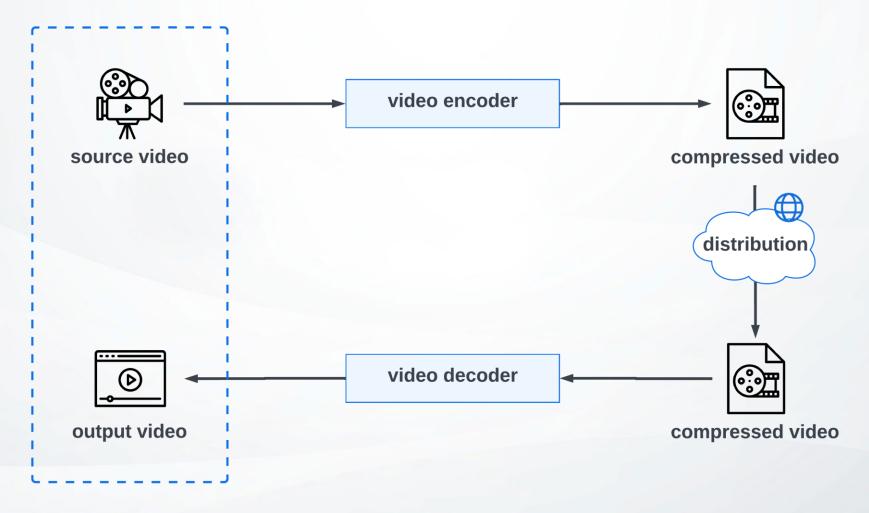


# Combining Deep Learning and Feature Engineering for No-Reference Video Quality Assessment

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Mile-High Video Conference 2024
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#### Why we need No-Reference metrics



#### State-of-the-art

#### **Feature-based metrics**

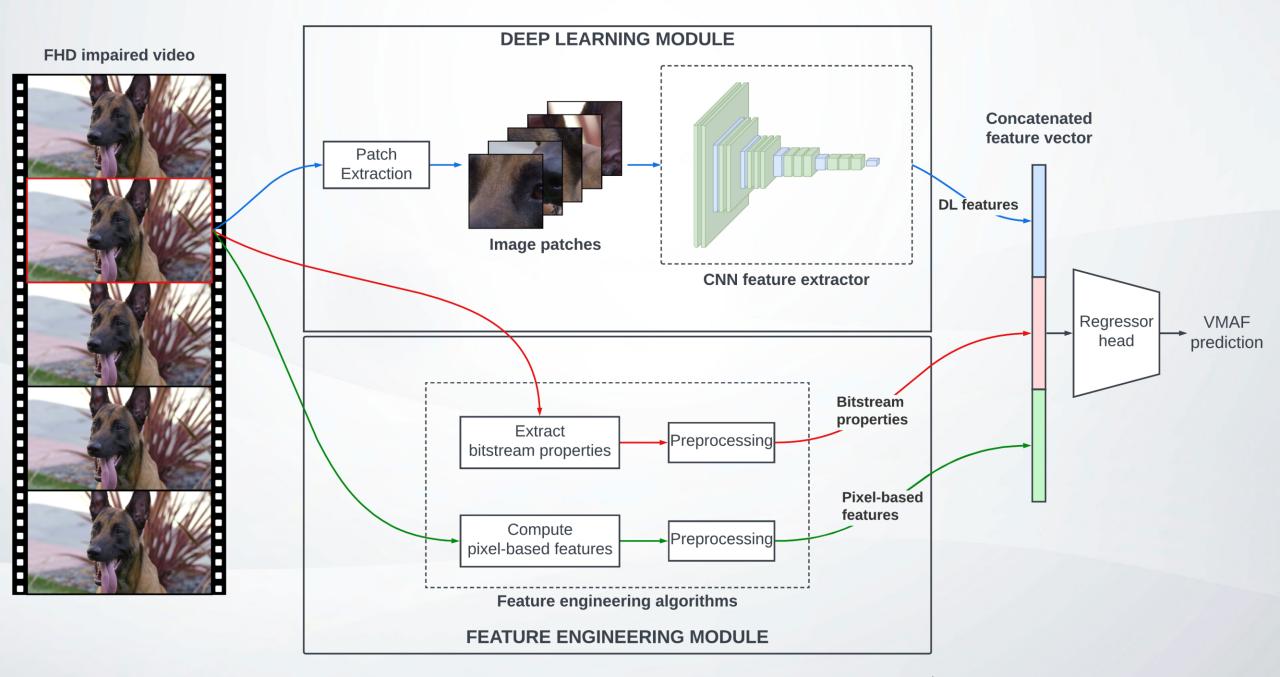
- Employ algorithmic solutions for feature extraction
- Advantages
  - Explainable Al
  - Low variance
- Disadvantages
  - Inaccurate

