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香港城市大學  
City University of Hong Kong

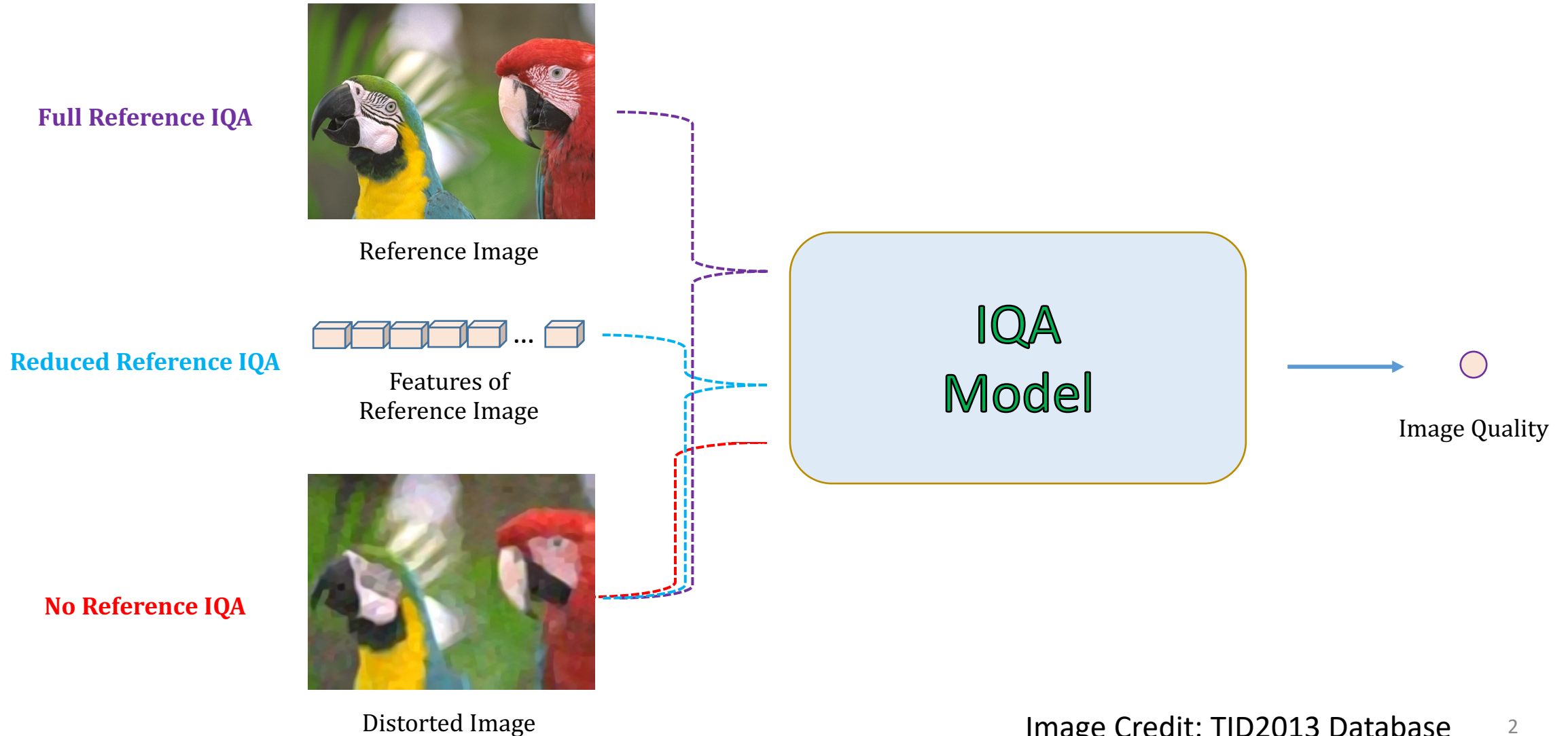
# No-reference Image Quality Assessment via Non-local Dependency Modeling

