out afterwards to justify their inclusion/removal. The 3 KPI's have their usual meaning and hence not elaborated over here. We only provide a brief description for the factors that we have introduced in this research.

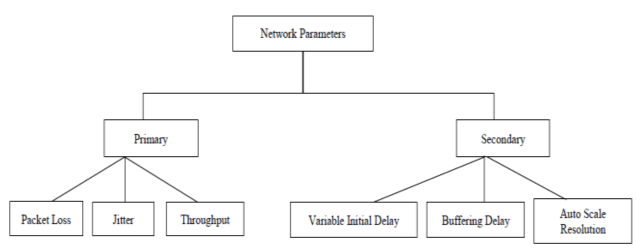

Figure 4: Various Network QoS Factors

2.3.1 Variable Initial Delay. In order to overcome the effect of jitter, every client is equipped with a play- out buffer. A streaming video will start to play only after the buffer has been filled up to a certain threshold value [28, 29, 30]. VID is defined as the time-gap between the arrival of the first frame in the buffer and its subsequent play-out on the client screen at the start of video playback. i.e. $VID = T_{Playout} - T_{Arrival}\ (1st\ Frame)$

2.3.2 Buffering Delay. During video playback, there can be a situation where the play-out buffer at the client is temporarily empty. In such cases, the video playback would be intermittent and the quality will be degraded seriously. The total playback time will be increased by each buffering delay interval.

2.3.3 Auto Scale Resolution. The network conditions can change rapidly. To compensate for this, streaming services like YouTube automatically scales up/down the resolution of the transmitted video depending upon the network condition in an attempt to improve the overall video QoE. This factor is also considered over here.

The simulated QoS parameter details have been provided in table 3.

Table 3: Simulated QoS Parameters

Parameter	Details
Video Codec	H.265, VP9
Encoder Version	Ffmpeg version 3.1.3
Video Format	Full HD progressive (1080p)
Packet Loss in %	0.1, 0.5, 1, 3, 5, 10
Jitter in milliseconds	1, 2, 3, 4, 5
Throughput in kbps	500, 1000, 2000, 3000, 5000
Variable Initial Delay in seconds	5, 15, 25, 35, 45
Buffering Delay in seconds	5, 10, 20, 30, 40
Auto Scale Resolution	1, 1.8, 2.08, 3.6, 4.68

3 RESULT ANALYSIS

3.1 Subjective Scores

We recorded a total of 20,768 (59 subjects × 88 impaired videos × 4 content types) subjective scores. To begin with, the process of outlier detection was carried out to remove any sort of data inconsistencies. If S_{ij} represents the score obtained by the j[th] subject for the i[th] test sequence, then S_{ij} would be considered as an outlier if $S_{ij} > q_3 + 1.5(q_3 - q_1)$ OR $S_{ij} < q_1 - 1.5(q_3 - q_1)$, q_1 and q_3 being the 25[th] percentile and 75[th] percentile of the score distribution respectively. This range is approximately equal to 99.3% of the normally distributed data. A subject will be removed from any further consideration if more than 20% of his/her scores are outliers. Following this method in our experiment, we did not find any outliers.

For a sample size N the MOS has been calculated as:

$$MOS_i = \sum_{j=1}^{n} S_{ij} / N \tag{1}$$

3.2 VQM Score vs. Subjective MOS

In previous sections through proper literature survey, we have already established that VQM is a very commonly used tool by many researchers due to its accuracy. For this work, we made VQM to predict the MOS values for our 2 target groups. Figures 5 and 6 show the variations between the VQM values obtained and the subjective MOS for the non-elderly and the elderly group respectively. It should be noted that the corresponding mapping between the VQM scores and the MOS values were carried out as per the procedure given in paper [31]. Fig. 7 represents the difference between the mean VQM scores and subjective MOS scores obtained across both the groups in the form of an error bar chart assuming 95% confidence interval. We observe that the VQM algorithm reasonably mimics the subjective MOS in case of the non-elderly population, while for the elderly group it fails to correctly predict the values. Generally for the second group, across all the video samples VQM tends to over predict the MOS. Figures 8 and 9 illustrates this fact further by depicting the scatter plot between the two. In the case of the non-elderly group, we obtain R^2 and Adjusted- R^2 values of 0.866 and 0.865 respectively, while for the elderly group it was 0.772 and 0.770. Hence, we can conclude that the VQM algorithm is not suitable for predicting the MOS which is obtained from the elderly people.