#### **Deep Learning metrics**

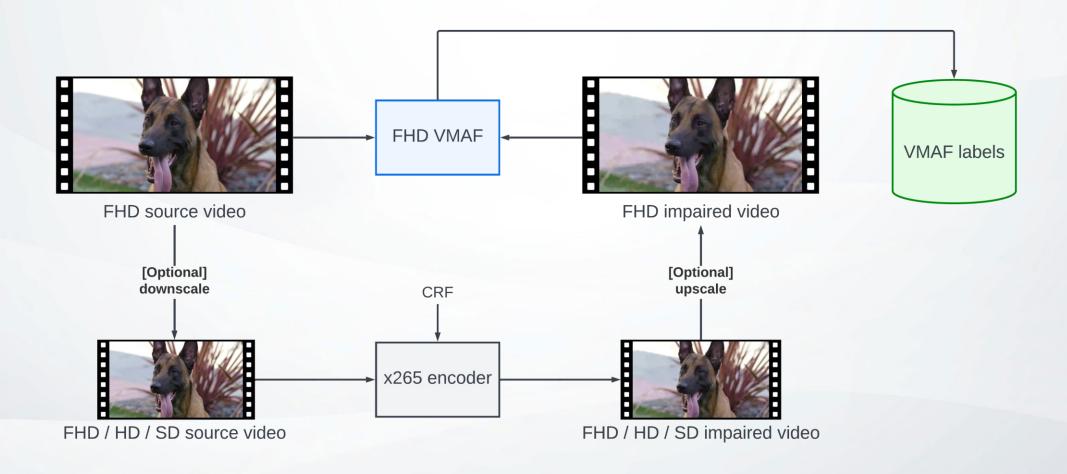
- Employ neural networks for feature extraction
- Advantages
  - Powerful predictive capabilities
- Disadvantages
  - Computationally expensive
  - Vulnerable to overfitting
  - Low interpretability

#### **Hybrid metrics**

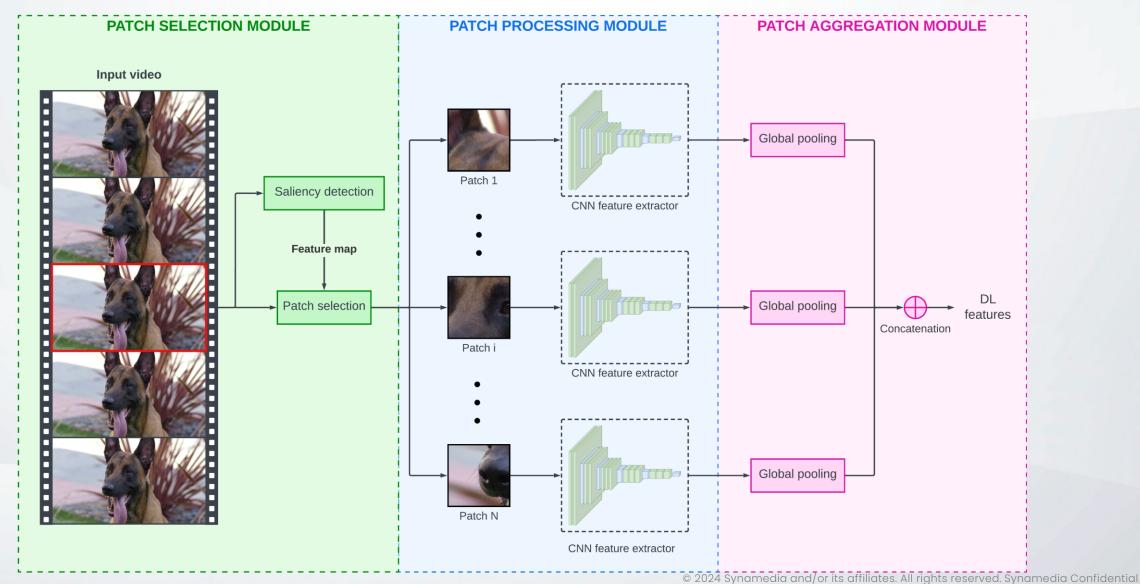
- Combine both methods for feature extraction
- Advantages
  - Benefits from strengths of both other types
- Disadvantages
  - Complex model architectures



