Deep-BVQM: A Deep-learning Bitstream-based Video Quality Model

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Outline

- Introduction
- Motivation
- Deep-BVQM
    - Frame level
    - Video level
- Performance Analysis
- Video Quality Prediction Pipeline
- Discussion
- Conclusion

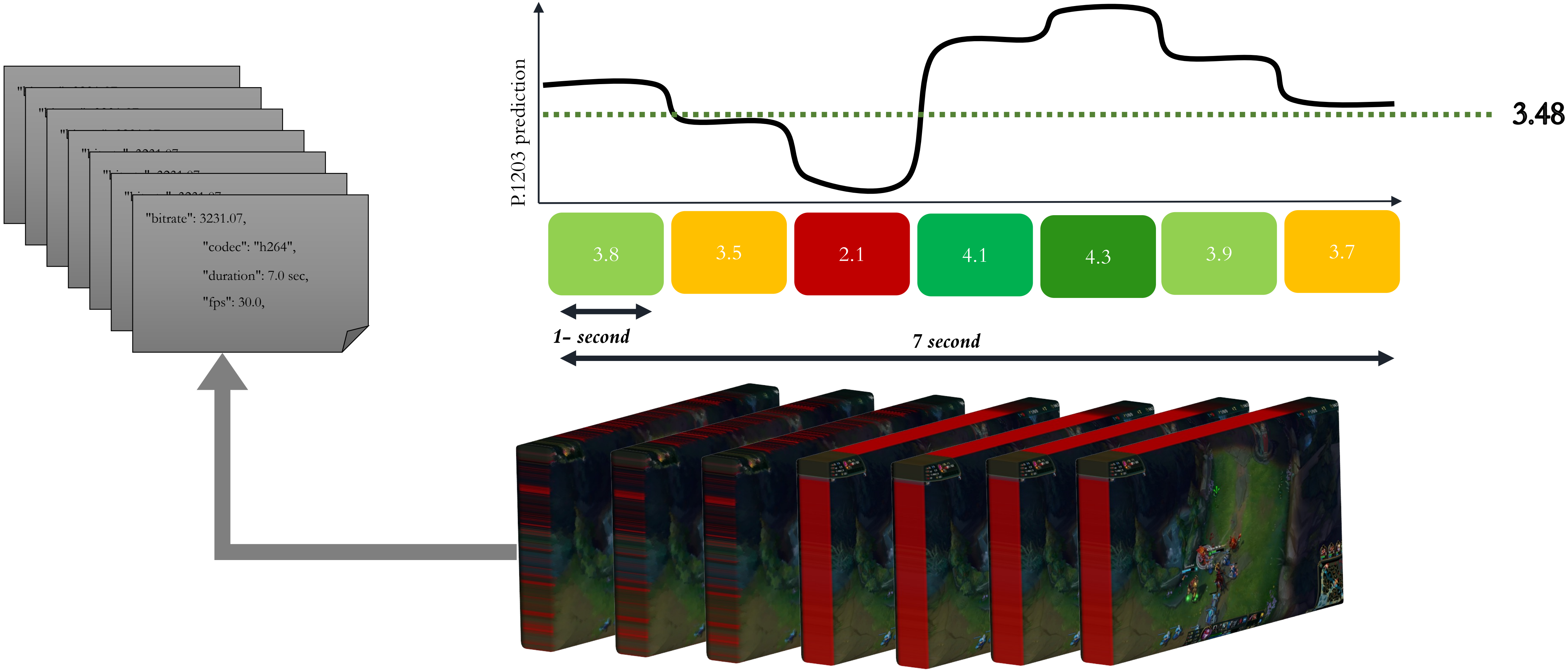
Introduction

- Video Quality
- Video Quality Assessment (VQA)
- Types of VQA methods
  - Subjective quality assessment
  - pseudo-objective models
    - planning models
    - bitstream-based models
    - signal-based models

