



IEEE MMSP 2022

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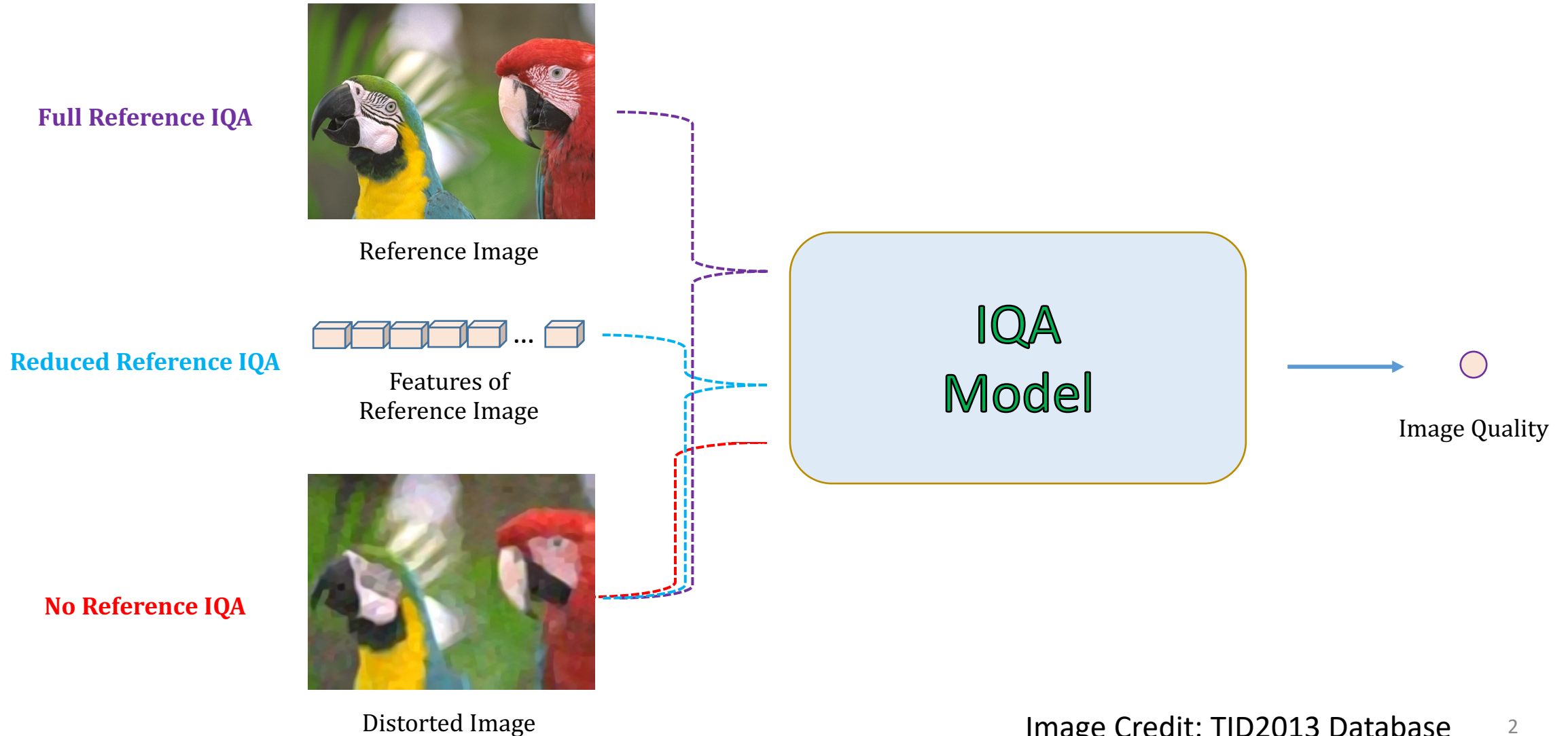
No-reference Image Quality Assessment via Non-local Dependency Modeling