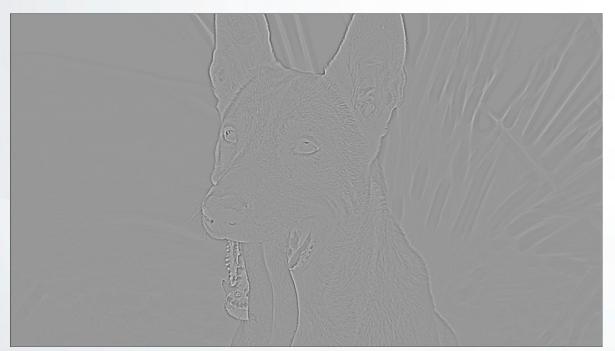
## Data generation methodology

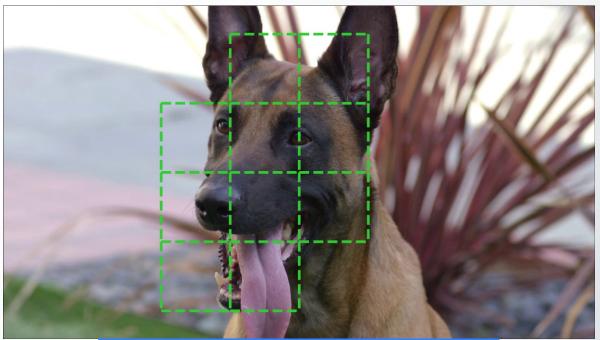


## Extracting DL features from pixel data



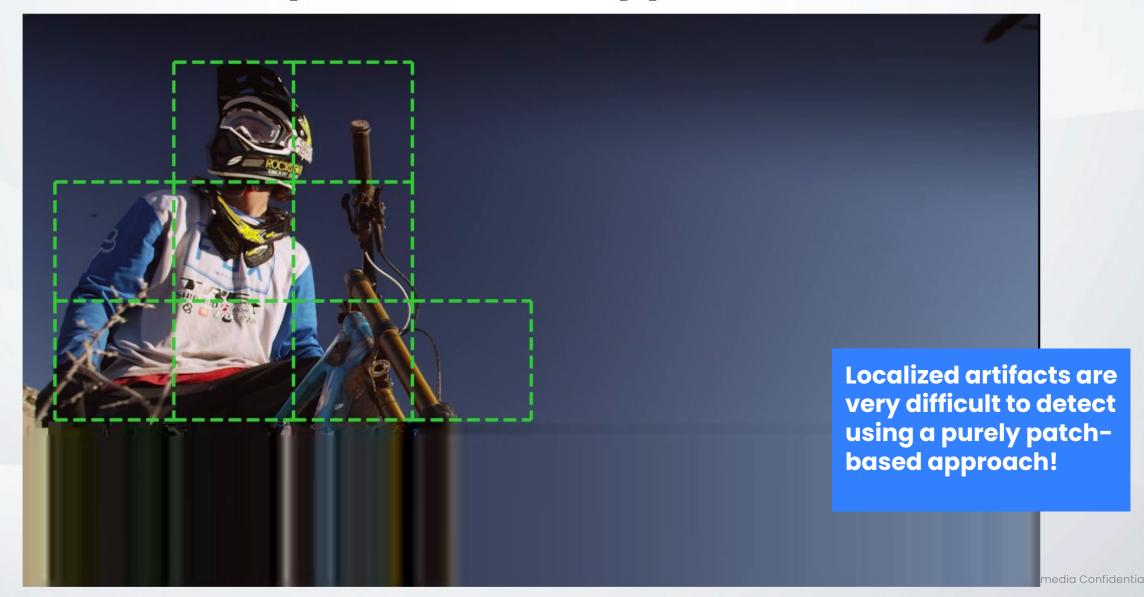
#### **Patch selection**





**Predicted Region of Interest** 

## Limitations of a patch-based approach



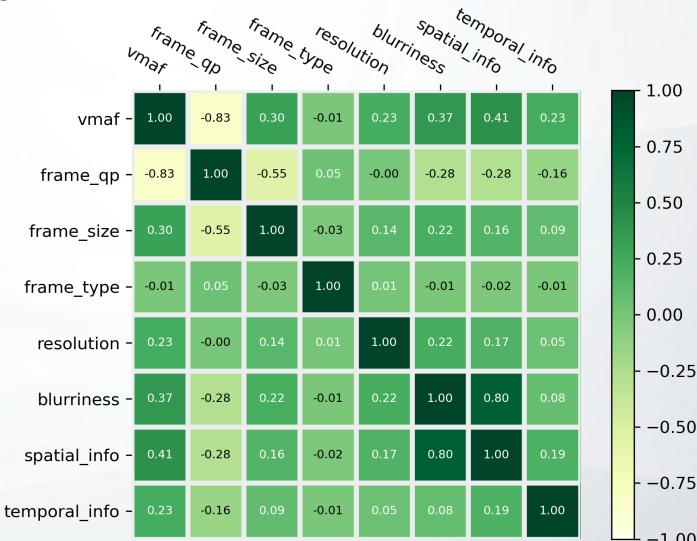
#### **Handcrafted features**

#### **Bitstream properties**

- Frame QP
- Frame size
- Frame type
- Resolution

#### **Pixel-based features**

- Blurriness