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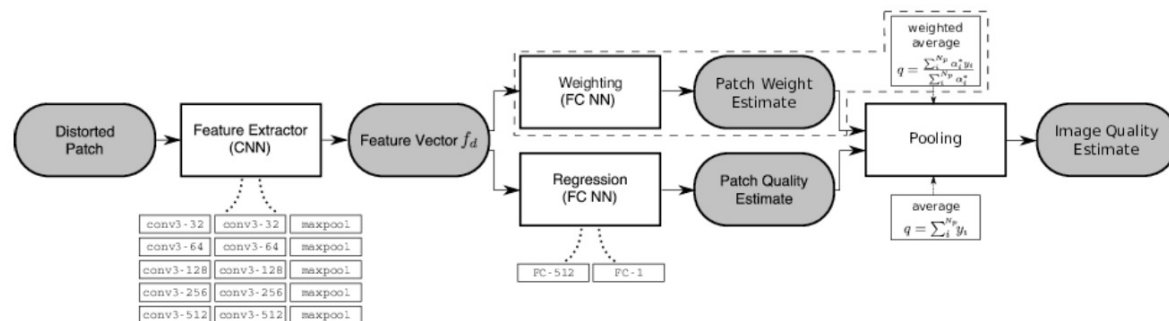
<sup>1</sup>City University of Hong Kong

<sup>2</sup>Peng Cheng Laboratory

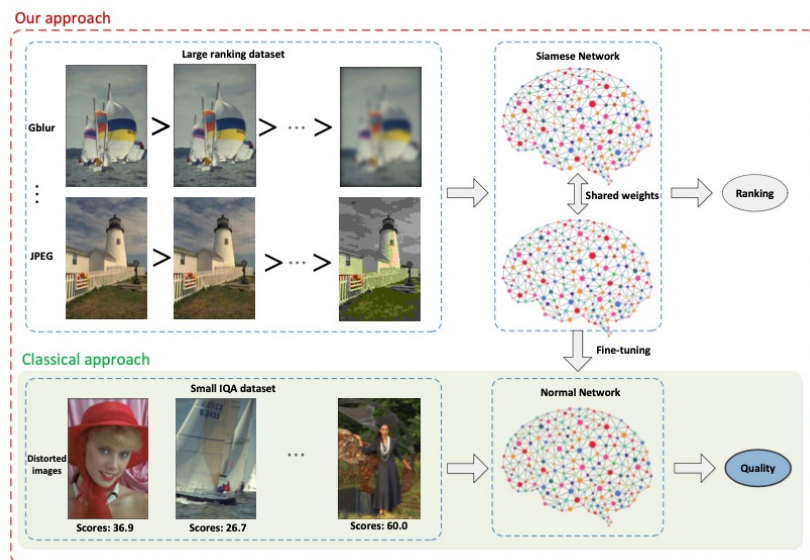
# Full / Reduced / No reference Image Quality Assessment (IQA)



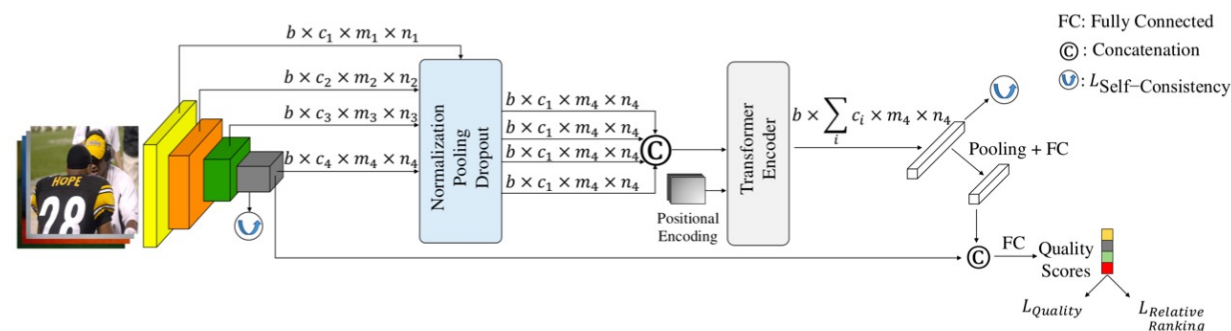
# Recent Progress on No-reference IQA



Learning-based Methods [1]



