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AN EXPERIMENTAL INVESTIGATION BASED ON SERVICES OF VIDEO STREAMING USING DEEP NEURAL NETWORK FOR CONTINUOUS QOE PREDICTION

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ABSTRACT

Now-a-days Global Internet traffic is created by video streaming which is a primary source of platform, this may create and contact with the worldwide audience. The user the contents high quality streaming to delivering a crucial role play with quality of experiences the continuous user predicting with video streaming services. By the temporal dependencies that can cause the complexity in data QoE and the factor influence QoE among non-linear relationship that can introduced challenge to prediction QoE continuous. To effectively capture Gated Recurrent Unit (GRU) that utilized the existing studies this can be deal, accuracy QoE prediction excellent resulting. Even-through, GRU complexity is high computational, architecture with characteristic processing sequential with it, power computational with limited devices it's performance about the serious question which has been raised. Meanwhile, Deep neural network with variation of Temporal convolutional network (TCN), for modelling task with sequences which has been proposed, computational complexity and accuracy prediction with terms GRU based on the method of baseline over the performances prediction supervisor has been provided. In this paper, based on the model TCN with improved, namely DNN-QOE, the QoE proposed is predictive continuous, sequential data with characteristic pose, to overcome the complexity computation based on the advantage of TCN leverage from drawback model of GRU based QoE, to improve the accuracy of the QoE prediction they improved the architecture that has been introduced at the certain time. The performances of the DNN-QoE are highly competitive.

Keywords: *Services, Video Streaming , Neural Net, QOE Prediction*

1. AIM AND BACKGROUND

In recent years, on internet the most dominant services is carried out by the video streaming services, the service provided by streaming create a huge profit. The services in the markets has the high competitive streaming, amazon, Netflix, or hot star were some the service that provide in the video streaming, the viewer expectation were to satisfy the video quality that has been provided in sufficient way, in a high quality of experiences was explain in the result. QoE deterioration has causing subsequently event that distorted which lead the network can condition that influence the dynamic network against the service of video streaming. QoE aware application that benefit significantly in real-time QoE user that predict accurately and quickly with QoE model development. At a client side designed stream switching for instance that can be replying model QoE a level video quality optimal request and predict can adaptively algorithm bitrate selection that can adaptive. Among QoE factor influencing with relationship non-linear . They introduce the Gated Recurrent Unit which is leverage with the model QoE prediction that has been challenged to deal with. Although, based on the over time of sequential used in the QoE user practical predicting required high computation cost under the architecture of GRU chain structure. Based on the output of previous process the steps of subsequence processing will be taken place. The model performances have been limited under the power about to open the lead. Such as the power computation has not enough in the mobile devices like the algorithm Qoe implementation.

At recent time, Temporal Convolutional Network has different Recurred Neural Network (RNN), the task modelling the sequence for alternate solution that promising the emergent. Convolutional cause the TCN adoption that dilated in the data sequential in dependencies temporal that extracting in powerful was which is provided with it . Modelling advantages and the computation which is provided with the parallel information that has been performed with TCN computation from various GRU.

In certain deployment, task of modelling sequences has across a range board with GRU and LSTM based on the recurrent architecture out-performs of TCN convincingly canonical [15]. The model of TCN based has been improved over the performances that we provided in this paper, on various view of device that predicted the QoE has continuous namely QoE-RNN.

The devices and platform were to support the diversity with complexity to minimizing computational while the QoE prediction enhances with accuracy is the goal.

- First, in real-time the QoE prediction is continuous for TCN which is an improved model for the model RNN-QoE.
- Second, the performances of QoE are predicted with the achiever that introduced in the proposed model it set a hyper-parameter with model optimal architecture.
- Third, with various baseline method in comparison the multiple QoE database has performed and it is evaluated under the comprehension of RNN-QoE. Among the mobile devices and personal computer the complexity computational and accuracy has been in the terms of superior performances that can achieves the RNN-QoE which is represented in the results.

