Lightweight NR Metrics

Kumar Awanish

Quality and Usability Lab (TU Berlin)

MOTIVATION

- Increase in popularity of Gaming videos and many vendors such as Twitch.tv, YouTube Gaming, Hitbox.tv.
- Due to advancement in hardwares and software, games are getting more complex.
- Gaming videos consist of synthetic and artificial content.
- More attention for Machine-learning based quality evaluation methods.

Quality Assessment(QA) Metrics

- Full Reference :
  - uses a complete reference signal information.

- Reduced Reference :
  - uses a part of the reference signal.

- No Reference :
  - does not use a reference signal.

VQA metrics comparison

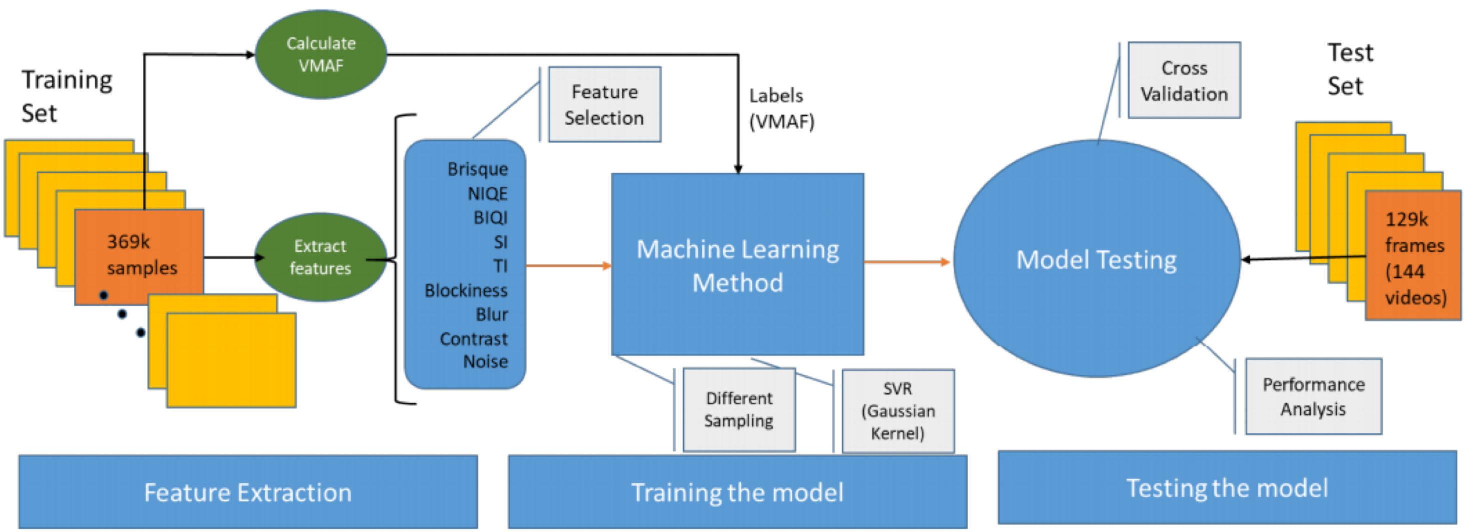
Metrics		480p		720p		1080p		All Data	
		PLCC	SROCC	PLCC	SROCC	PLCC	SROCC	PLCC	SROCC
FR Metrics	PSNR	0.67	0.64	0.80	0.78	0.86	0.87	0.74	0.74
	SSIM	0.57	0.43	0.81	0.78	0.86	0.90	0.80	0.80
	VMAF	**0.81**	**0.74**	**0.95**	**0.94**	**0.97**	**0.96**	**0.87**	**0.87**
RR Metrics	ST-RREDOpt	-0.61	-0.51	-0.82	-0.85	-0.79	-0.92	-0.71	-0.74
	SpEEDQA	-0.63	-0.52	-0.83	-0.87	-0.77	-0.93	-0.71	-0.75
NR Metrics	BRISQUE	-0.57	-0.48	-0.83	-0.89	-0.88	-0.91	-0.49	-0.51
	BIQI	-0.53	-0.51	-0.73	-0.72	-0.81	-0.80	-0.43	-0.46
	NIQE	-0.73	-0.74	-0.85	-0.81	-0.89	-0.90	-0.77	-0.76

Traditional NR metrics like BRISQUE, NIQE failed to predict gaming content.