Rank-based Methods [2]



Transformer-based Methods [3]

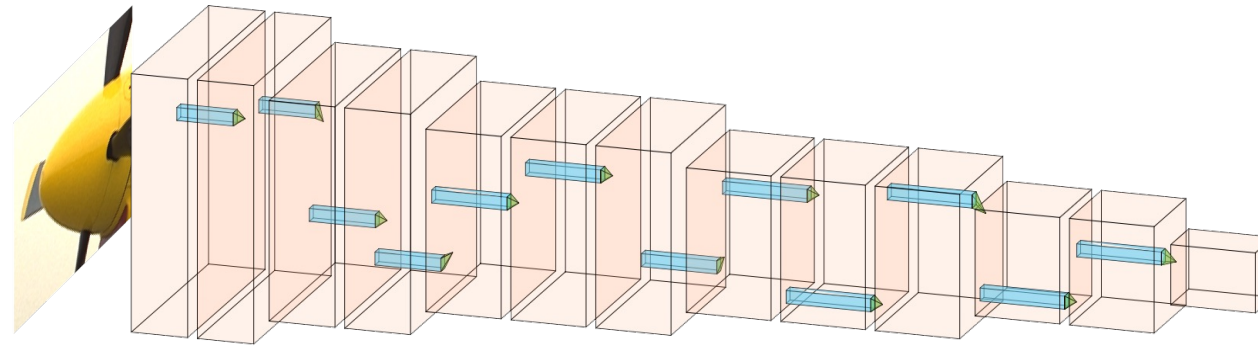
Credit:

[1] Bosse *et al.*, Deep Neural Networks for No-Reference and Full-Reference Image Quality Assessment, In TIP 2018

[2] Liu *et al.*, RankIQA: Learning from Rankings for No-reference Image Quality Assessment, In ICCV 2017

[3] Golestaneh *et al.*, No-Reference Image Quality Assessment via Transformers, Relative Ranking, and Self-Consistency, In WACV 2022

# Challenges

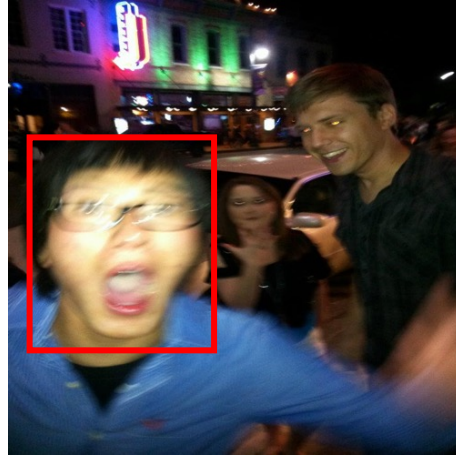


Input Patch

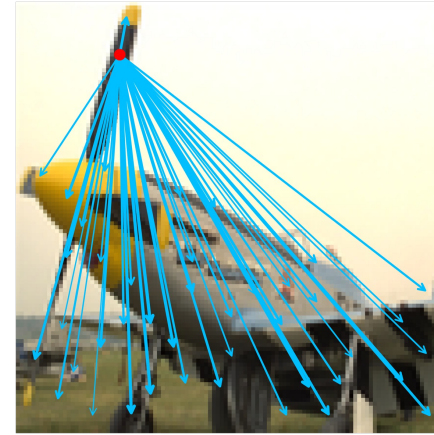
Convolutional Neural Networks (CNNs)