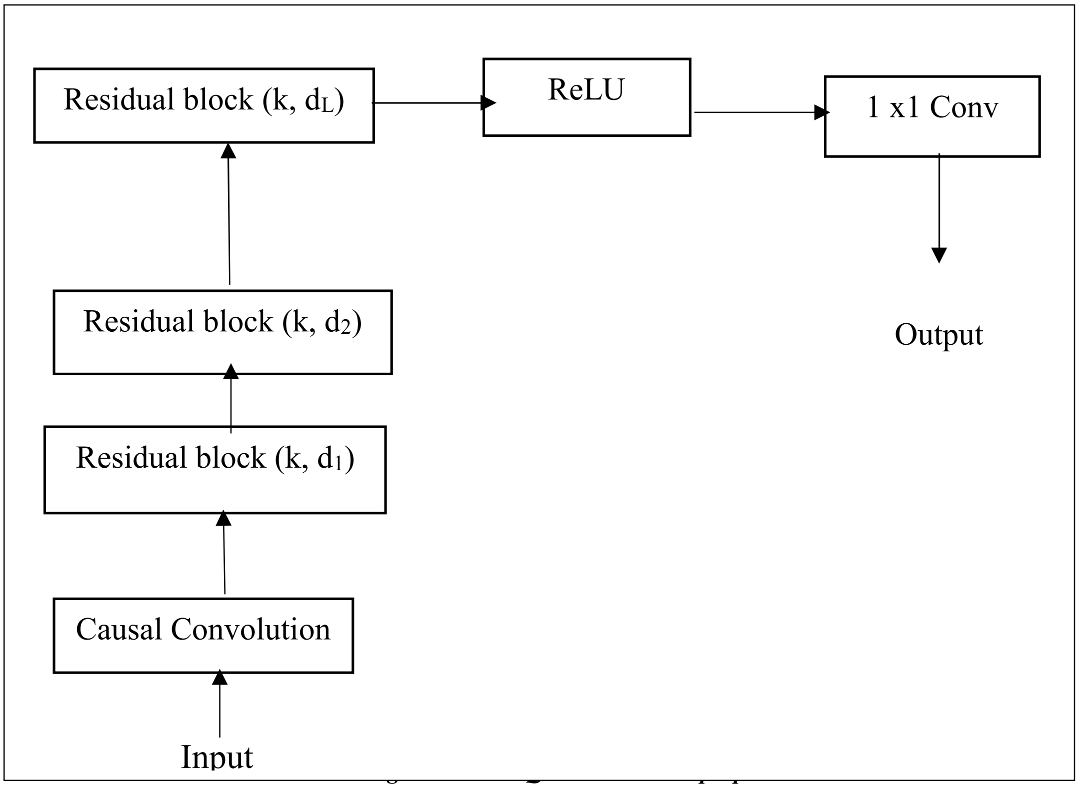
2. EXPERIMENTAL SETUP

The TCN architecture that can handle the problem and the advantage to be in leverage can be introduces in RNN-QoE with proposed model for the services of video streaming task prediction in QoE. The computational complexity to minimize and accuracy prediction QoE that enhance our study with main objective. The following subset discussed about the RNN-QoE model that we proposed in the employed architecture. The optimal value has to find analysed with hyper-parameter with model architecture accuracy can be improved with QoE prediction, the computational complexity which is minimized.

Proposed Model Architecture -For 1D convolution the advantage of RNN-QoE is leverage with the architecture, in TCN architecture the residential block and convolution causal dilated were solved. To improve the number with the prediction mask to adapt RNN to QoE were as follows

- To residual block that connect the input that added with layer of convolution causal were initial which indicate the layer convolution causal dilated.
- Scaled Exponential Linear unit were advantage leverage that simplify the residual block [20]

Causal Convolution to Extract Local Features **-** The convolution causal dilated with stack and layer of one convolution causal were compared with proposed model in architecture, the convolution causal dilated were the open consider for the TCN. The first block residual and time-series were among the input layer of convolution causal, from the figure 1. The data QoE sequential were adjacent with time-step that can adjusted the local feature that can extract the layer convolution causal. The time steps among the global feature to extract the leverage with layer convolution causal dilated with it. In higher accuracy that resulting the time series with feature that informed with model layer.



3. ARCHITECTURE HYPER-PARAMETERS SELECTION

The best performances to achieve the selection of hyper-parameter is based on set of architecture that adequate the model training in the system. A filter size with convolutional causal dilated contain with each layer of residual block based on the proposed model. The filter size and depth of network was depends on the proposed model. The model with computational complexity and prediction accuracy among QoE based on the control trade-off with these hyper-parameter. The hyper-parameter optimize the effectively, the value of hyper-parameter which is possible for the space to set the boundary which is important.