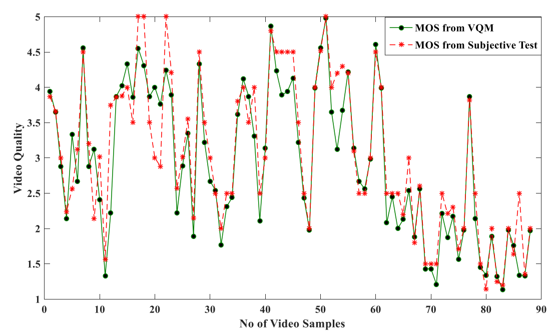

Figure 5: VQM vs. Subjective MOS (non-elderly group)

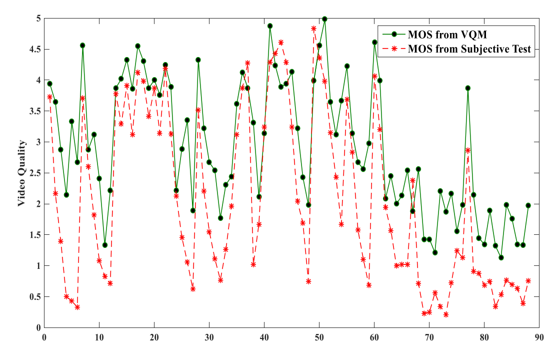

Figure 6: VQM vs. Subjective MOS (elderly group)

This motivated us to build our own video quality prediction model for the elderly based upon an artificial neural network which we discuss next.

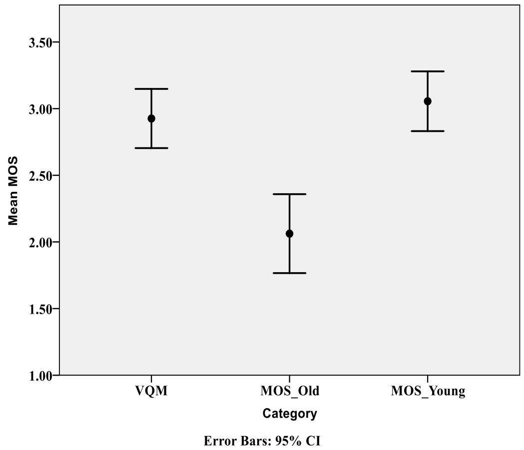

Figure 7: Error bar Plot for both Groups

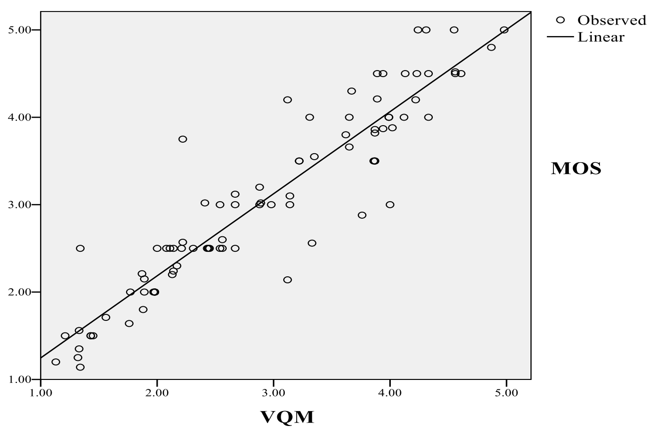

Figure 8: Scatter Plot of VQM vs. Subjective MOS (non-elderly group)

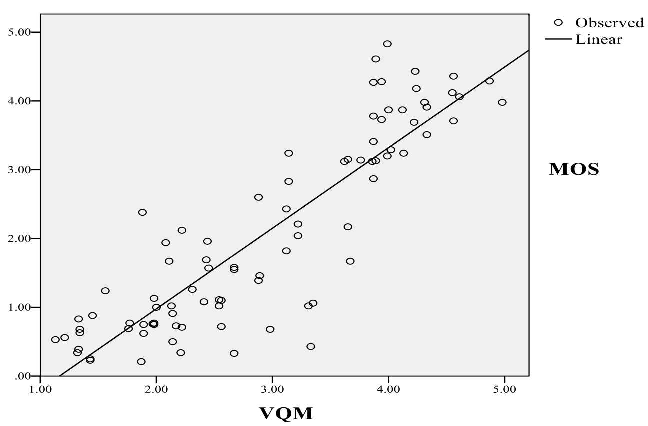

Figure 9: Scatter Plot of VQM vs. Subjective MOS (elderly group)