Dataset used : GamingVideoSET.

Quality & Usability Lab

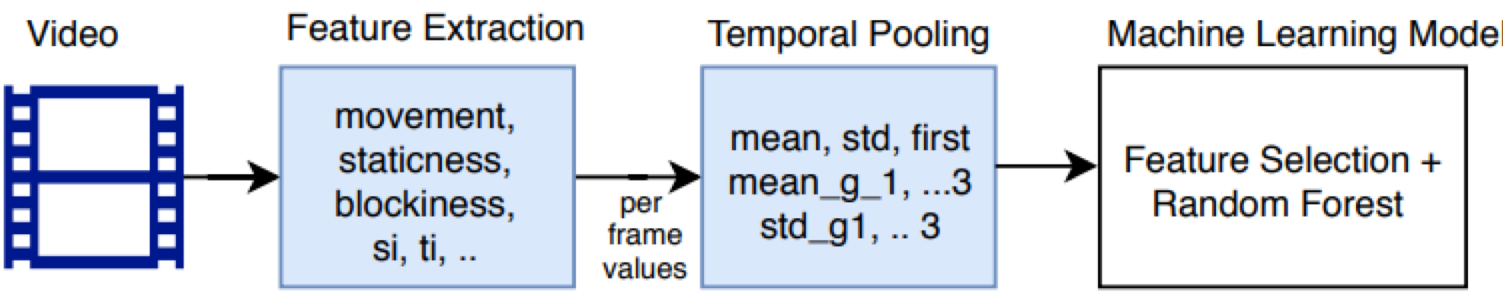
Existing NR Metrics for Gaming content : NR-GVQM



NR-GVQM Architecture.

- Uses Frame-level features and model with VMAF.
- Pre-Trained BRISQUE, NIQE score.
- Only GamingVideoSET data for model development.

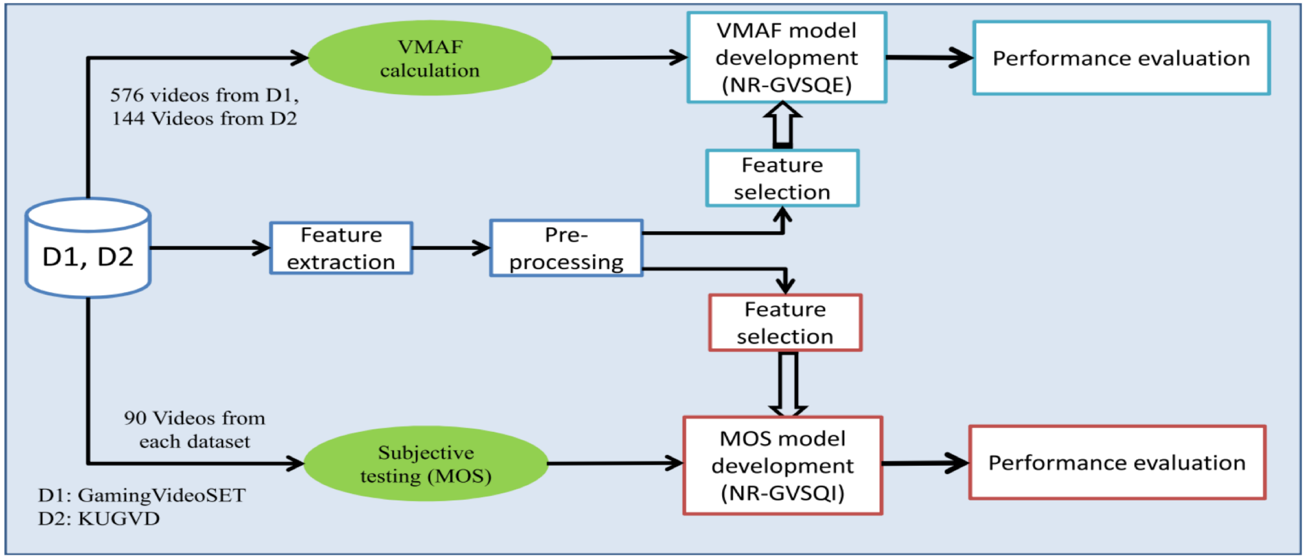
Existing NR Metrics for Gaming content : NOFU



NOFU Framework.

