

July 2022



# PATCH-BASED END-TO-END IMAGE LEARNED CODECS USING OVERLAPPING

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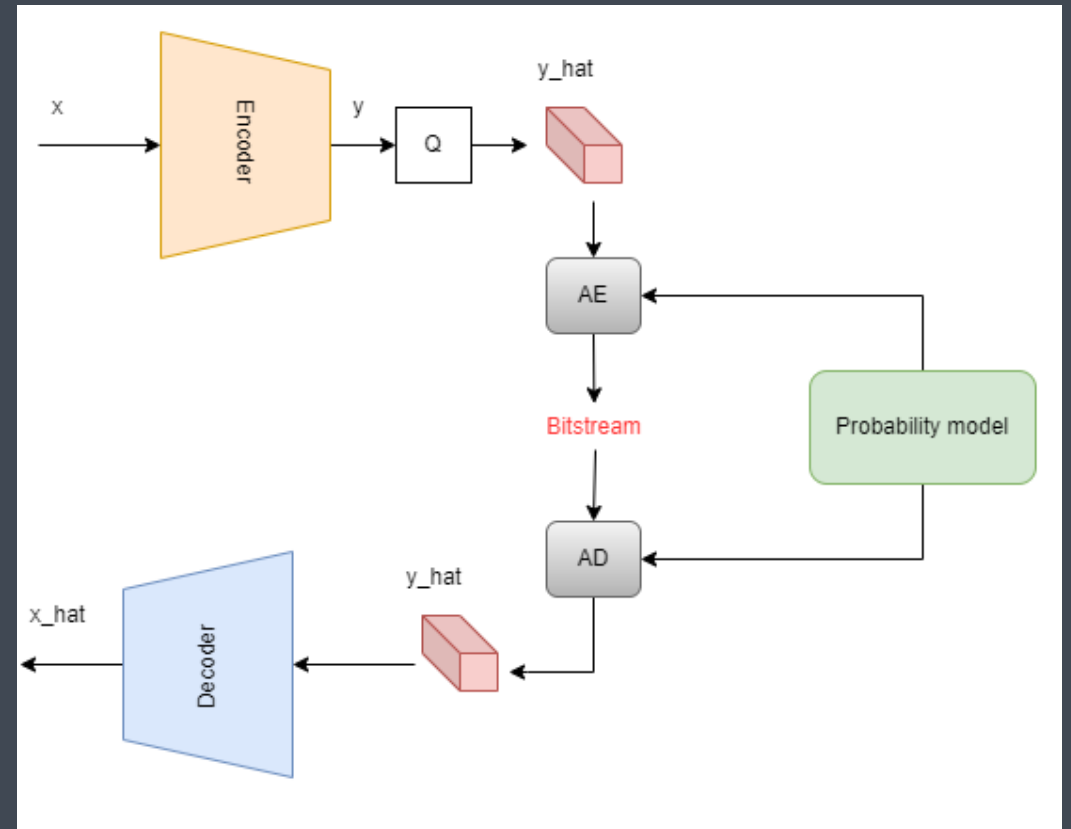
# OUTLINE

1. End-to-end Learned image codecs
2. Patch-based End-to-end image learned codecs using Overlapping
3. Results
4. Conclusion