3.3 ANN Based Prediction Model

The ANN which we have used in our work is a Multi-Layer Perceptron model having one hidden layer. Considering the number of inputs that we have i.e. 7, going for more number of hidden layers would have increased the overall complexity of the system unnecessarily and also resulted in over fitting problems. Hence, we opted for the one hidden layer architecture. Training of the neural network was done using the Levenberg-Marquardt (LM) algorithm by issuing the *trainlm* command in Matlab. The *trainlm* command is a network training function that updates the weight and biases of the different nodes according to the LM optimization. It is considered to be one of the fastest back propagation algorithms and is highly recommended as a first-choice supervised algorithm, although it consumes more computer memory as compared to the other algorithms. For the hidden layer, we used a hyperbolic tangent sigmoid transfer function by issuing the *tansig* command; while for the output layer a pure linear transfer function was used by giving the *purelin* command. Although, other transfer functions are available; we chose the linear relationship at the output layer as it has been widely used by other researchers previously in function fitting problems. For the neural network input we use the same 6 network QoS parameters that we have discussed previously, plus one extra factor for the type of codec used and as the output we have the score that predicts the quality of the video as perceived by a human observer.

We used a 70:30 split ratio of the input data as training, testing and validation sets. To find the configuration of the network that achieved the best performance, several rounds of tests were conducted by varying the number of neurons in the hidden layer and observing the output. Since, we have 7 inputs and 1 output; hence we varied the number of hidden neurons from 2 to 12. Optimal performance was observed with 9 hidden nodes. The system architecture showing the best configuration has been given in Fig. 10. In the figure the symbols w and b stand for the weight and bias factors for each node respectively. The value of w and b for our configuration set for both input and hidden layer has been provided in tables 4 and 5 respectively.

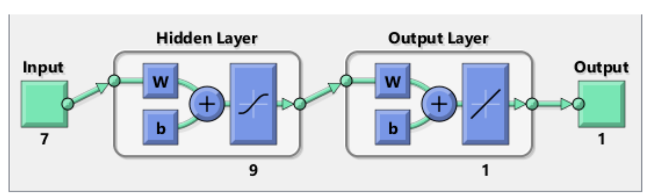

Figure 10: Best Architecture for our ANN

The performance of our model across the training, testing and validation sets has been shown in Fig. 11. The best validation performance is obtained at epoch 11 and marked in the figure. Also, we find that as the model learns during the training phase, the mean squared error (MSE) across all the three sets decrease at a rapid rate.

Table 4: Final Weight and Bias for Input Layer

Weights							Bias
PL	J	T	VID	BD	ASR	Codec	
1.700	0.756	0.188	-0.192	0.166	0.051	0.186	-2.07
-0.404	-0.739	-0.267	-1.757	0.759	1.352	-0.050	1.10
0.230	0.234	-0.979	1.624	0.142	0.060	-0.260	-0.89
-0.947	0.011	1.148	1.788	-0.641	-0.125	-0.123	0.70
-3.112	0.372	1.311	0.488	-0.342	0.211	-0.045	-1.95
-1.567	0.719	0.545	1.837	1.669	-1.433	-0.029	1.16
0.498	1.421	0.353	0.587	0.307	-1.162	2.152	0.61
-2.629	-0.030	-3.39	1.557	1.401	-0.937	-0.020	4.21
0.150	1.119	0.670	2.431	0.161	0.063	0.051	2.30

Table 5: Final Weight and Bias for Hidden Layer

Weights									Bias
-0.324	-1.576	-1.195	1.313	2.325	-2.088	0.097	2.108	-0.751	-0.404

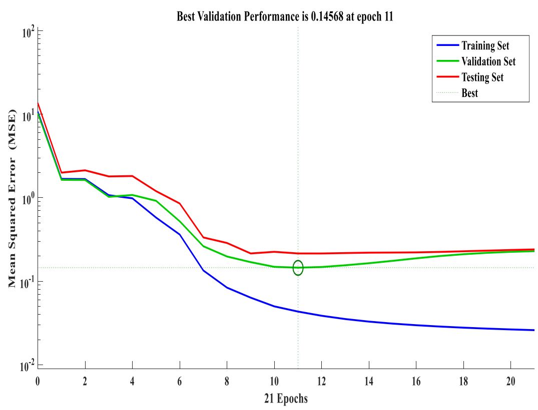

Figure 11: MSE Variation across all sets

Fig. 12 shows the regression plot across all the 3 sets. We obtain R^2 values of 0.989, 0.925 and 0.960 for the training set, test set and validation set respectively. The overall R^2 value for all the video sequences is 0.978 which is pretty high. This is also evident from Fig. 13 which shows the MOS variation across both the models for all the video samples.