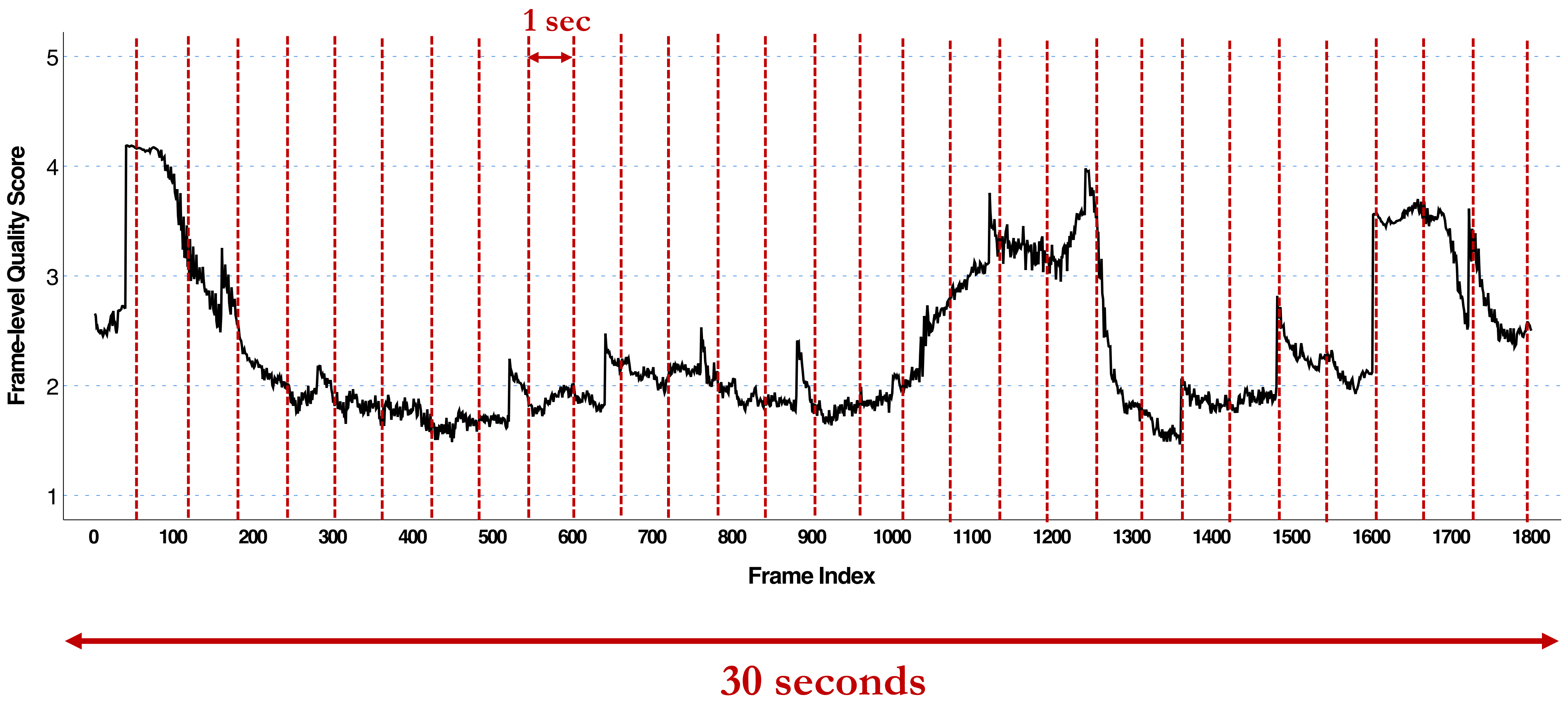
Motivation

- Bitstream-based models are simple, accurate and good choice for monitoring models.
- Each bitstream model takes a few years to be developed.
- Require collecting massive subjective tests.
- Any codec updates requires development of a new model.
- They predict the quality at minimum 1 second not at frame-level.

P.120X Quality Prediction



Quality variation in gaming video



"Deep-BVQM has been developed at two levels:

- Frame Level
  - Using CNN
- Video Level
  - Using LSTM

Deep-BVQM (frame-level)

- Take 89 x 89 patches from the QP values.
- Train a CNN model
  - Deep model
  - Simple model
- Use VMAF classes for training

[0-20]	→	[0-17]
[20-40]		[23-37]
[40-60]		[43-57]
[60-80]		[63-77]
[80 -100]		[83 -100]

Deep-BVQM (frame-level)(incl. CNN architecture, dataset)

Training Dataset used for frame-level module

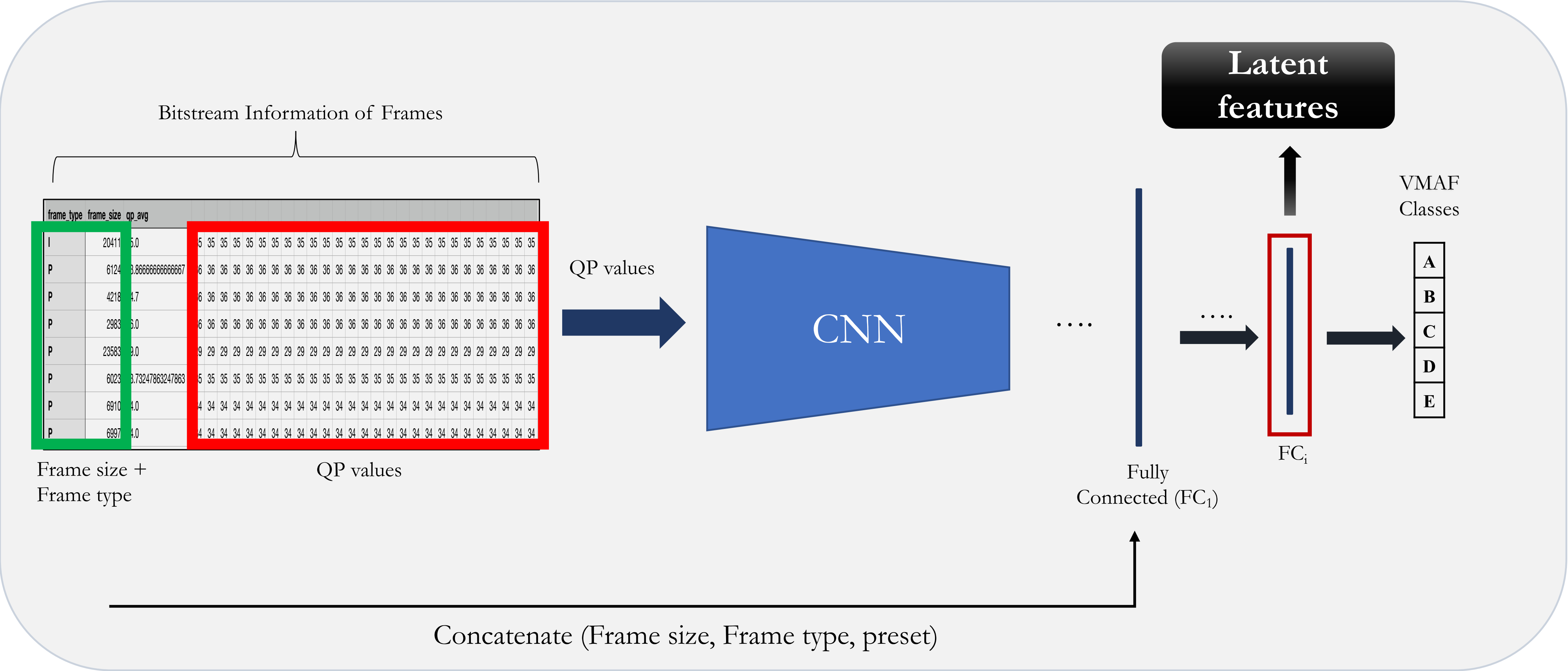
Parameters	Quantity	Values
Source videos	38 SRC	CGVDS + GVSET
Rate controller	1	CBR
Preset	3	Slow, veryfast, Llhq
Bitrate	9	300 kbps to 10 mbps
Codec	1	H.264
Resolution	1	1080p
Frame rate	1	30, 60 fps

38 x 1 x 3x 9x 1 x 1 x 1 = 1026 video files
≈ 300 k frames (training)

CNN Architecture

Layer	Output Size
Input	1x89x89
Pool	1x44x44
Conv1	16x44x44
Pool	16x22x22
Conv2	32x22x22
Conv3	64x22x22
Pool/Dropout (20%)	64x11x11
Conv4	64x11x11
Fc1	7744
Fc2	1000
Fc3	5

Deep-BVQM (frame-level)



Scheme of the model design at frame level

Extraction of bitstream information

- Using the <u>ffmpeg_debug_qp</u> to extract the bitstream information.
  - Requires pre-processing to be used for deep learning task.
- Each row conveys the information including **Frame type**, **Frame size**, **Quantization parameter (Qp) average**, and **Qp values.**