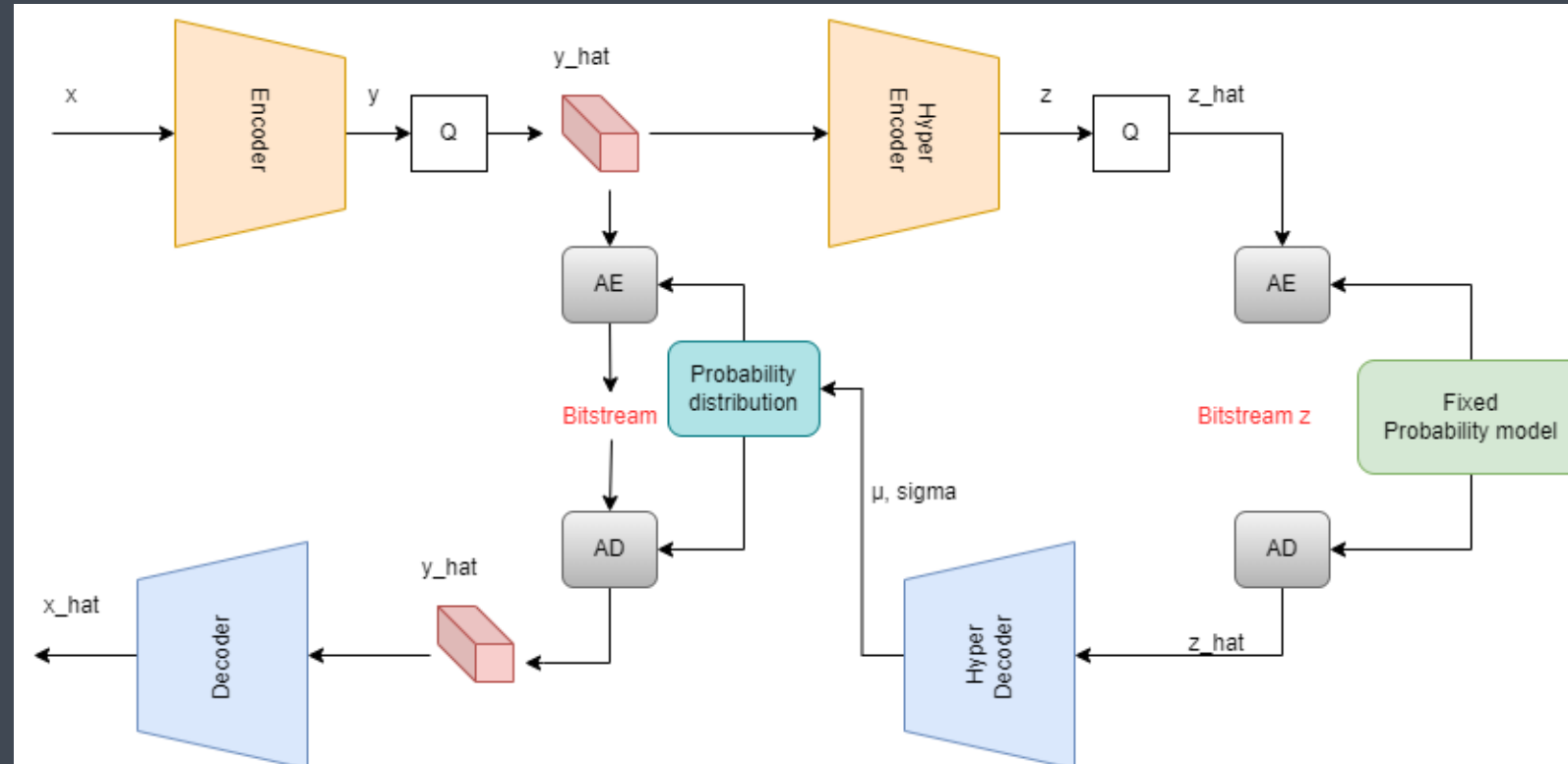


# END-TO-END IMAGE LEARNED CODECS

- End-to-end image learned codecs based on auto-encoder architecture
- Encoder : Transform the input image  $x$  to a latent representation  $y$
- Probability model : Estimation the probability distribution of the latent representation
- Decoder : Reconstruct the input image from the latent representation

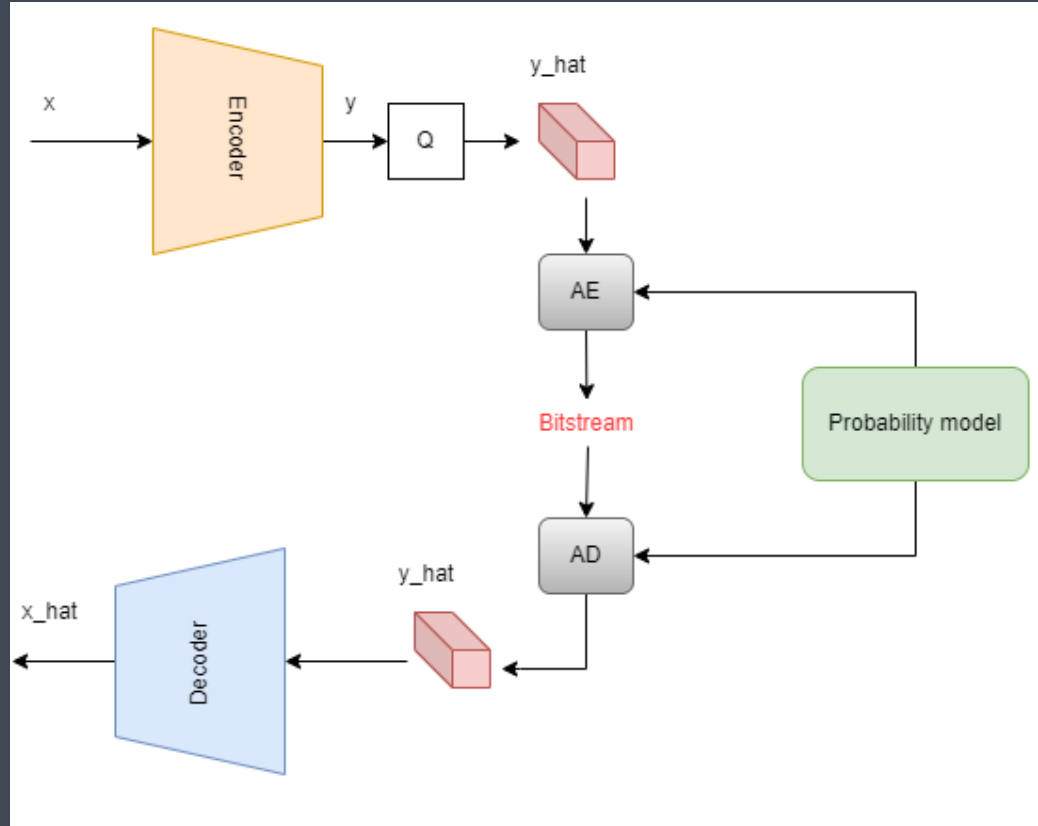


# END-TO-END IMAGE LEARNED CODECS



[1] J. Balle, D. Minnen, S. Singh, and N. Johnston S.J Hwan,  
“Variational image compression with a scale hyper-prior,” ICLR 2018 - Conference Track Proceedings, 2018.