- Uses MOS score of 90 videos from GamingVideoSET.
- Temporal pooling approach before feeding to ML model.
- Lacks validation set.

Existing NR Metrics for Gaming content : NR-GVSQI



NR-GVSQI Framework.

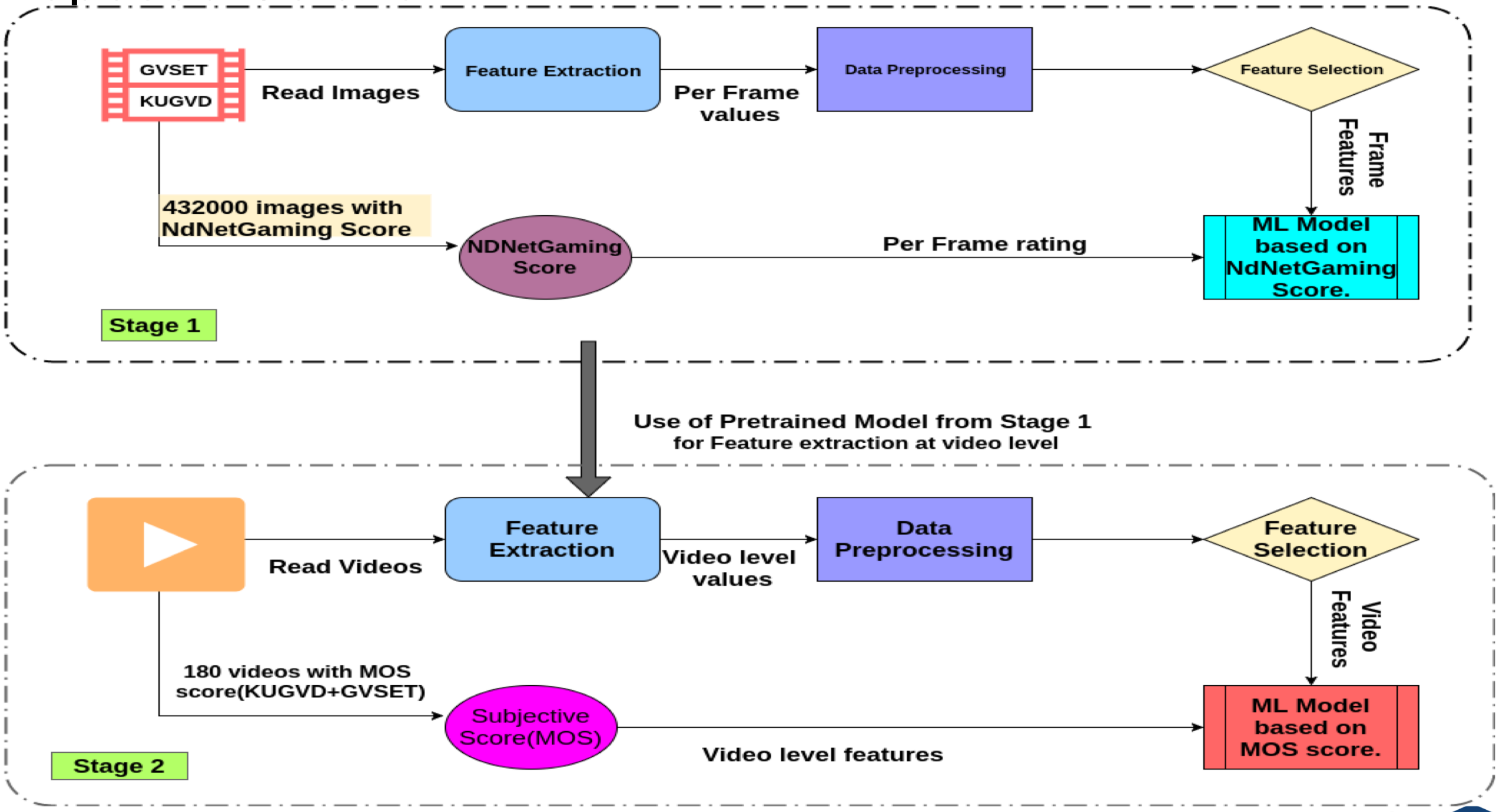
- Uses GamingVideoSET and KUGVD dataset.
- Proper training and validation.
- Uses pre trained BRISQUE, NIQE.