Qp values

frame_type	frame_size	qp_avg																											
I	20411	35.0	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
P	6124	33.8666666666667	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36
P	4218	34.7	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36
P	2983	36.0	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36
P	23583	29.0	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29
P	6023	33.73247863247863	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35
P	6910	34.0	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
P	6997	34.0	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34

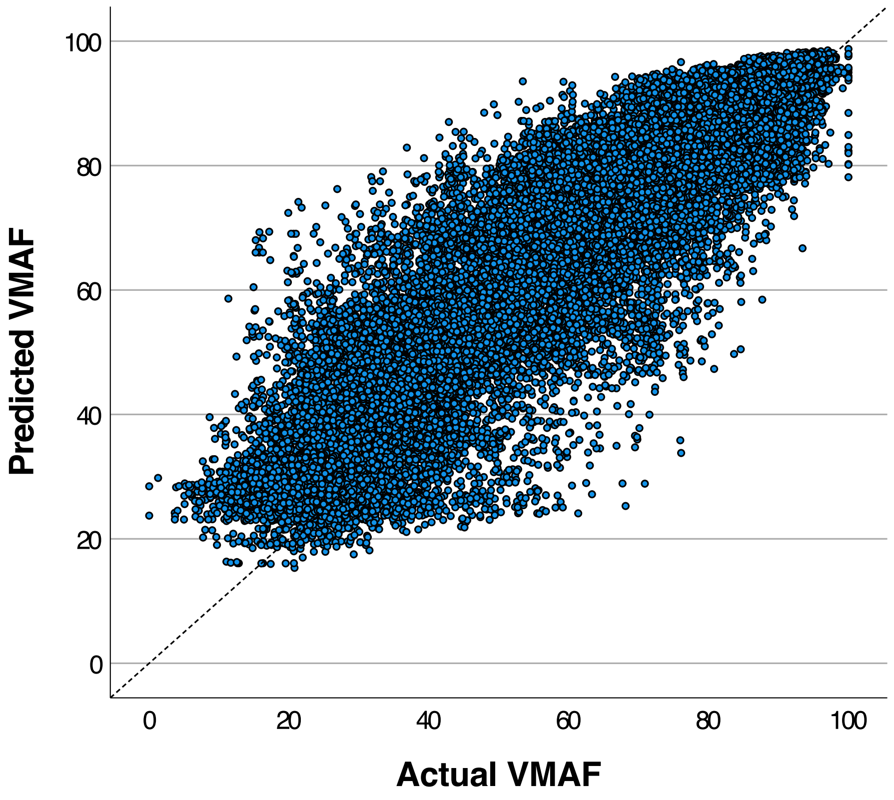
Bitstream Information of Frames

Results on validation set – frame level (1)

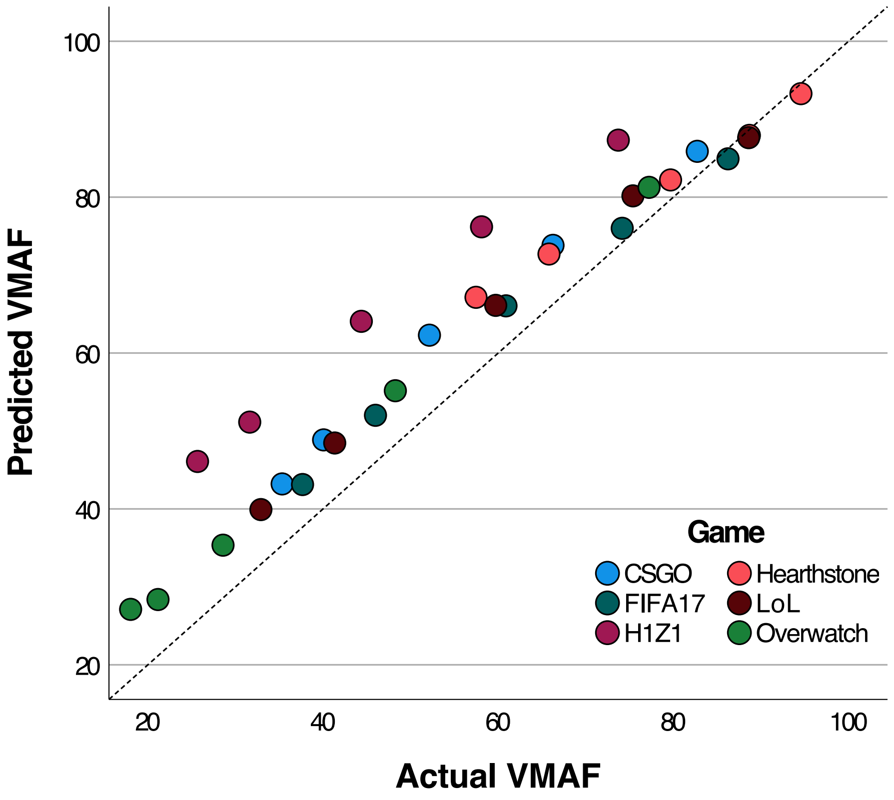
- *Use a Random Forest model to see how well the latent features are trained.*