The Pearson Correlational Coefficient (PCC) has been found out to be 0.978 in case of our ANN based model while 0.879 for VQM.

3.4 Impact of QoS Parameters on Video Quality

In order to study the influence of the different network QoS factors that we have used in this research on the MOS we perform a ANOVA (analysis of variance) test on the MOS data set.

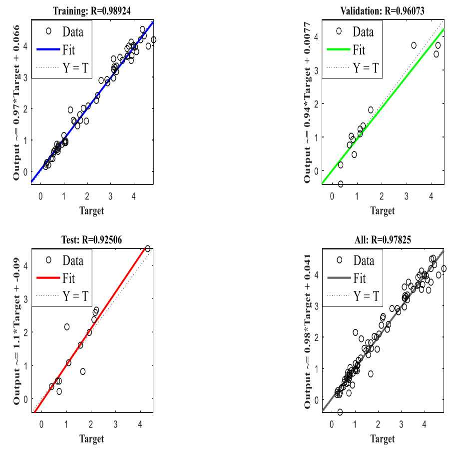

Figure 12: Regression Plot across all sets

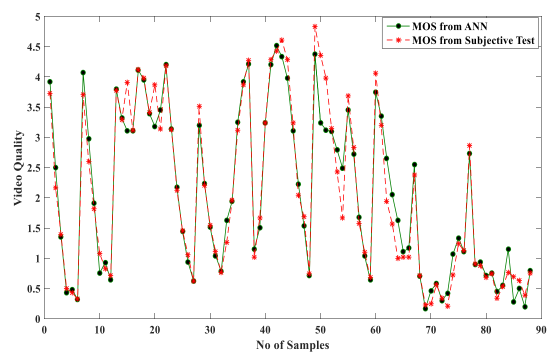

Figure 13: ANN vs. Subjective MOS

The results are shown in table 6. The second column shows the Sum of Squares, third column is the Degrees of Freedom associated with the model, fourth column is the Mean Squares i.e. the ratio of the Sum of Squares to the Degrees of Freedom, fifth column shows the F-statistic value and the sixth column represents the p-value.

We observe from the above table that for both the 3 KPI's as well as the 3 factors that we have introduced in this paper; all the predictors are statistically significant (p-value of less than 0.01). Hence, we justify their inclusion in this research.

Table 6: ANNOVA Result for the Predictors

Parameter	Sum of Squares	Degrees of Freedom	Mean Squares	F Statistic	p- Value
PL	15.747	5	3.149	37.382	1.91×10^{-4}
J	8.505	4	2.126	114.556	4.2×10^{-5}
T	15.695	4	3.923	109.568	4.7×10^{-3}
VID	18.561	5	3.712	13.798	0.003
BD	12.51	4	3.128	43.038	4.59×10^{-4}
ASR	1.433	4	0.358	59.70	2.08×10^{-4}

4 CONCLUSIONS

The aim of this paper was to develop a video quality prediction model for the elderly people. Although, research related to perceived video quality by a human subject has been attempted by several researchers in the past, having the older generation as the target sample group is a new concept. In order to prove this concept, after conducting a subjective test, we used the well-known VQM algorithm to predict the MOS scores. Surprisingly; while it was able to predict the scores of the non-elderly group with a reasonable accuracy rate; it grossly overestimated the MOS in case of the elderly group. Although, VQM takes into consideration the effect of the human visual system; yet it could not account for the common visual disabilities that the older people suffer with. Hence, there was a mismatch in the MOS values.

We attempted to solve this problem by building our own prediction model based upon an ANN. The ANN based model provides a high degree of performance for the parameters that we have considered. This model is unique in the sense that it is capable of accurately predicting the video quality as perceived by the old age people. We concluded the paper by doing an ANOVA analysis over the parameters that we had taken in order to justify their inclusion.

In this paper, we studied the effect of the network QoS factors only on the viewing quality. However; other codec related parameters like bit-rate, frame-rate, and resolution of the videos can also affect the viewing quality which we did not take into account. The effect of these factors will be investigated as part of our future work. We also want to conduct similar subjective tests on a large scale and validate the results with our model.

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