# END-TO-END IMAGE LEARNED CODECS : LIMITATIONS

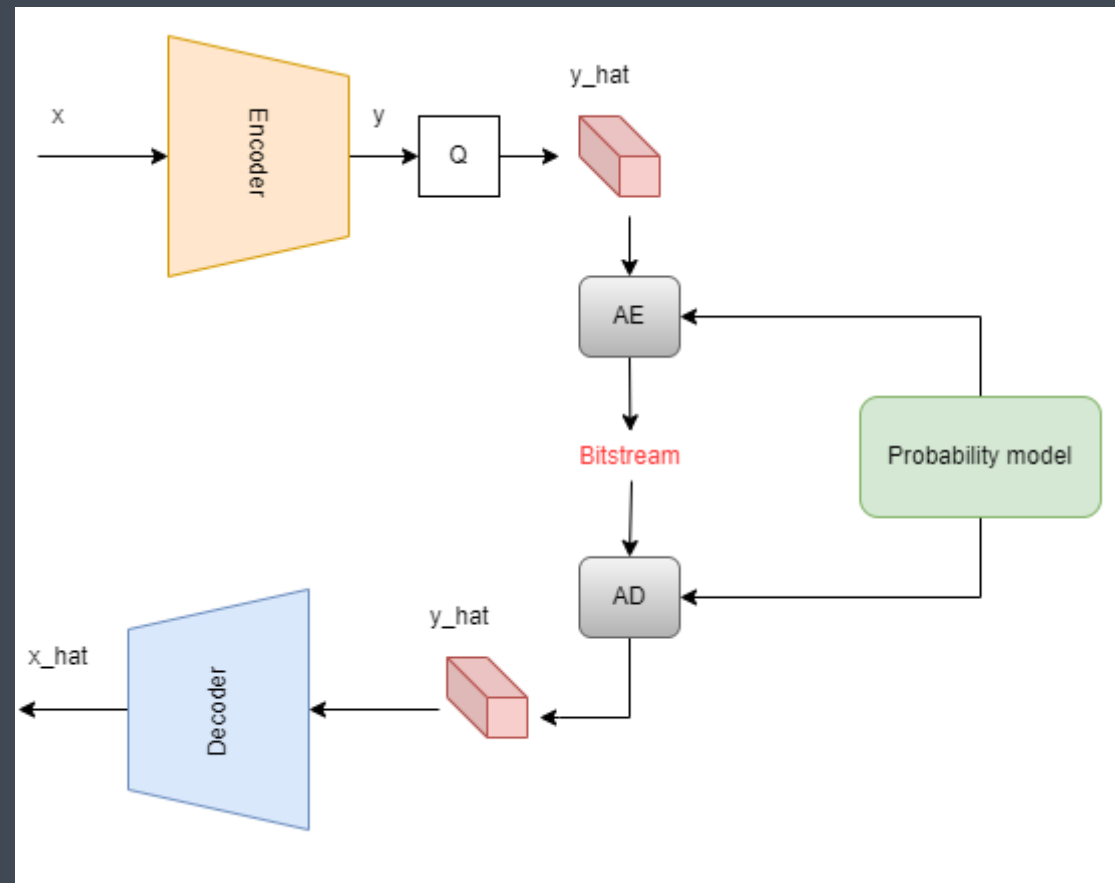
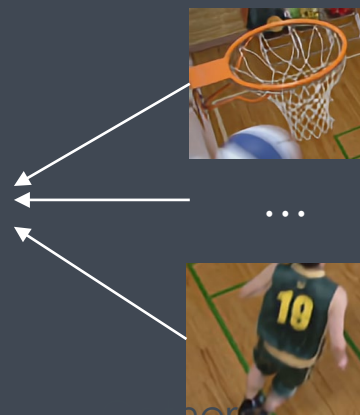
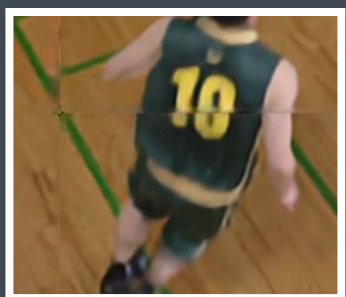
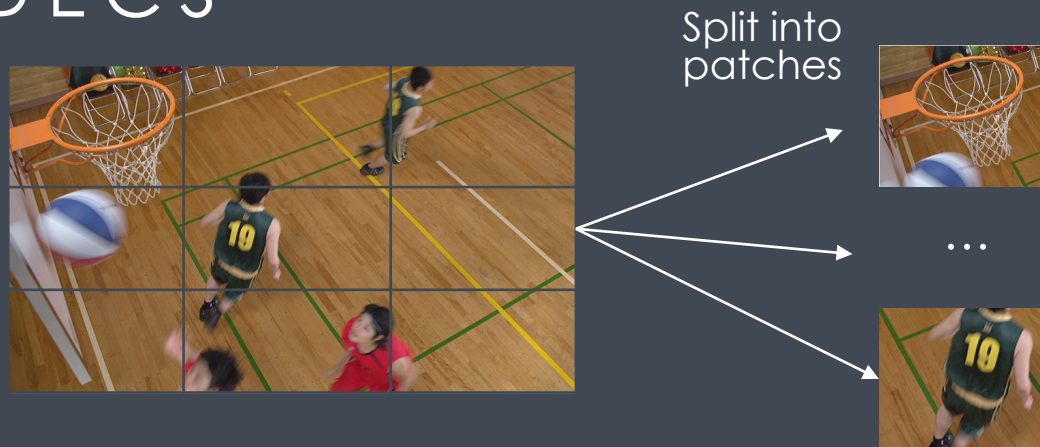


Architecture allows multi-resolution image coding.

➔ Hardware limitation (memory saturation) for big resolutions

➔ Ex : OOM error for coding HD Image on GPU 2080ti with 11Go

# PATCH-BASED END-TO-END IMAGE LEARNED CODECS



**Border artifacts**

# PATCH-BASED END-TO-END IMAGE LEARNED CODECS USING OVERLAPPING

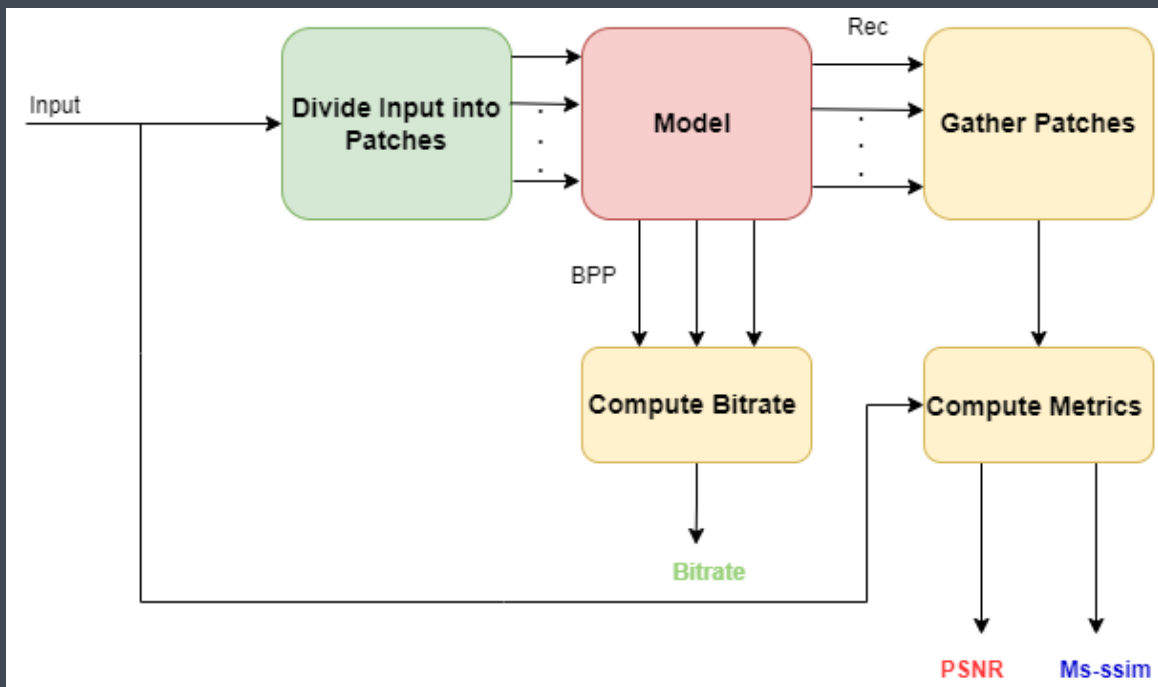
## Goal

- > Benefit from the advantages of patch-based solutions to address the hardware limitation
- > Eliminate Border artifacts from the decoded images