PLCC = 0.97
RMSE = 0.33

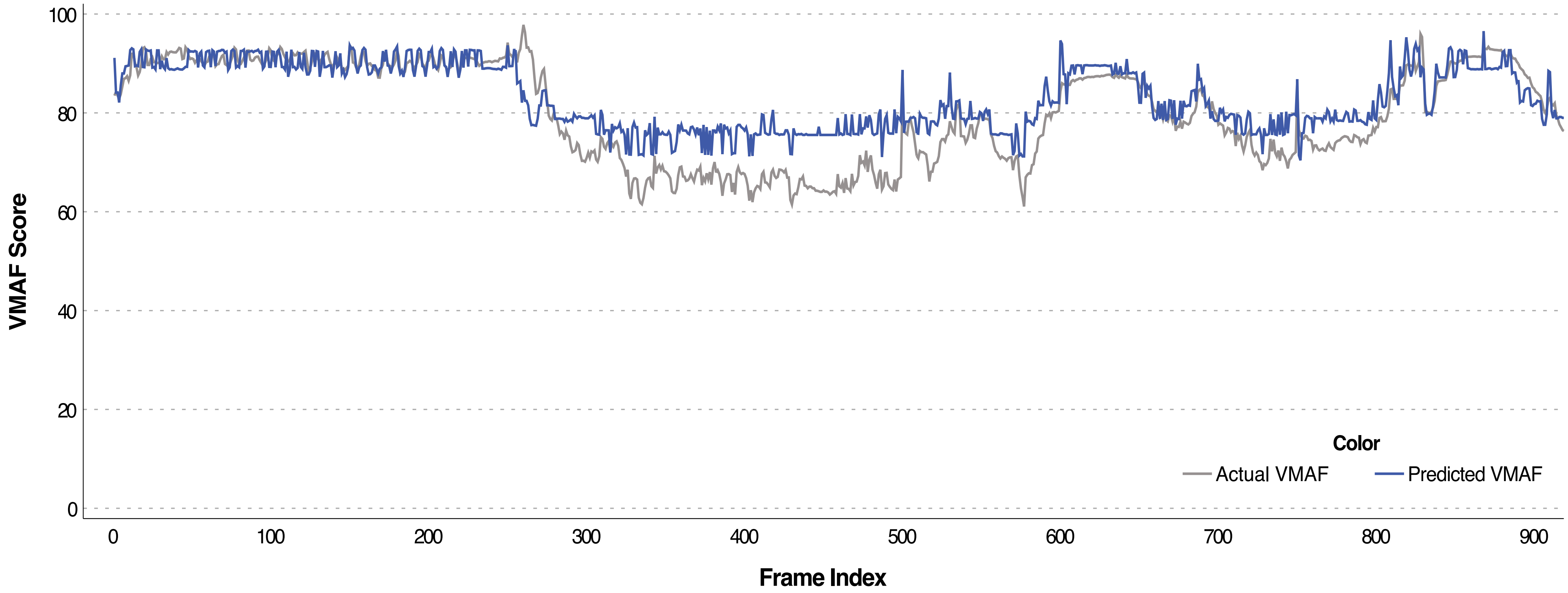
Per frame



Per video



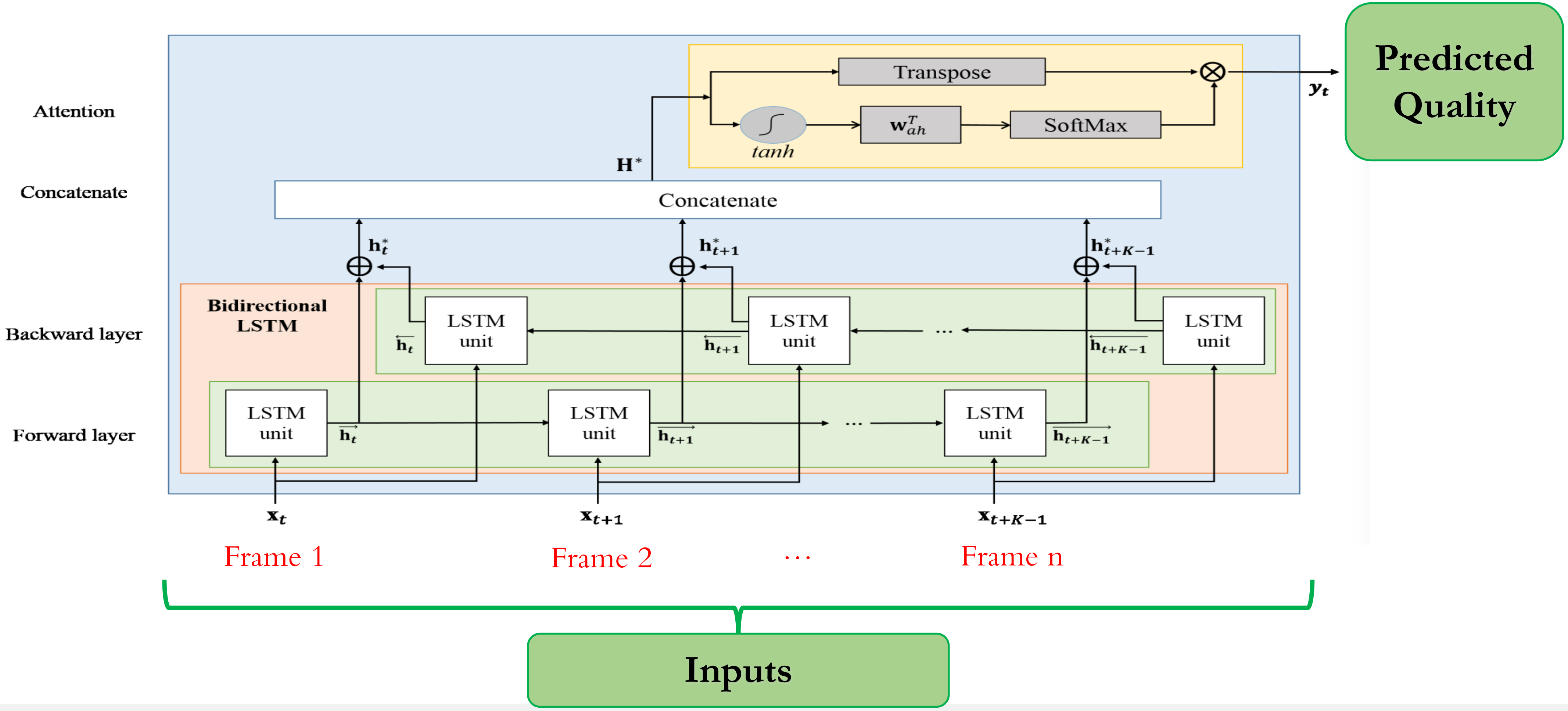
Results on validation set – frame level (2)