Table 1: Performances Of Hyper Model

Architecture Hyper-parameter	Description	Derived Value
r	Reception field size	8k
k	Filter size	2
L	Number of dilated causal convolution layer	3
n	Number of filter on each convolution layer	32

4. RESULT AND DISCUSSION

The complexity computation and accuracy prediction in terms of QoE were performed with RNN-QOE based on the evaluation. Mobile device and personal computer among database that across multiple baselines behind the model with numerous baseline that proposed model that can be compared with performances evaluation. The baseline model was here to explain the QoE prediction iver the feature input. The present complexity computational and accuracy is based on the result that evaluated. The QoE prediction for real capability illustration is discussed with model that e proposed with overall performances.

Table 2: Qoe Database Used In Proposed Model.

Database	Device Type	Rebuffering Events	Bitrate Fluctuations	Duration	QoE range
LFOVIA video QoE Database	TV	Yes	Yes	120 second	[0, 100]
LIVE Mobile stall video Database II	Mobile	Yes	No	29-134 second	[0, 100]
LIVE Netflix video QoE Database	Mobile	Yes	Yes	At least 1 minute	[-2.28, 1.53]

Input features for QoE prediction - The video quality are sensitively affected by the user in the video streaming [14]. The metrics of robust video assessment quality were used to prediction and the user being rendered the videos visual quality. The datasets of video quality is a wide spectrum that been tested with model VQA based on the high-performances in the STRRED demonstration [21]. The user QoE is a huge impact for Re-buffering [22]. Based on this they investigate Re-buffering number, position, and length, with this information they produce the input. The session is consider with the time instant that starts when it happens [22].

Baseline Model - The QoE has been compared with GRU based on the personal computer that proposed with model that accurate that can be evaluated with QoE. The same network user model with RNN-QoE. The QoE prediction in the short with original model that can compared with the worth of nothing. On mobile device the proposed model has been complexity with computation and accuracy has been predicted the QOE evaluation, higher accuracy is accuracy is higher with exceptional achieve with model prediction based on QoE with RNN that has been focused with it. A fair compassion that ensure the respective words to report were model hyper-parameter with GRU-QoE.

Accuracy-

Databases **-**On personal computer the accuracy of QoE prediction to evaluate, on w=each database to perform the evaluation that has be described as follows:

- The duration of 120 seconds were based on the video sequence that consider with 36 distorted with LFOVIA database [23].The train-test set were various among the division of the dataset. In the testing set the video with each sets of train test. The test video play out pattern and the same content that do not include the video with training set. For each test video for trading the model that choses the video.
- LIVE Netflix database the employed database has been described with the procedure that evaluated. In this database to each video for sets corresponding the train-test of 112 [24].
- LIVE Mobile database: the databases has been one applied with slight difference that procedure evaluation. The video across randomly distributed patters distortion.

Here, with training set the sets of testing and training were divided with database video of 36 distorted set. In testing set 8 video and set training were used in 28 videos.

Evaluation Criteria - The accuracy assessment for QoE prediction has been consider with RMSE, SROCC, and PCC with evaluation metrics. The relationship with monotonic measurement, prediction and subjective were measured with degree of linearity, for good result.

Result -On personal computers model RNN-QoE proposed with database with performance QoE prediction from the table 3, 4, and 5. The events re-buffering without and with situation performance QoE prediction consistent and procedure superior model proposed. the proposed model that capture still adequate in the subjective QoE in the subjective varying trends these fluctuation. With existing model in comparison each database that can result performance QoE prediction. A fair comparison to ensure in their work employed reported. In terms of RMSE especially within all the criteria the existing QoE model outperforms RNN-QoE that revealed. The model comprehensive efficient marking the databases across consistent the RNN-QoE the accuracy produced. Factor QoE influence

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among non-linear relationship and inter-dependencies complex the capturing the RNN-QoE architecture, from the figure 5. A model comprehensive efficient the marking, the dataset across consistent RNN-QoE architecture accuracy produced. With TCN-QOE comparing that has been accuracy QoE prediction to improving significant interesting. For QoE prediction for more suitable model made architecture proposed enhancement has been means. As per the table 6 on various platform they performances of TCN-QoE and RNN-QoE were accurate with QoE prediction. As well as, the GRU-QoE, based on the mobile device performances accuracy has been loss with significant in QoE prediction which leads to suffer. The mobile device the GRU architecture has been connected re-current to convert because of the failed tensor flow.