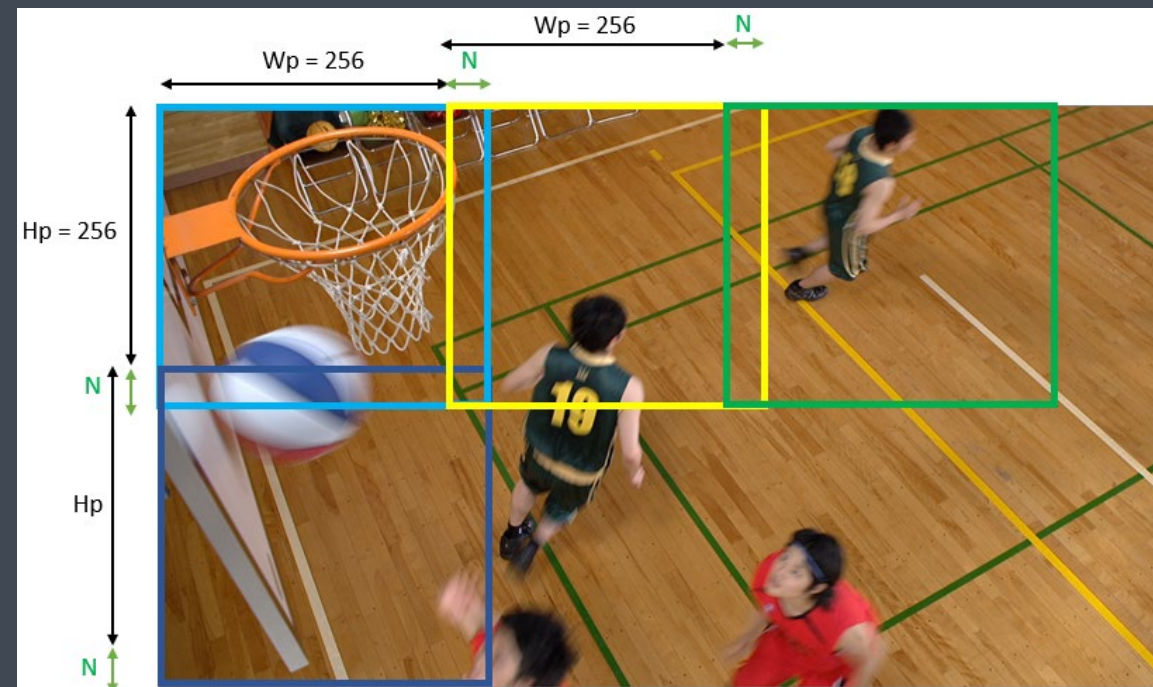
## Contribution

- > Patch-based end-to-end learned image codec using overlapping method
- > The proposed method is compatible with any learned codec based on an auto-encoder architecture

# PATCH-BASED END-TO-END IMAGE LEARNED CODECS USING OVERLAPPING



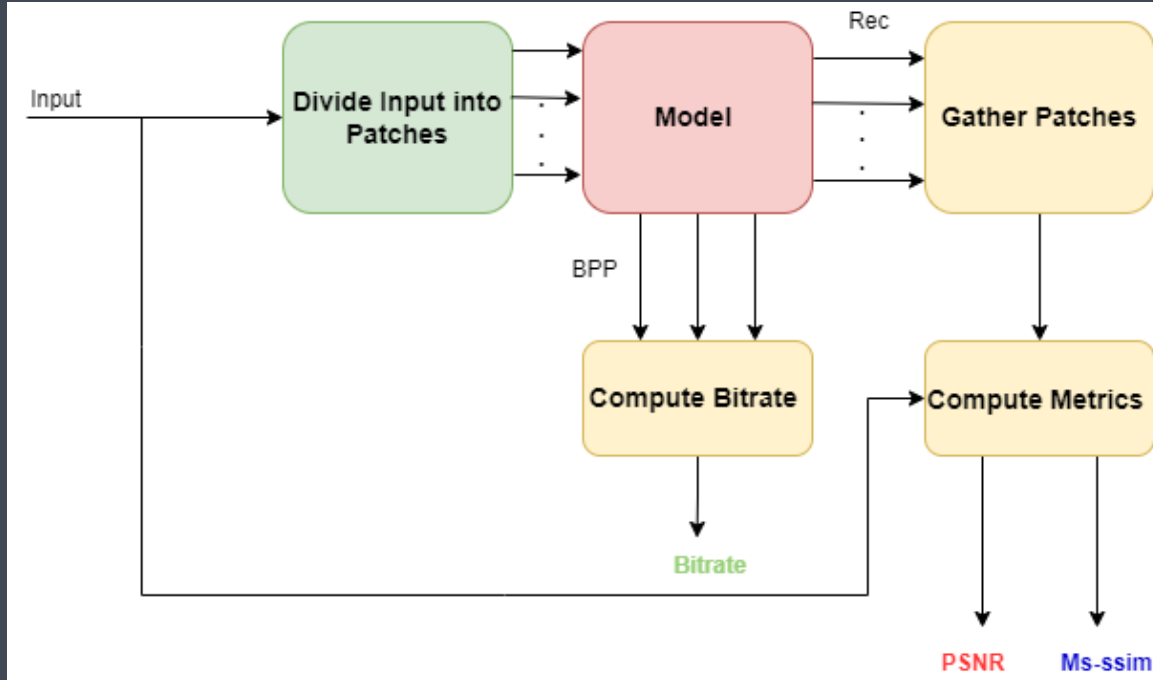
Steps to patch-based image coding



Divide into patches



# PATCH-BASED END-TO-END IMAGE LEARNED CODECS USING OVERLAPPING



## Steps to patch-based image coding

[2] Z. Cheng, H. Sun, M. Takeuchi, and J. Katto, "Learned image compression with discretized gaussian mixture likelihoods and attention modules," Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 7936–7945, 2020.