- Spatial information
- Temporal information



-1.00

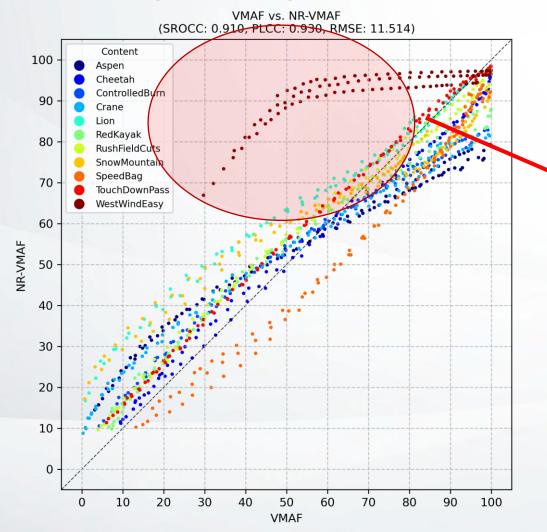
## **Reproducing VMAF**

	Frame-level			Video-level		
	SROCC	PLCC	MAE	SROCC	PLCC	MAE
NR-VMAF	0.921	0.934	8.20	0.955	0.965	6.69
NR-PB-VMAF	0.972	0.970	5.88	0.986	0.985	4.54
Difference	+0.051	+0.037	-2.32	+0.031	+0.020	-2.15

Correlation and error measures between VMAF and NR-VMAF/NR-PB-VMAF averaged across different test datasets

## **Reproducing VMAF**

DL model (NR-VMAF)