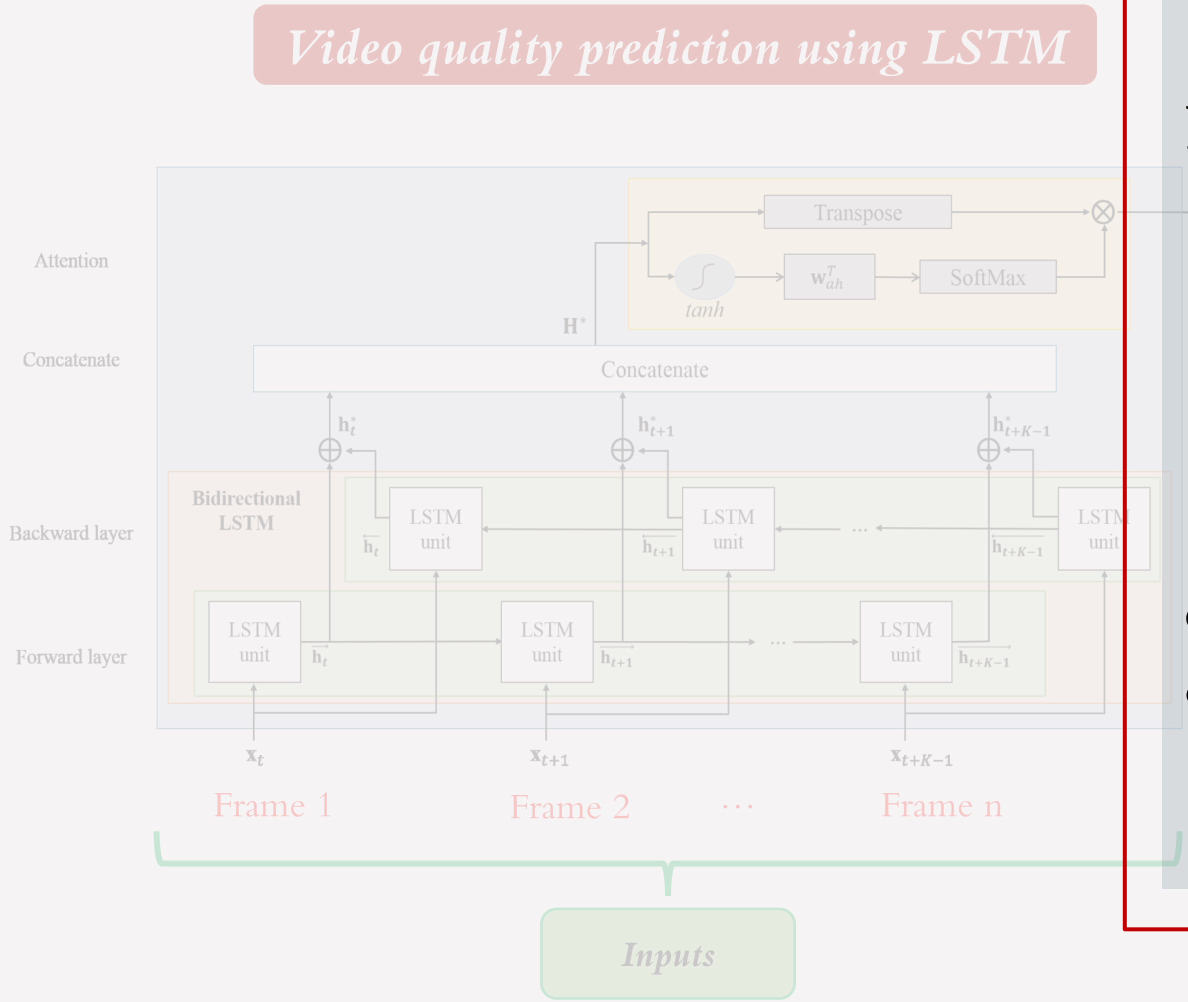
Comparison of predicted VMAF, blue line, vs actual VMAF scores, grey line, over 900 frame.

Deep-BVQM (video-level)

Video quality prediction using LSTM



Deep-BVQM (video-level)



Properties of LSTM network:

- Input window: 15 frames taken from 1 sec duration
- Each frame vector: 8 features
 [5 Latent features, Frame type, Frame size, Preset]
- Training based on a small dataset of
900 input windows (≈13’500 frame vectors) and validated on unknown datasets to the model.
- Ground truth: MOS values

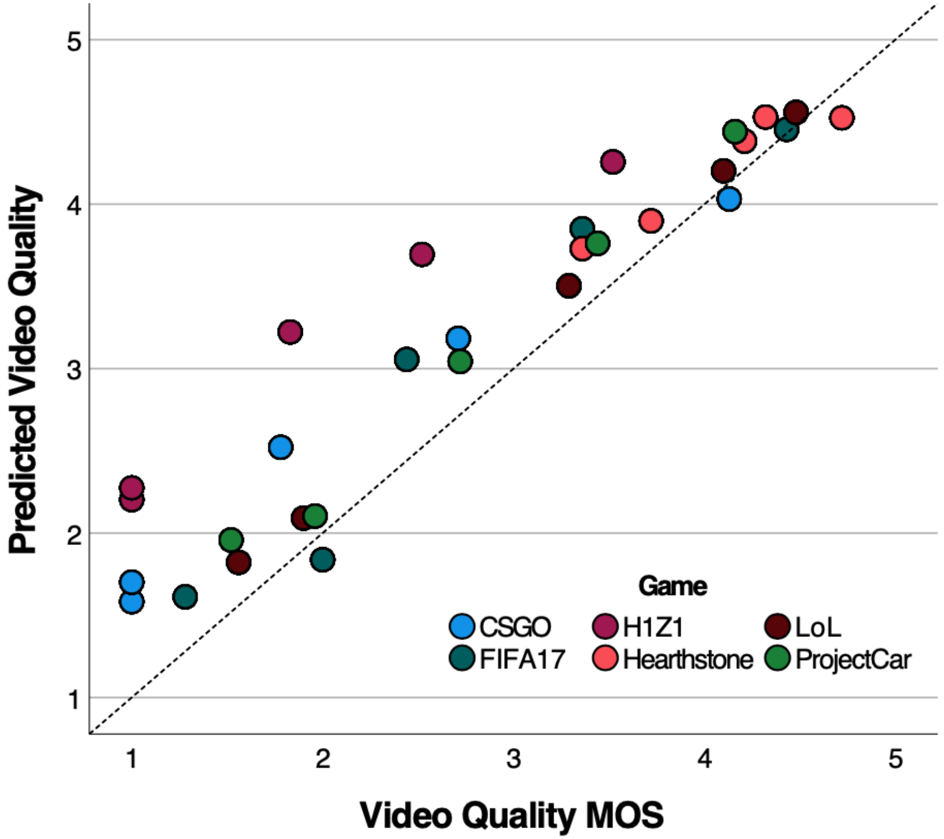
Deep-BVQM (video-level)(incl. LSTM architecture)