> End-to-end model is an implementation of cheng 2020 [2].

> Training process :

> Dataset : Clic 2020

> Training resolution : 256x256

> Total number of steps 500 000

> Loss function :

$$J = D + \lambda R$$

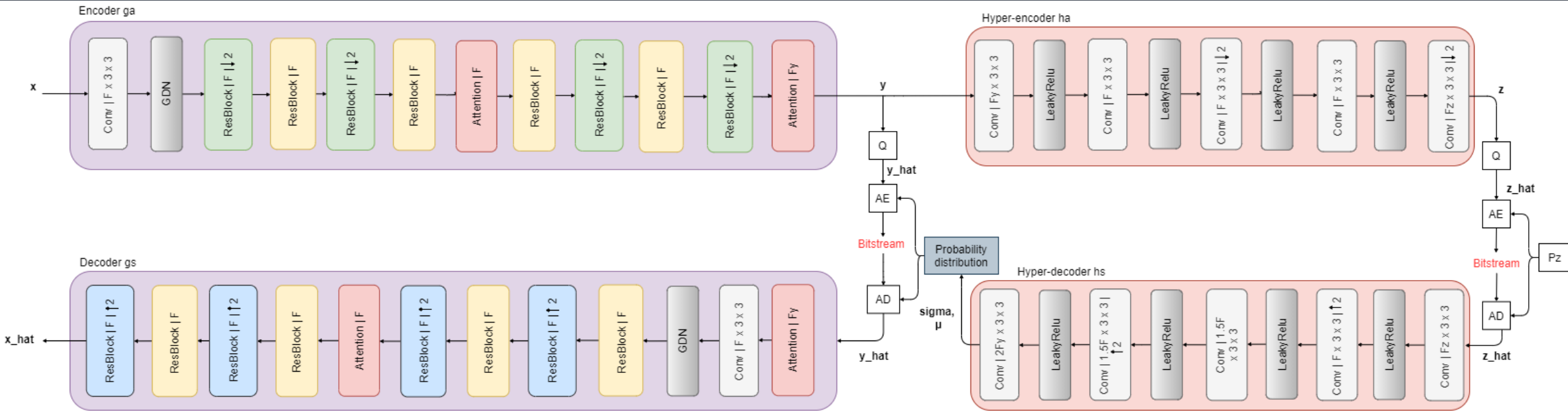
>  $D$  : distortion measured By MSE or MS-SSIM

>  $R$  : rate used to transmit the bitstream, estimated using the shannon entropy

>  $\lambda$  Lagrangian multipliers

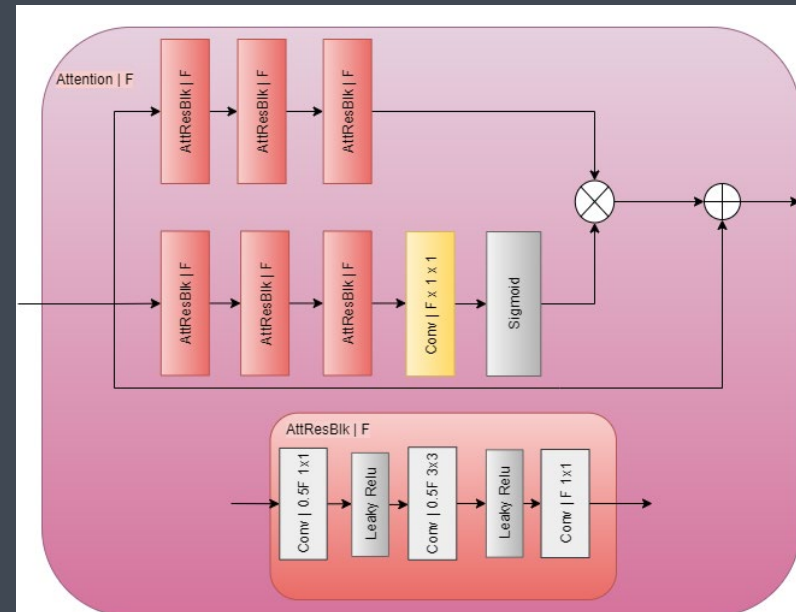
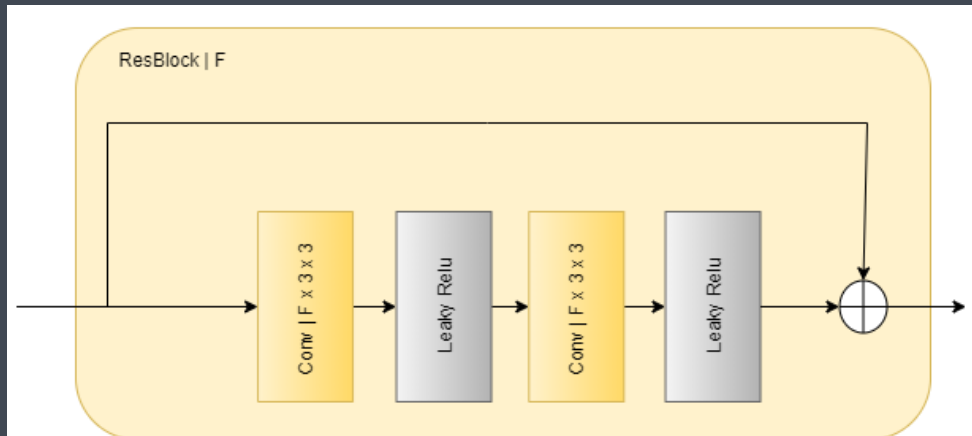
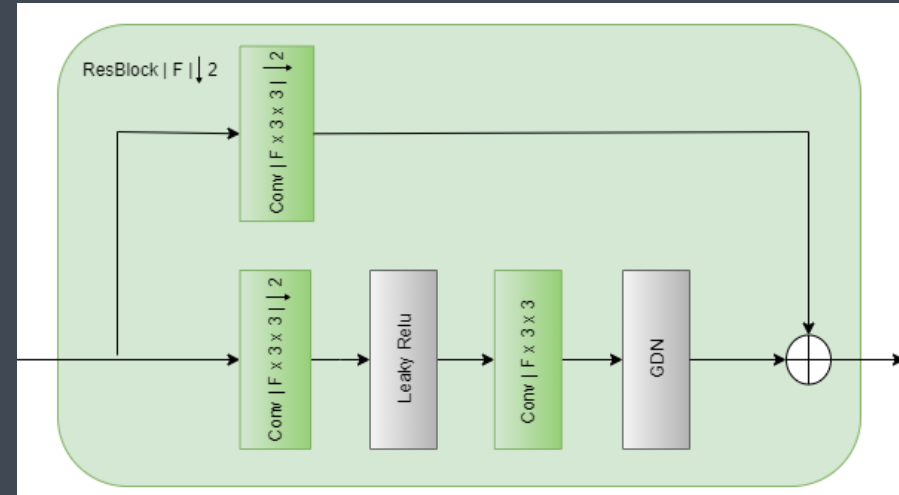
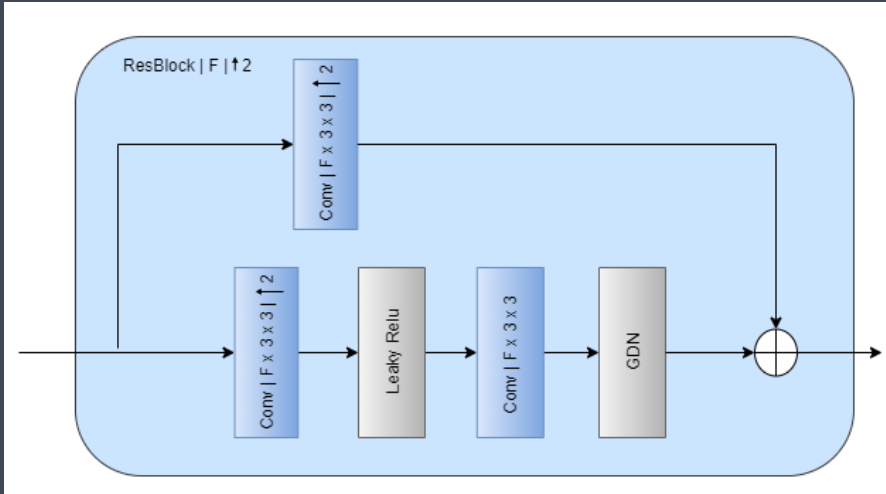
Model