Why need new NR metrics for gaming content!!

- ❑ Traditional NR metrics din't able to predict the quality of Gaming content with high performance.
- ❑ Lack of Training and Validation support.
- ❑ Performance of traditional metrics like NIQE, BRISQUE haven't checked on training for gaming based contents.
- ❑ Lack of Lightweight NR gaming metrics.

Quality & Usability Lab

Proposed Solution



Proposed Solution: Stage 1

- Focus on Spatial aspect of the Video Data.

- Feature Extraction at Frame level:
  - BRISQUE Feature :
    - Total of 36 features extracted.
    - Retain the BRISQUE model on gaming content.
    - Find presence of distortion.
  - Histogram of Oriented Gradients (HOG) Features :
    - Total of 36 features extracted.
    - Metrics for texture descriptor i.e edge detection.
  - Grey Level Co-occurrence Matrix(GLCM) Features:
    - Total of 4 features extracted.
    - Metrics for texture analysis.
- Data Processing: Finding Outliers.

Feature Selection and Modelling

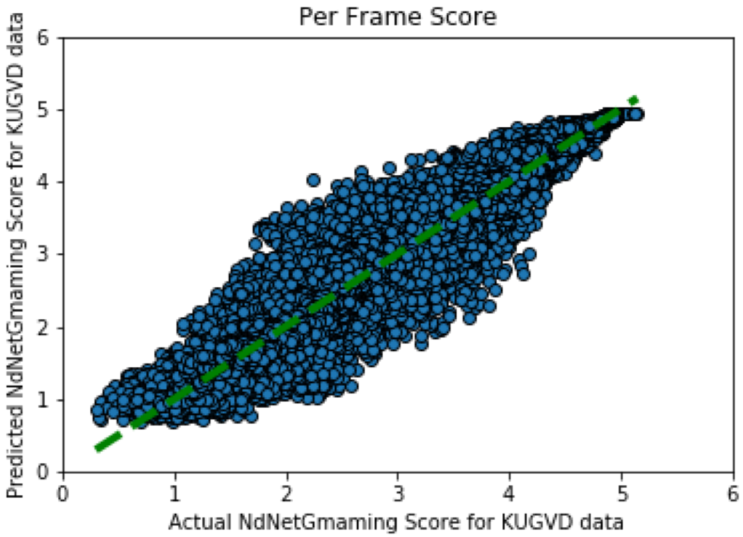
- TrainSet : GamingVideoSET with 351000 frames.
- TestSet: KUGVD with 81000 frames.
- Label: NdNetGaming.
- ML Algorithm: XgBoost Regressor, SVR.
- Best selected model saved to use in Stage 2.

Features	PLCC	RMSE
F1	0.82848	0.47848
F2	-0.51723	0.98857
F3	-0.57449	0.98529
F1+F2	0.50244	0.73867
F1+F3	0.90571	0.36214
F1+F2+F3	0.90764	0.35861
F1: BRISQUE, F2: HOG, F3: GLCM		

Proposed Solution: Stage 1

Per Frame Result:

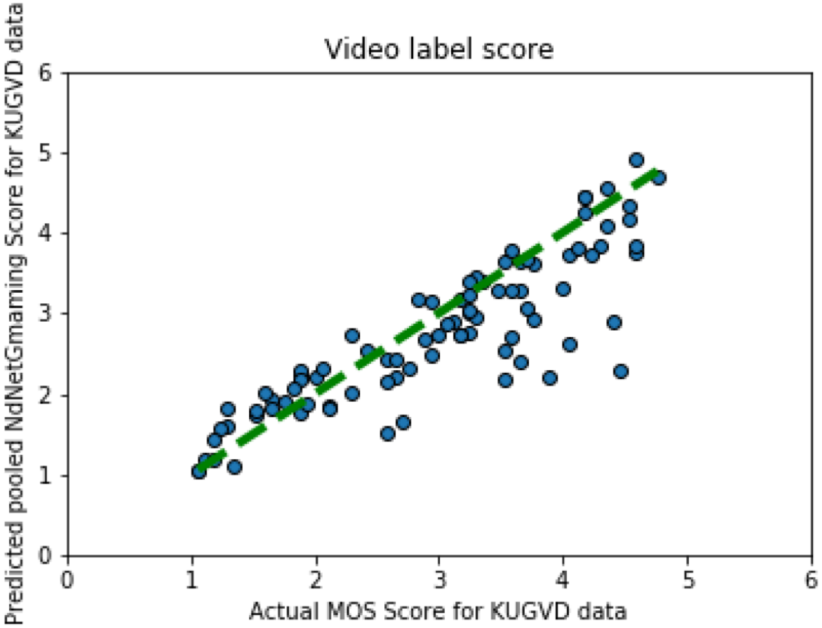
- TestSet: KUGVD data with NdNetgaming Score Per Frame
- SROCC: 0.967
- PLCC is : 0.968
- RMSE : 0.064



Proposed Solution: Stage 1

Video Level Result:

- TestSet: KUGVD data with pooled NdNetgaming Score.
- SROCC: 0.871
- PLCC is : 0.842
- RMSE : 0.321

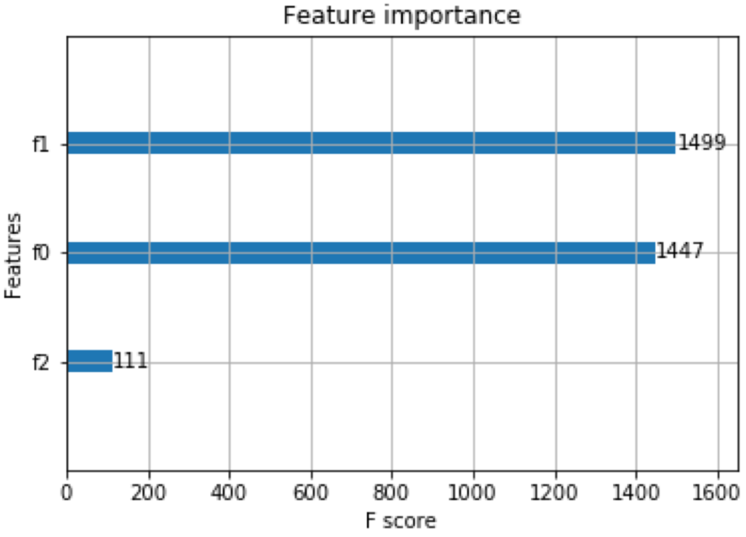


Proposed Solution: Stage 2

- Focus on Temporal aspect of the Video Data.
- Feature Extraction at Video level:
    - Absolute Motion using block Motion.
    - Temporal Information(TI)
    - Trained model from Stage1 as an input.
- Data Processing: Finding Outliers.

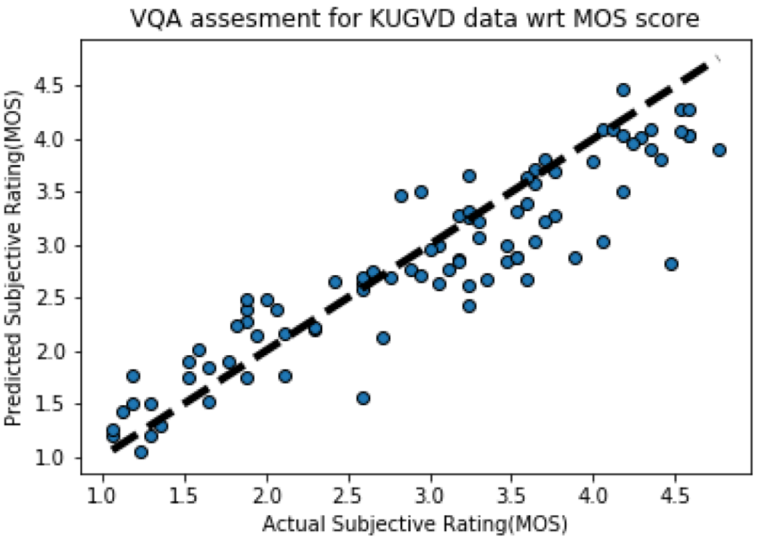
Feature Extraction at Video Level

- ❖ Selected based on F score.
- ❖ F score is measure for feature selection.
- ❖ Features notation:
  - ➢ f0: Motion Vector
  - ➢ f1: Predicted pooled score
  - ➢ f2: TI