- Convolutional Neural Networks (**Local Modeling**):
  1. Translation invariance (Pooling)
  2. Translation equivalence (Convolution)
  3. Fewer trainable parameters (Weights sharing)
- **Limitations** of the local-modeling method:
  1. Small-sized receptive field → Extracted features are too local
  2. Parameters fixed across the whole image → Contents are equally treated
  3. Lack of geometric and relational modeling → Complex relations and layouts

# Motivation of NLNet



Local Feature Extraction is critical



Non-local Dependency  
Learned by the NLNet

## 1. HVS is **adaptive to local contents**:

→ Local appearance artifacts affect the overall quality

## 2. HVS perceives image quality with **long-dependency** constructed among different regions

→ Non-local feature extraction for long-range dependency modeling



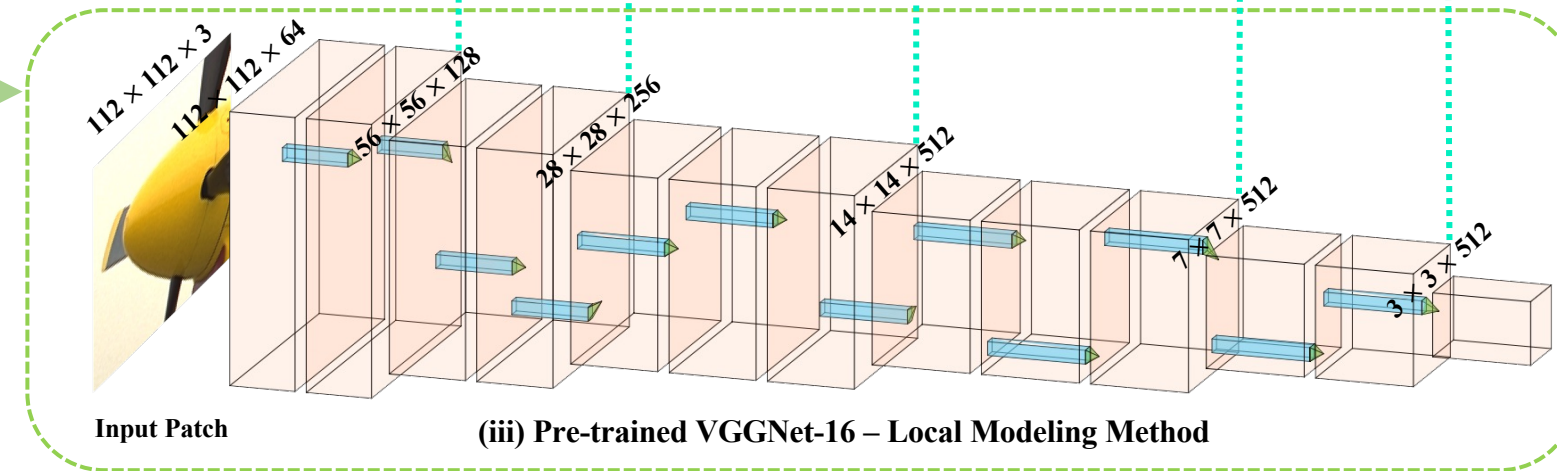
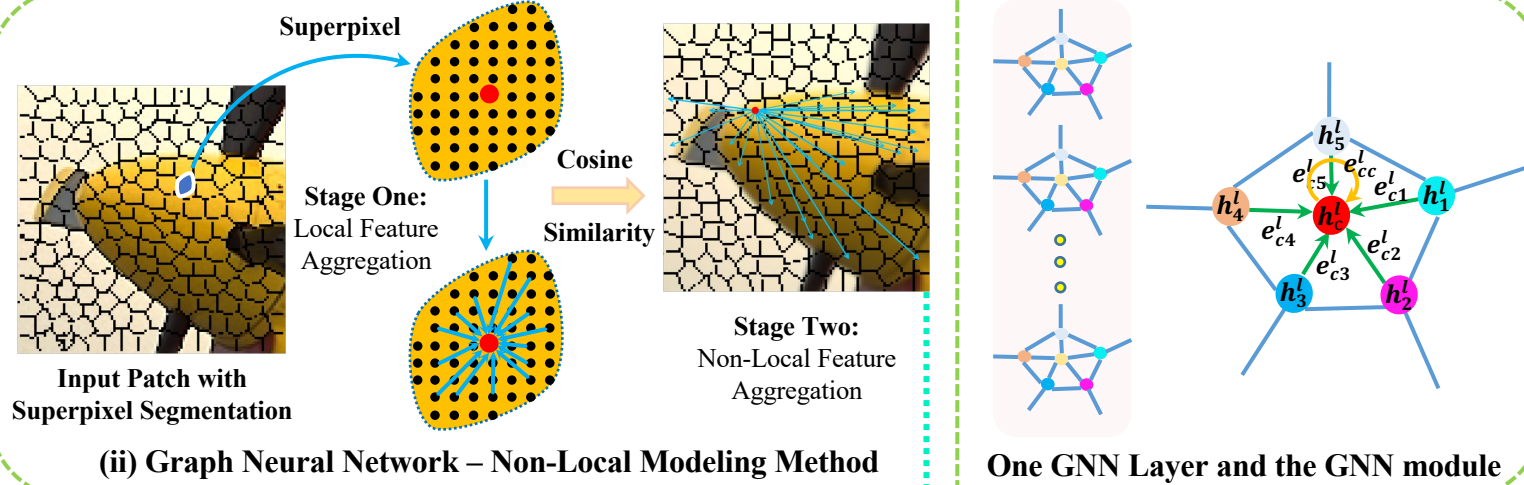
# NLNet Architecture