# END-TO-END MODEL ARCHITECTURE

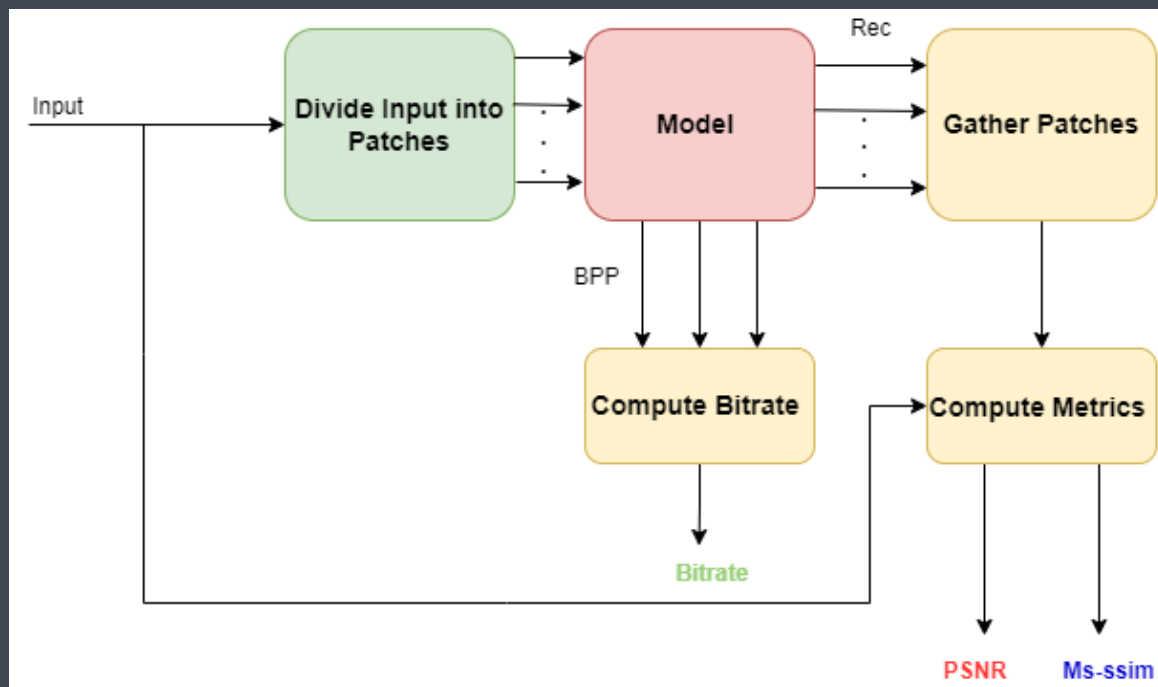


[2] Z. Cheng, H. Sun, M. Takeuchi, and J. Katto, "Learned image compression with discretized gaussian mixture likelihoods and attention modules," Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 7936–7945, 2020.