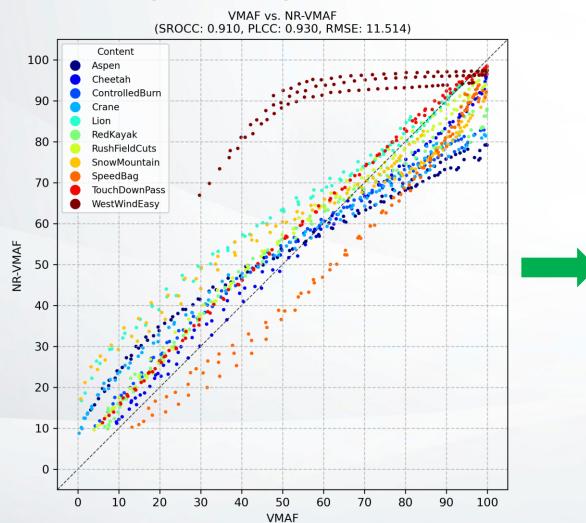
Severe overestimations of the actual VMAF scores, but why?

#### Limitations of a patch-based approach II



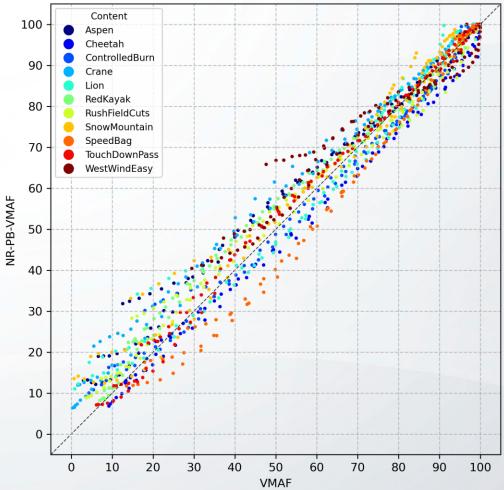
## **Reproducing VMAF**

DL model (NR-VMAF)



#### Hybrid model (NR-PB-VMAF)

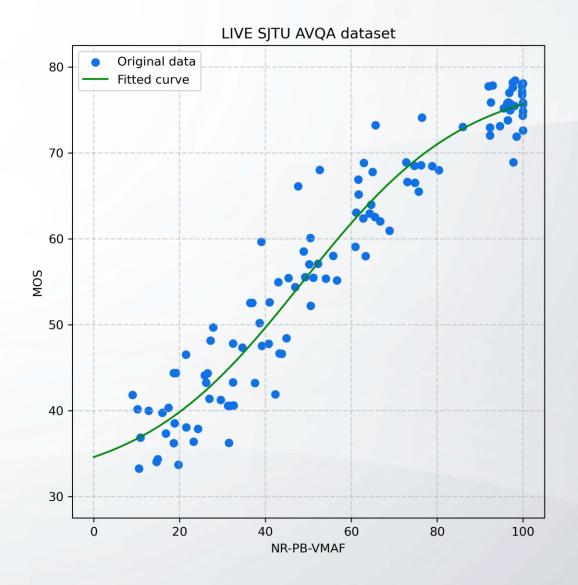
VMAF vs. NR-PB-VMAF (SROCC: 0.987, PLCC: 0.986, RMSE: 5.226)



## Predicting human opinions

Cat.	Metric	SROCC	PLCC	RMSE
FR	PSNR	0.816	0.811	8.927
	SSIM	0.933	0.898	6.259
	MS-SSIM	0.914	0.885	6.639
	VMAF	0.946	0.959	4.028
NR	NIQE	0.334	0.244	13.771
	BRISQUE	0.631	0.579	11.592
	VIIDEO	0.068	0.127	14.080
	NR-VMAF	0.950	0.955	4.209
	NR-PB-VMAF	0.950	0.963	3.825