The Evaluated Image

(i) Image Preprocessing

Input



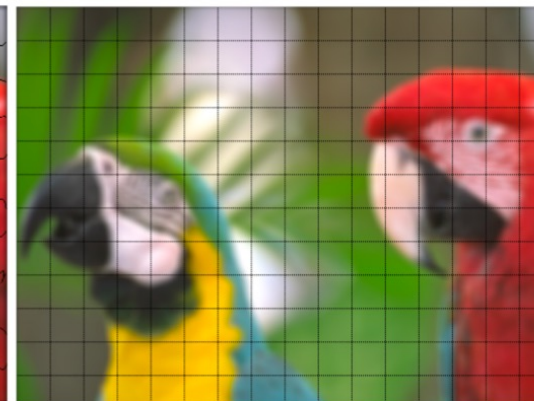
# SLIC Superpixel Segmentation

## Superpixel *versus* Square Patch

1. Adherence to boundaries and visually meaningful
2. Accurate feature extraction



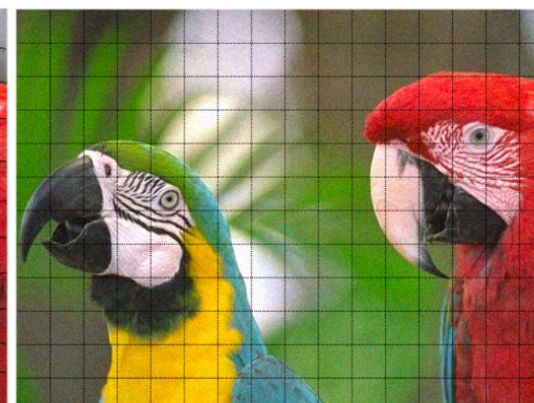
(a) The superpixel segmentation of the parrot image distorted by the Gaussian blur.



(b) The square patch representation of the parrot image distorted by the Gaussian blur.



(c) The superpixel segmentation of the parrot image distorted by the white Gaussian noise.