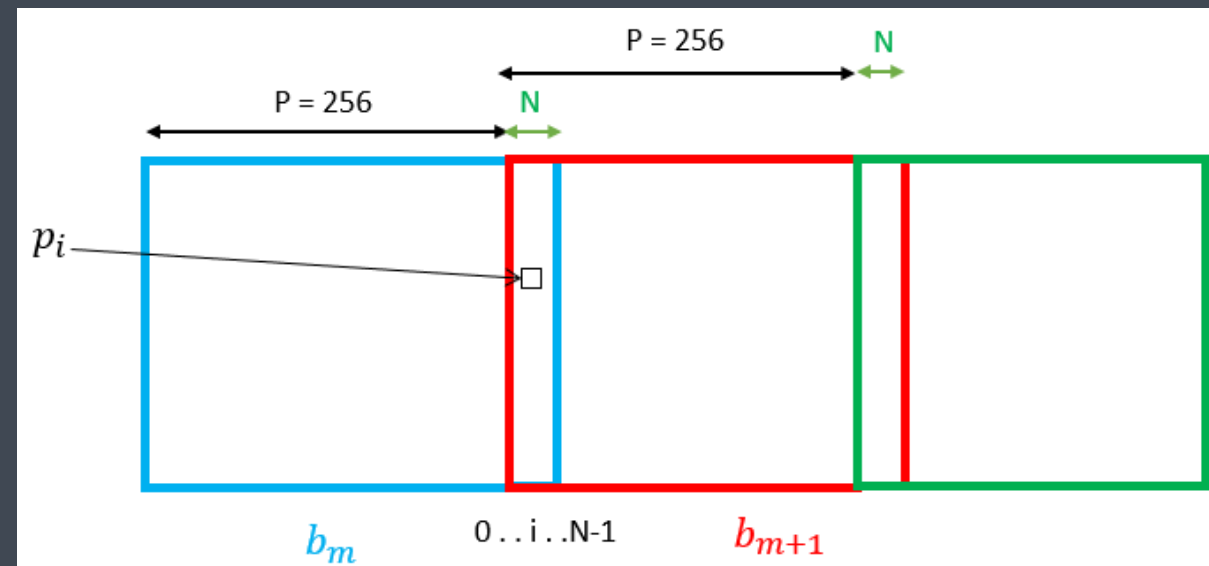
# END-TO-END MODEL ARCHITECTURE



# PATCH-BASED END-TO-END IMAGE LEARNED CODECS USING OVERLAPPING



Steps to patch-based image coding



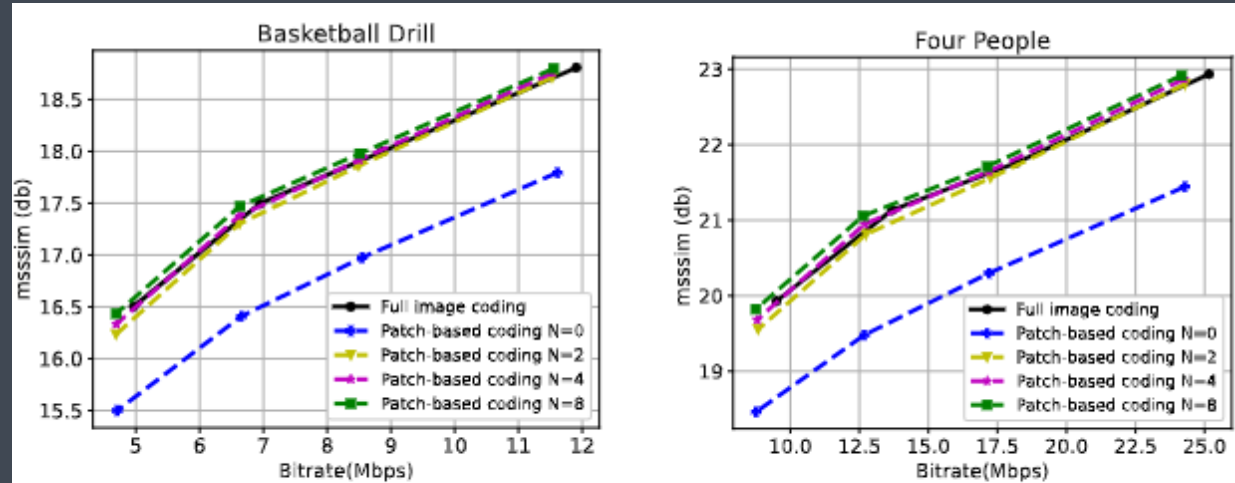
$$p_i = \left(1 - \frac{i}{N-1}\right)p_{b_m}(P+i) + \left(\frac{i}{N-1}\right)p_{b_{m+1}}(i)$$

Gathering patches

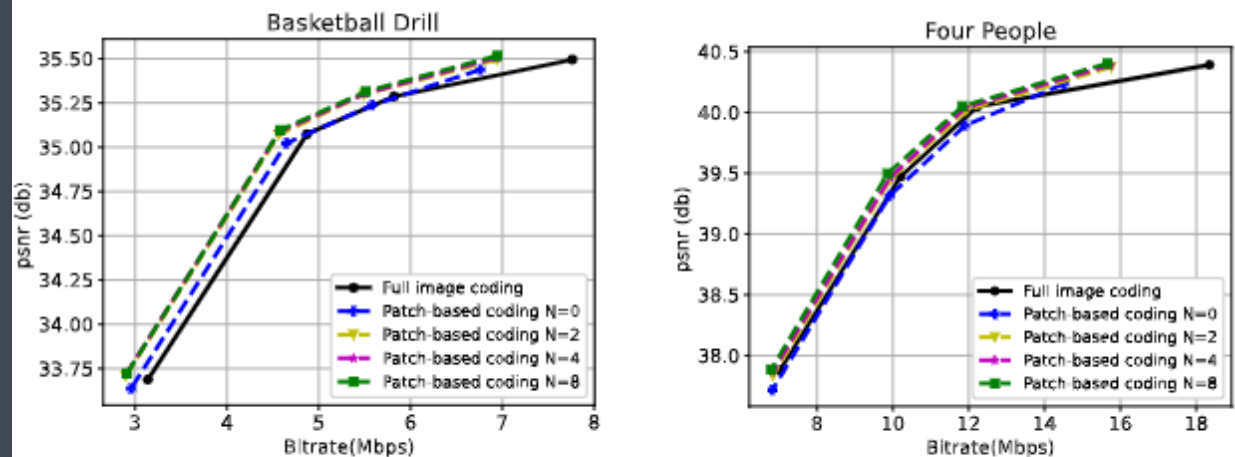
# EVALUATION PROCESS

- > Models : Eight models were trained. 4 for each quality metric (MSE and MS-SSIM) .
  - > Metric MSE :  $\lambda = \{4096, 3140, 2048, 1024\}$
  - > Metric MS-SSIM :  $\lambda = \{420, 220, 120, 64\}$
- > Evaluation Sequences : Frame extracted from JVET Common Test Condition (CTC).
- > Frame is compressed in :
  - > Full resolution
  - > Per patch without overlapping
  - > Per patch with overlapping  $N \in \{2, 4, 8, 16, 32\}$