Table 3: Qoe Prediction Performances Over RNN-Qoe Over LFOVIA Video Qoe Database

	PCC	**SROCC**	**RMSE (%)**
RNN-QoE	0.827	0.759	4.81
TCN-QoE	0.675	0.730	5.48
GRU-QoE	0.854	0.730	9.65
NLSS-QOE [24]	0.777	0.680	7.52
SVR-QoE [22]	0.682	0.641	10.41

Table 4: Qoe Prediction Performances Over RNN-Qoe Over LIVE Mobile Qoe Database

	PCC	**SROCC**	**RMSE (%)**
RNN-QoE	0.890	0.858	5.63
TCN-QoE	0.668	0.605	9.75
GRU-QoE	0.788	0.854	7.89
NLSS-QOE [24]	0.690	0.585	9.65

Table 5: Qoe Prediction Performances Over RNN-Qoe Over LIVE Netflix Qoe Database

	PCC	**SROCC**	**RMSE (%)**
RNN-QoE	0.884	0.753	6.79
TCN-QoE	0.753	0.72	7.65
GRU-QoE	0.802	0.724	7.79
NLSS-QOE [24]	0.655	0.487	1.52
NARX [23]	0.68	0.59	9.54

Table 6: Comparison Of RNN-QOE Predicted Performances Of Personal Computer And Mobile Device LFOVIA Video Qoe Database With Ratio 83:17

	PCC		**SROCC**		**RMSE (%)**	
	PC	**Mobile**	**PC**	**Mobile**	**PC**	**Mobile**
RNN-QoE	0.875	0.875	0.879	0.879	5.78	5.78
TCN-QoE	0.732	0.732	0.798	0.798	6.72	6.72
GRU-QoE	0.865	0.254	0.821	0.658	6.87	22.45

Computational Complexity - The investigation of mobile device and personal computer were proposed in the model were basically complexity computation. With methods baseline among the comparison devices low and high computation the RNN-QoE has the effectiveness. The test and training ratio of the model LFOVIA video database if 83:17

Evaluation Settings - The system used with LTS Intel i7-8750H @2.20 GHz that computer running18.04 LTS in personal that predict the model QoE based on deep learning. On the site of android Sony Xperia XA2 with android 9.0 and Qualcomm Snapdragon 630 64 bit RAM process has been used. Depending on the 1.8-2.2 GHz among the various clock speed in CPU core has been used. On smartphone and personal computer the power of computation GPU has been noted and not utilized in it.

Evaluation Criteria- Four evaluation metrics used in the personal computer which helps to evaluate to conduct them:

- Inference time: time taken for user prediction
- Model Size: size of storage in the hard drive of driving model
- FLOP: performances of number of operation
- Number of Parameters: learnable parametric model

Therefore, using two metric on smartphone they have compare the complexity of RNN-QoE with inference time and Model size.

Table 7: On The Personal Computer Of The RNN-Qoe Computation Complexity

	Inference Time (ms)	Model Size (kB)	FLOP	Number of Parameters
RNN-QoE	0.678	82.15	175,498	9578
TCN-QoE	0.854	145.8	255075	1366
GRU-QoE	1.999	41.56	30958	6364

Table 8: On The Smartphone Of The RNN-Qoe Computation Complexity

	Inference Time (ms)	Model Size (kB)
RNN-QoE	0.581	56.222
TCN-QoE	0.60	88.65
GRU-QoE	1.550	77.14

5. CONCLUSION

GRU-QoE and TCN-QoE has been comparing under the proposed model RNN-QoE under the result of complexity computation from the table 7 and 8. High accuracy has been achieve from the GRU-QoE that has been compared with FLOP and the higher parameter is required with RNN-QoE. The smartphone and personal computer were fathering than the model GRU-QoE that inference with 3 time which is larger under the proposed model. The computing speed were boosted up from computational power of parallel that is efficiently leverage among the proposed model. Based on the table 7 TCN-QoE architecture is higher complexity that FLOP and number of parameter terms were extreme in the RNN-QoE proposed model. Based on table 6 the RNN-QoE has been compared with TCN-QOE accuracy. RNN-QoE allow the architecture of TCN to adapt the improvement of proposed model to capture the QOE data sequence. Therefore, the system of QoE prediction has excellent choice that can be RNN-QoE or mobile application of video streaming is driven with QoE. Deep neural network, recurrent neural network, Long-Short term memory/Reg-Gated Recurrent Unit.

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