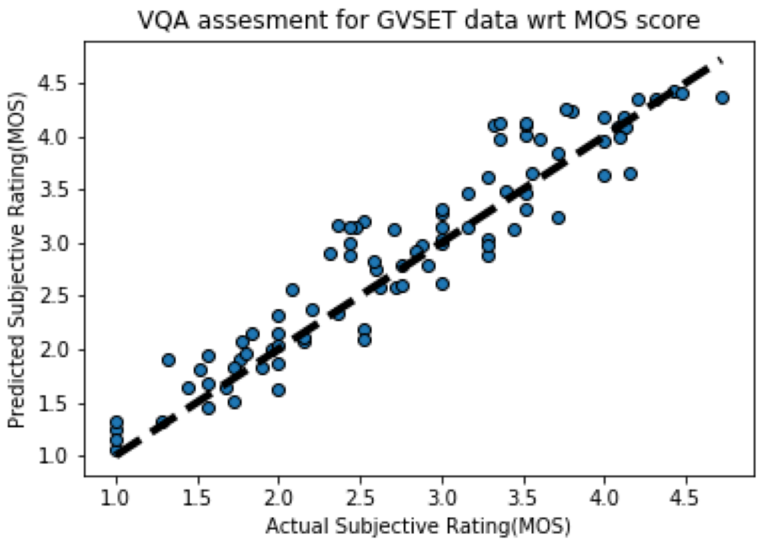
Scatter plot of MOS scores

- Trained on MOS values of 90 videos from GVSET.
- Tested on KUGVD data with 90 MOS values.
- All the games that we have subjective results are excluded for training part of stage1.



Scatter plot of MOS scores

- Trained on MOS values of 90 videos from KUGVD.
- Tested on GVSET data with 90 MOS values.
- All the games that we have subjective results are excluded for training part of stage1.



Quality & Usability Lab

Result

NR Metrics	GVSET		KUGVD	
	PCC	SROCC	PCC	SROCC
BRISQUE	-0.44	-0.46	-0.62	-0.60
NIQE	-0.72	-0.71	-0.85	-0.84
NR-GVQM	0.89	0.87	0.91	0.91
NR-GVSQI	0.87	0.86	0.89	0.88
NOFU	0.91	0.91	-	-
LightweightNR	0.93	0.94	0.90	0.91

Conclusion

- Training BRISQUE on gaming content enhances the performance of model.
- Two steps model development helped in robust model.
- Proposed model is lightweight and can be used in real time.
- Designed machine learning based NR metrics have a high correlation with subjective (MOS) score.

Reference

1. Barman, S. Zadtootaghaj, S. Schmidt, M. G. Martini, and S. M¨oller, “Gamingvideoset: a datasetfor gaming video streaming applications,” in2018 16th Annual Workshop on Network and SystemsSupport for Games (NetGames). IEEE, 2018, pp. 1–6.
2. N. Barman, S. Schmidt, S. Zadtootaghaj, M. G. Martini, and S. M¨oller, “An evaluation of videoquality assessment metrics for passive gaming video streaming,” inProceedings of the 23rd PacketVideo Workshop. ACM, 2018, pp. 7–12.
3. S. Zadtootaghaj, N. Barman, S. Schmidt, M. G. Martini, and S. M¨oller, “Nr-gvqm: A no refer-ence gaming video quality metric,” in2018 IEEE International Symposium on Multimedia (ISM).IEEE, 2018, pp. 131–134.
4. S. G¨oring, R. R. R. Rao, and A. Raake, “nofu—a lightweight no-reference pixel based video qualitymodel for gaming content,” in2019 Eleventh International Conference on Quality of MultimediaExperience (QoMEX). IEEE, 2019, pp. 1–6.
5. N. Barman, E. Jammeh, S. A. Ghorashi, and M. G. Martini, “No-reference video quality estimationbased on machine learning for passive gaming video streaming applications,”IEEE Access, vol. 7,pp. 74 511–74 527, 2019

Thank You !!