# RESULTS

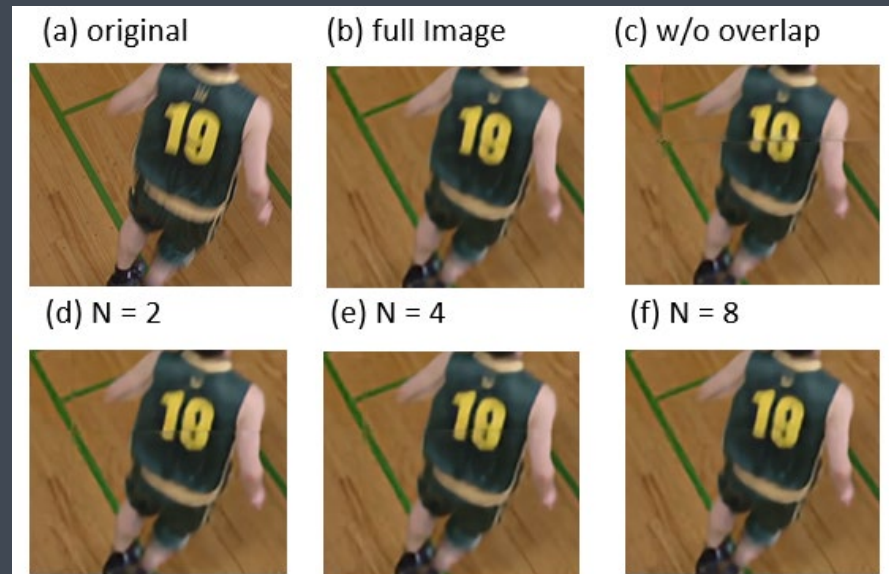


(a) MS-SSIM Rate-Distortion results

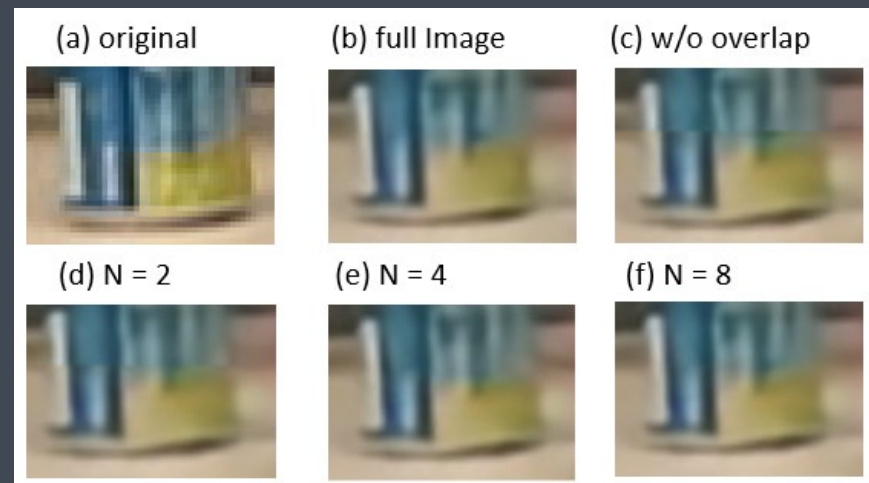


(b) PSNR Rate-Distortion results

## Rate-distorsion Results



## Visual results for MS-SSIM models



## Visual results for MSE models

# RESULTS

BD-rate (MS-SSIM) gains of patch-based coding schemes compared to full resolution coding system for CTC sequences.

	Patch w/o Overlapping	Patch with Overlapping				
		N = 2	N = 4	N = 8	N = 16	N = 32
Class B	0.649	0.029	-0.009	-0.046	-0.066	-0.066
Class C	0.536	0.030	0.0002	-0.029	-0.044	-0.041
Class D	0.231	0.022	0.008	-0.009	-0.016	-0.013
Class E	0.958	0.057	0.016	-0.021	-0.045	-0.047
Class F	0.685	0.045	0.010	-0.018	-0.033	-0.032

BD-rate (PSNR) gains of patch-based coding schemes compared to full resolution coding system for CTC sequences.

	Patch w/o Overlapping	Patch with Overlapping				
		N = 2	N = 4	N = 8	N = 16	N = 32
Class B	-0,006	-0.061	-0.067	-0.072	-0.080	-0.074
Class C	0,0065	-0.030	-0.035	-0.038	-0.040	-0.035
Class D	0,0042	-0.010	-0.011	-0.014	-0.014	-0.007
Class E	0.035	-0.002	-0.014	-0.027	-0.050	-0.036
Class F	0.030	-0.022	-0.025	-0.027	-0.030	-0.023

## BD-rate Results

# CONCLUSION

- > Hardware problem addressed.
- > Block artifacts removed.
- > Slight gains are observed comparing to Full resolution coding
- > Other applications of this method such as denoising.



# REFERENCES

- [1] J. Balle, D. Minnen, S. Singh, and N. Johnston S.J Hwan, “Variational image compression with a scale hyper-prior,” ICLR 2018 - Conference Track Proceedings, 2018.
- [2] Z. Cheng, H. Sun, M. Takeuchi, and J. Katto, “Learned image compression with discretized gaussian mixture likelihoods and attention modules,” Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 7936–7945, 2020.
- [3] “Workshop and c. on learned image compression,” <https://www.compression.cc/>, 2020.

**THANK YOU FOR YOUR ATTENTION**

# RESULTS

Resolution	Method	Coding Time GPU 2080 11Go	Coding time GPU 3090 24Go	Total Number of patches	Batch size	N
HD	Full Resolution	OOM	OOM	-	-	-
	Patch in parallel w/o overlapping	3.40s	1.967s	40	8	-
	Patch in parallel with overlapping	3.82s	2.05s		8	16
	Patch sequentially with overlapping	6.15s	2.861s		-	16
1280x720	Full Resolution	OOM	0.93s	-	-	-
	Patch in parallel w/o overlapping	1.75s	0.95s	15	5	-
	Patch in parallel with overlapping	1.91s	1.012s		5	16
	Patch sequentially with overlapping	2.73s	1.25s		-	16
832x480	Full Resolution	1.06s	0.52	-	-	-
	Patch in parallel w/o overlapping	1.05s	0.54s	8	8	-
	Patch in parallel with overlapping	1.109s	0.55s		8	16
	Patch sequentially with overlapping	1.586s	0.70s		-	16

## Coding time Results