(d) The square patch representation of the parrot image distorted by the white Gaussian noise.

# Experimental Setup

- **Dataset:**

- LIVE, CSIQ, TID2013

- **Evaluation metrics:**

- SRCC (Spearman Rank-order Correlation Coefficient)
- PLCC (Pearson Linear Correlation Coefficient)

- **Experimental setting:**

- Intra-database Experiments:
  - 60% training, 20% validation, and 20% testing, with random seeds from 1 to 10
- Cross-database Experiments:
  - One database as the training set, and the other databases as testing set
  - Report the last epoch's performance

TABLE I  
BRIEF SUMMARY OF THE LIVE, CSIQ, AND TID2013 DATABASES

Database	LIVE	CSIQ	TID2013
Number of Reference Images	29	30	25
Number of Images	779	866	3,000
Number of Distortion Types	5	6	24
Number of Distortion Levels	5 ~ 8	4 ~ 5	5
Annotation	DMOS	DMOS	MOS
Range	[0, 100]	[0, 1]	[0, 9]



# Experimental Results

TABLE II  
PERFORMANCE COMPARISONS ON THE LIVE, CSIQ, AND TID2013  
DATABASES

Method	LIVE		CSIQ		TID2013	
	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC
BRISQUE (2012) [3]	0.939	0.935	0.746	0.829	0.604	0.694
CORNIA (2012) [6]	0.947	0.950	0.678	0.776	0.678	0.768
M3 (2015) [40]	0.951	0.950	0.795	0.839	0.689	0.771
HOSA (2016) [7]	0.946	0.947	0.741	0.823	0.735	0.815
FRIQUEE (2017) [41]	0.940	0.944	0.835	0.874	0.68	0.753
DIQaM-NR (2018) [42]	0.960	<b>0.972</b>	-	-	0.835	0.855
DB-CNN (2020) [11]	0.968	<b>0.971</b>	<b>0.946</b>	<b>0.959</b>	0.816	0.865
HyperIQA (2020) [12]	0.962	0.966	0.923	0.942	0.729	0.775
GraphIQA (2022) [14]	<b>0.968</b>	0.970	0.920	0.938	-	-
TReS (2022) [15]	<b>0.969</b>	0.968	0.922	0.942	<b>0.863</b>	<b>0.883</b>
NLNet (Proposed)	0.962	0.963	<b>0.941</b>	<b>0.958</b>	<b>0.856</b>	<b>0.880</b>

TABLE III  
CROSS-DATABASE PERFORMANCE COMPARISONS

Training Testing	LIVE		CSIQ		TID2013	
	CSIQ	TID2013	LIVE	TID2013	LIVE	CSIQ
BRISQUE (2012) [3]	0.562	0.358	0.847	0.454	0.790	0.590
CORNIA (2012) [6]	0.649	0.360	0.853	0.312	0.846	0.672
M3 (2015) [40]	0.621	0.344	0.797	0.328	0.873	0.605
HOSA (2016) [7]	0.594	0.361	0.773	0.329	0.846	0.612
FRIQUEE (2017) [41]	0.722	0.461	0.879	0.463	0.755	0.635
DIQaM-NR (2018) [42]	0.681	0.392	-	-	-	0.717
DB-CNN (2020) [11]	<b>0.758</b>	<b>0.524</b>	0.877	<b>0.540</b>	<b>0.891</b>	<b>0.807</b>
HyperIQA (2020) [12]	0.697	<b>0.538</b>	<b>0.905</b>	<b>0.554</b>	0.839	0.543
NLNet (Proposed)	<b>0.771</b>	0.497	<b>0.923</b>	0.516	<b>0.895</b>	<b>0.730</b>

1. Competitive performances compared with those 80% train and 20% test methods.
2. Superior cross-database performances.



# THANK YOU!

Code: <https://github.com/SuperBruceJia/NLNet-IQA>

## Acknowledgement:

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