Video quality prediction using LSTM

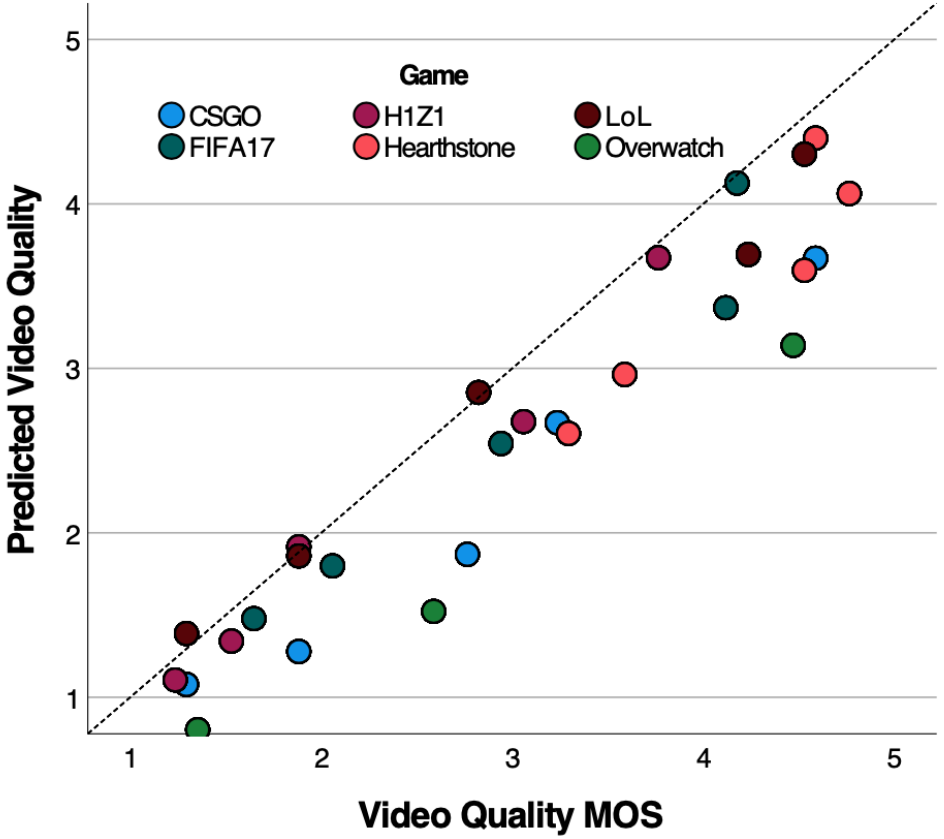
LSTM Architecture

Layer	Output Shape	Parameters
Input	1 x 15 x 8	0
$LSTM_1$	(None, 15, 64)	18688
$LSTM_2$	(None, 15, 32)	12416
$LSTM_3$	(None, 15, 32)	8320
$LSTM_4$	(None, 16)	3136
Dropout	(None, 16)	0
Dense	(None, 17)	17
Total trainable params: 42,577		