Correlation of various metrics with MOS on the LIVE SJTU AVQA dataset



#### Summary

- Deep learning architecture extracts informative features from patches
- Additional handcrafted features provide frame-level context
  - Advantages
    - Reduces outliers
    - Improves accuracy & robustness
  - Disadvantages
    - Makes the model more codec-specific
    - Cannot be (effectively) used on raw or transcoded videos
- · Viable approach to No-Reference quality assessment for certain use cases

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Q&A

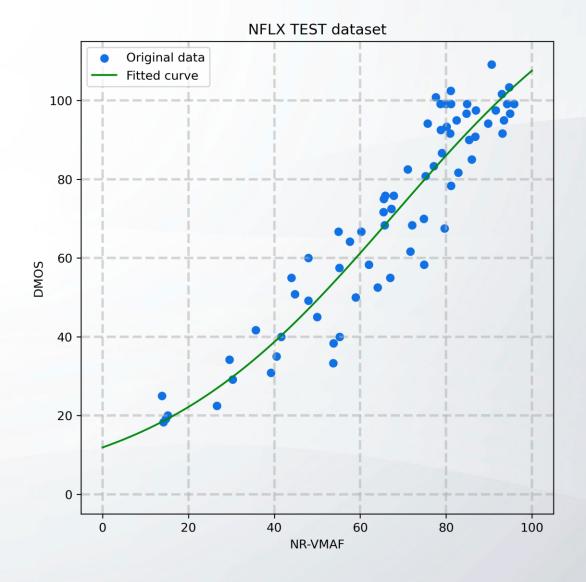
## Synamedia

## **Extra slides**

## **Predicting human opinions II**

Cat.	Metric	SROCC	PLCC	RMSE
FR	PSNR	0.660	0.701	18.234
	SSIM	0.766	0.748	17.063
	MS-SSIM	0.738	0.754	16.875
	VMAF	0.911	0.935	9.071
NR	NIQE	0.702	0.671	19.042
	BRISQUE	0.785	0.832	14.232
	VIIDEO	0.548	0.555	21.353
	NR-VMAF	0.910	0.937	8.969

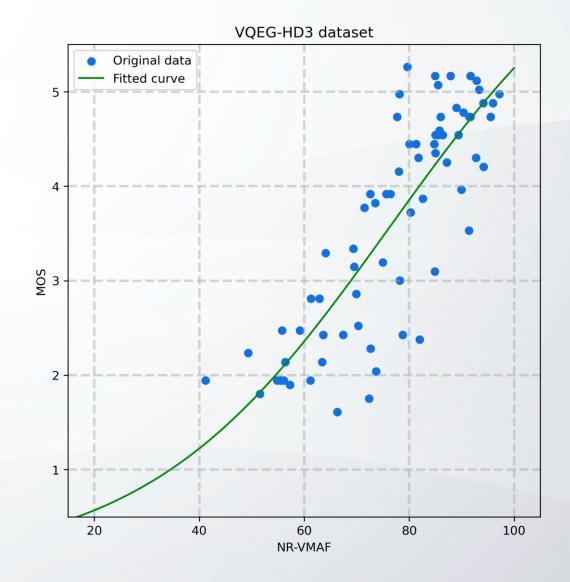
Correlation of various metrics with DMOS on the NFLX TEST dataset



## **Predicting human opinions III**

Cat.	Metric	SROCC	PLCC	RMSE
FR	PSNR	0.784	0.787	0.697
	SSIM	0.906	0.880	0.539
	MS-SSIM	0.897	0.873	0.552
	VMAF	0.921	0.934	0.404
NR	NIQE	0.264	0.068	1.139
	BRISQUE	0.535	0.523	0.973
	VIIDEO	0.092	0.087	1.138
	NR-VMAF	0.813	0.834	0.630

Correlation of various metrics with MOS on the VQEG-HD3 dataset



#### **Future directions**

#### 1. Increase the computational efficiency

- Experiment with lightweight CNN architectures
- Drop redundant features
- Advantages
  - Faster inference
  - More energy-efficient
  - Reduced training times

#### 2. Increase the applicability of our metric

- New distortion types
- New devices
- Varying video characteristics

# Synamedia