Performance on two gaming datasets – video level



GVSET Dataset



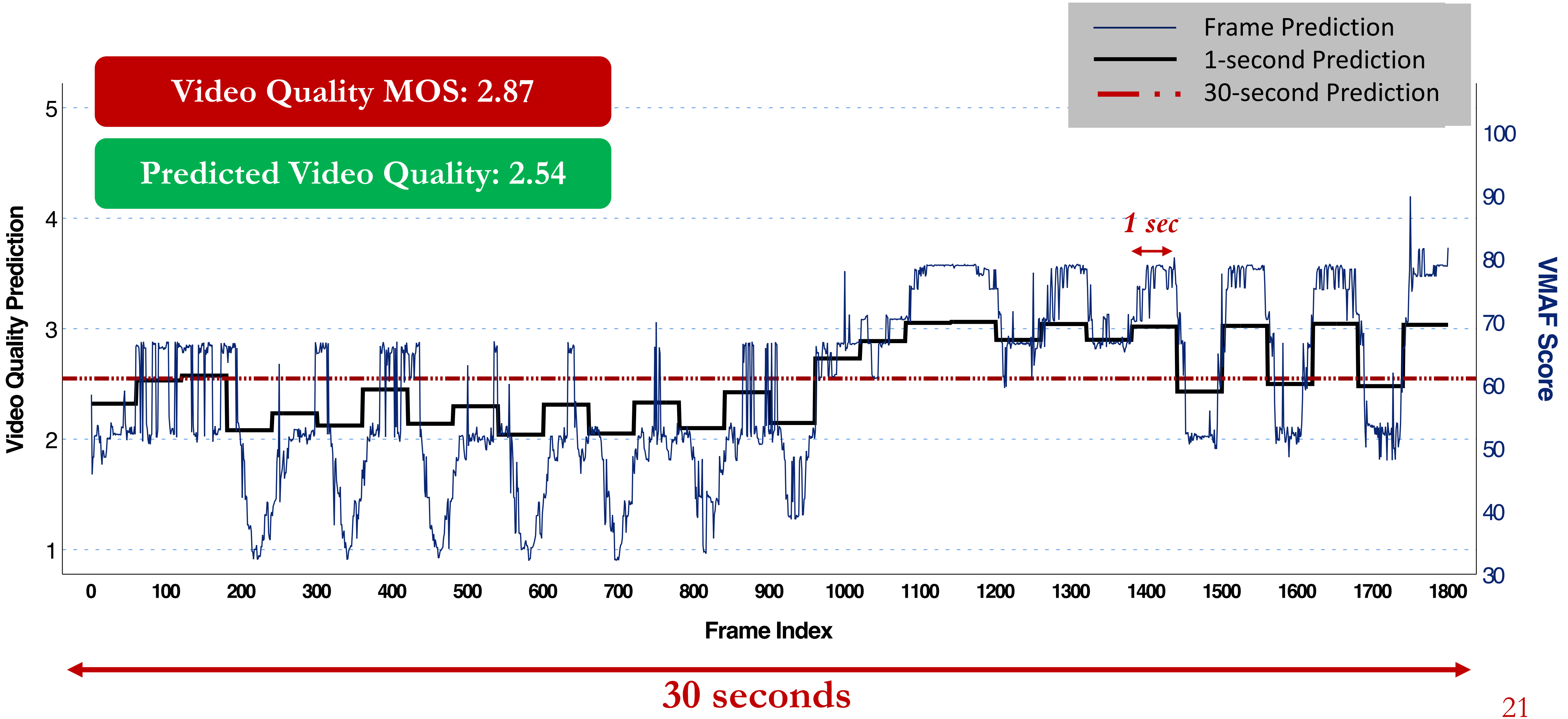
KUGVD Dataset

Performance of bitstream-based models

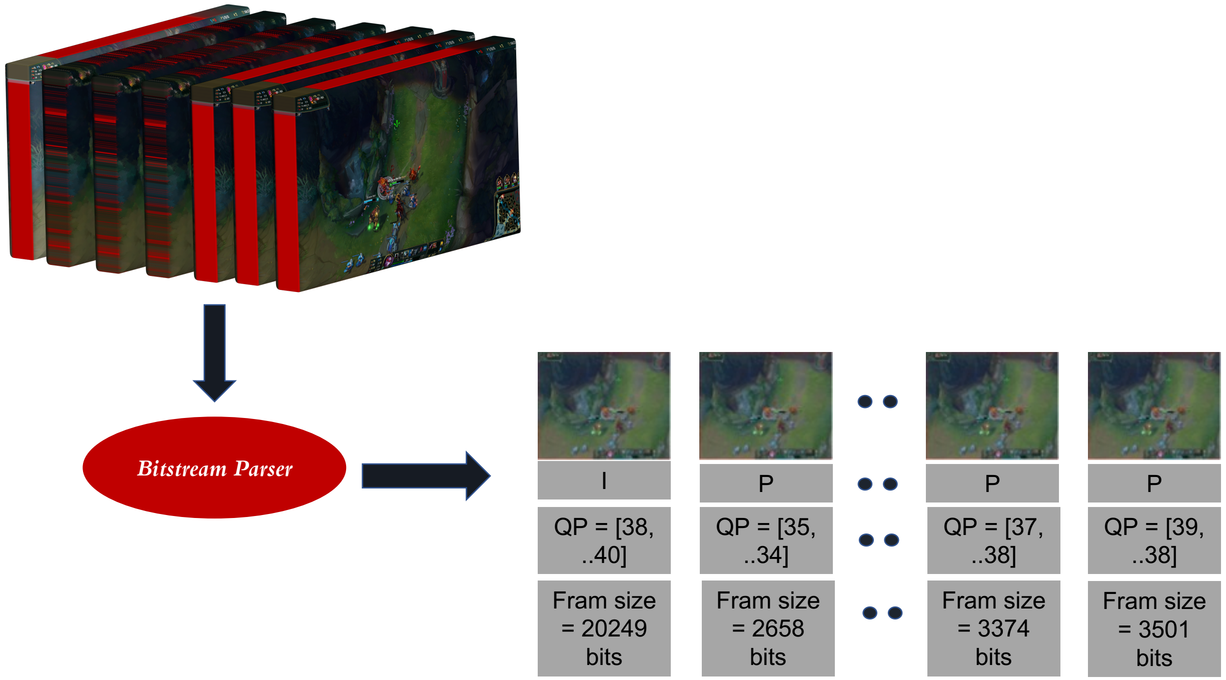
Dataset		*P.1203 m1*	*P.1203 m3*	*P.1204.3*	*BQGV*	*Proposed Model*
GVSET	PLCC	0.67	0.91	0.92	0.68	***0.95***
	RMSE	1.53	0.86	0.53	0.98	***0.36***
KUGVD	PLCC	0.65	0.92	0.96	0.74	***0.96***
	RMSE	1.45	0.59	0.41	0.87	***0.32***
CGVDS	PLCC	0.80	0.86	0.83	0.88	***0.96***
	RMSE	0.70	0.49	0.52	0.40	***0.24***

Performance of bitstream-based models on all three gaming dataset, only at 1080p resolution.

Model Prediction

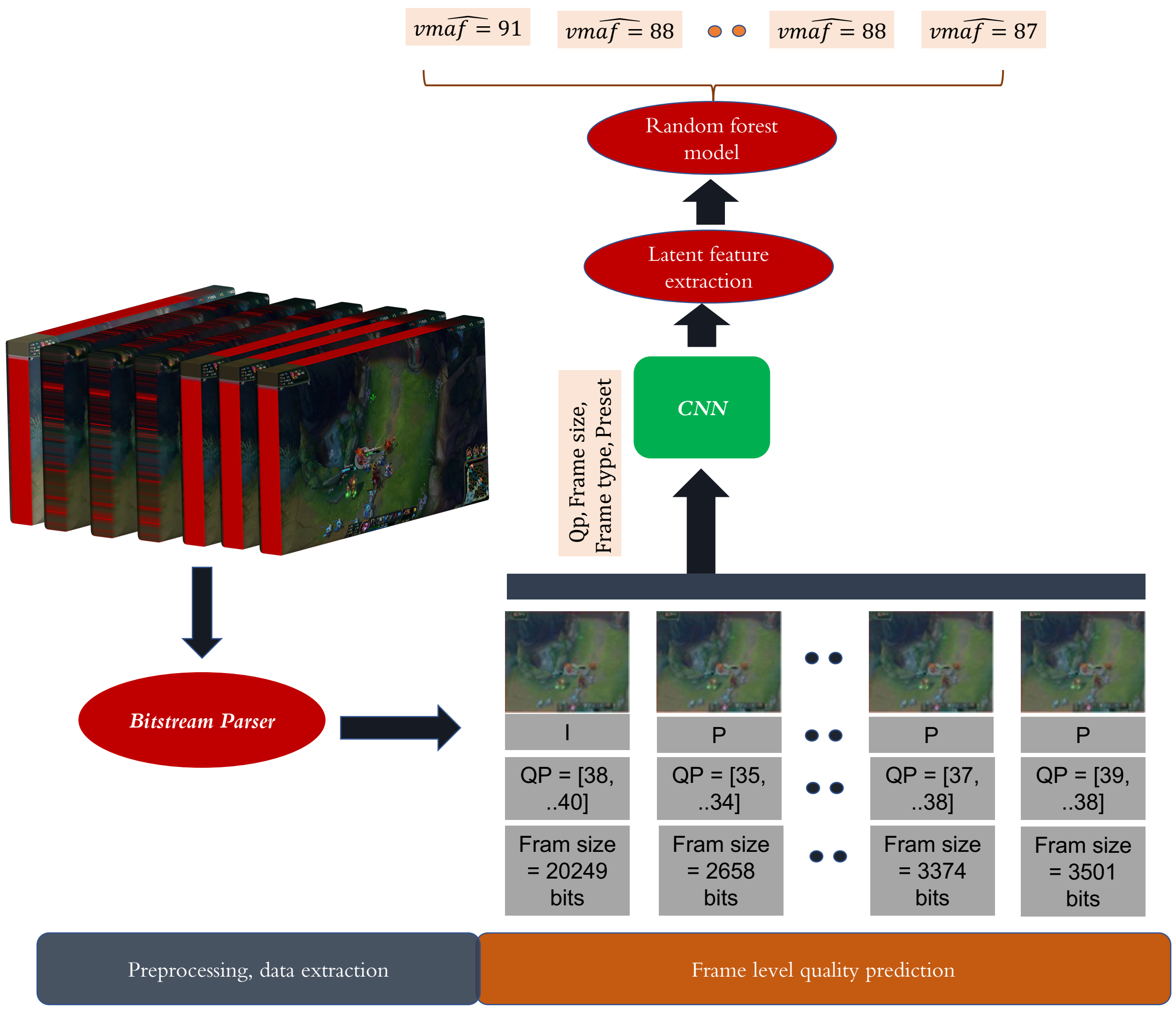


Video Quality Prediction Pipeline (Pre-processing, data extraction)

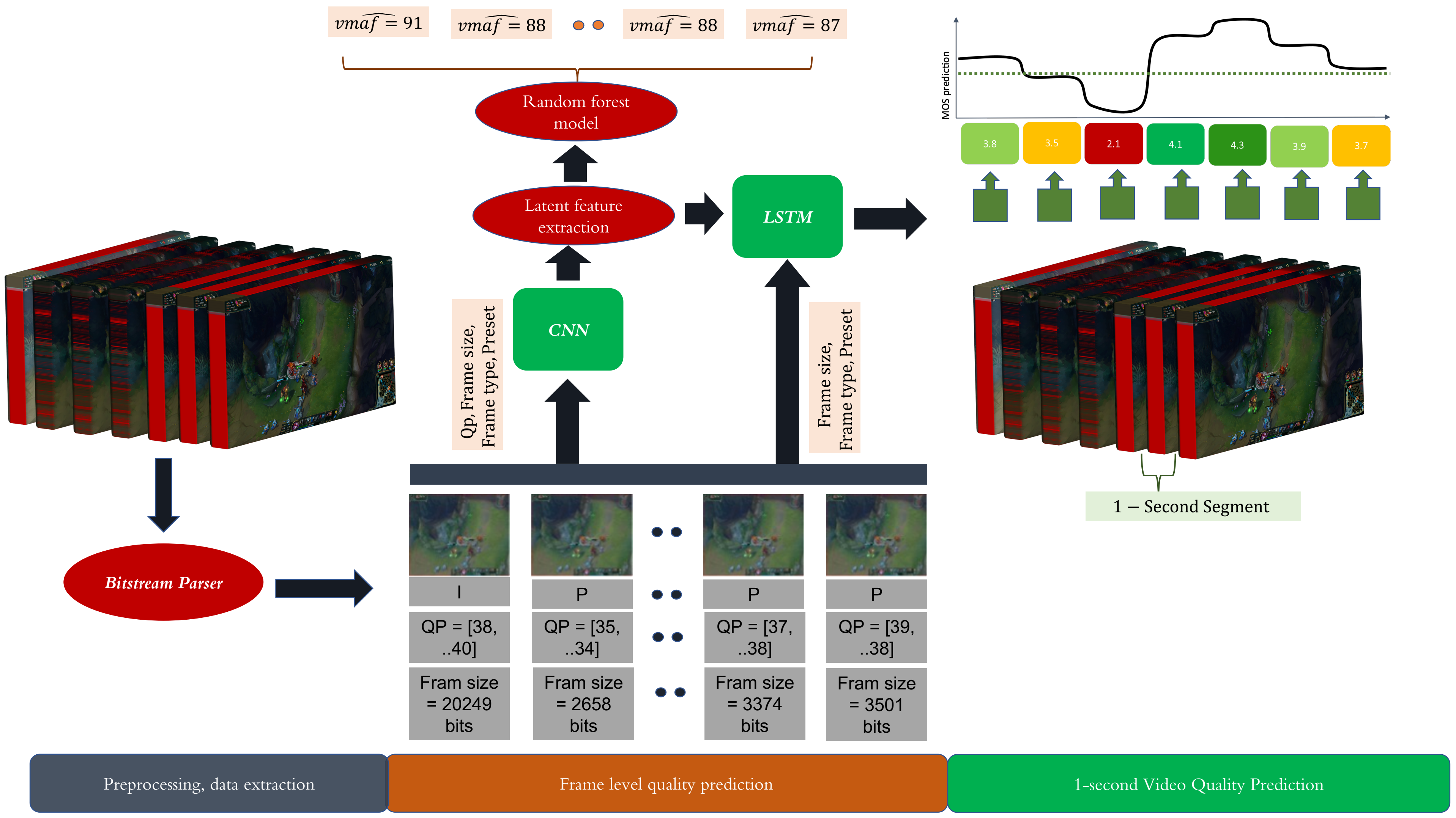


Preprocessing, data extraction

Video Quality Prediction Pipeline (at frame level)



Video Quality Prediction Pipeline (in 1-sec duration)



Discussion

- ***Future Extension***

  - Extend the codec type ➡ select a constant block size.
  - Extend the resolution ranges
    - development of multiple models for different resolutions.
    - rescaling the input to 89 × 89 that is used for 1080p resolution.
    - upscaling 720p ➡ PLCC = 0.92 , RMSE = 0.49

- ***Capability to predict non-gaming content***

  - Used a dataset with 2160p (4k)resolution and different encoding setting
    ➡ PLCC = 0.74, RMSE = 0.67

- ***Computational Complexity***

  - Less than 1 second on GPU

Conclusion

**Deep-BVQM
is a bitstream-based model
which…**

- is capable to predict at the frame level.
- is developed for gaming encoding setting.
- simplifies the model extension and expansion.
- is a lightweight prediction method.

Thanks!

Any questions?

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