Shuyue Jia¹, Baoliang Chen¹, Dingquan Li², Shiqi Wang¹

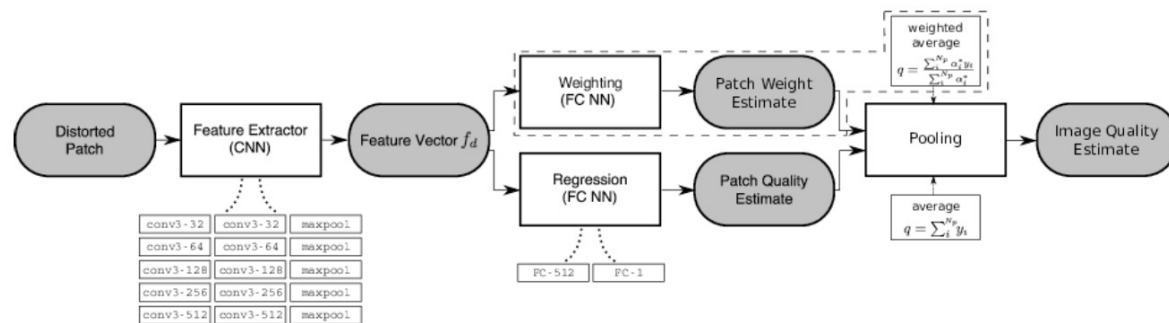
¹City University of Hong Kong

²Peng Cheng Laboratory

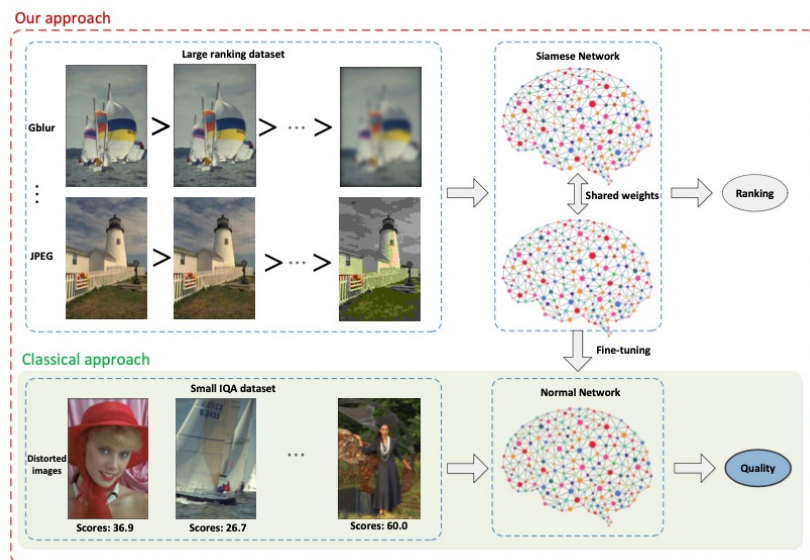
Full / Reduced / No reference Image Quality Assessment (IQA)



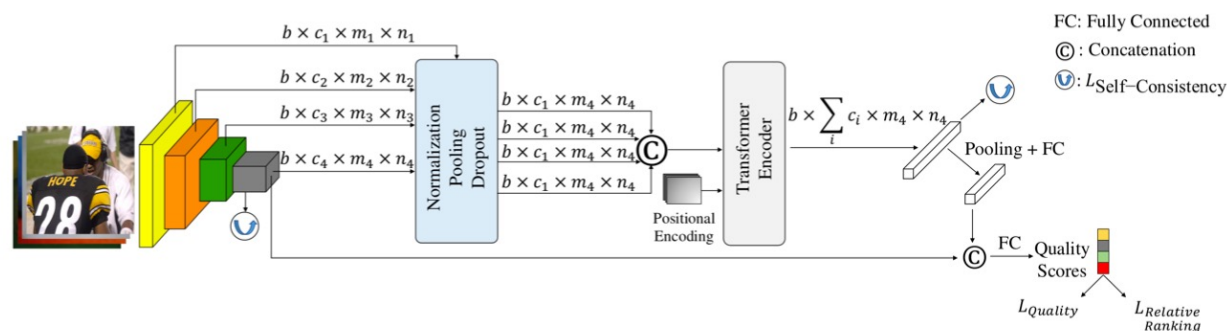
Recent Progress on No-reference IQA



Learning-based Methods [1]



Rank-based Methods [2]



Transformer-based Methods [3]

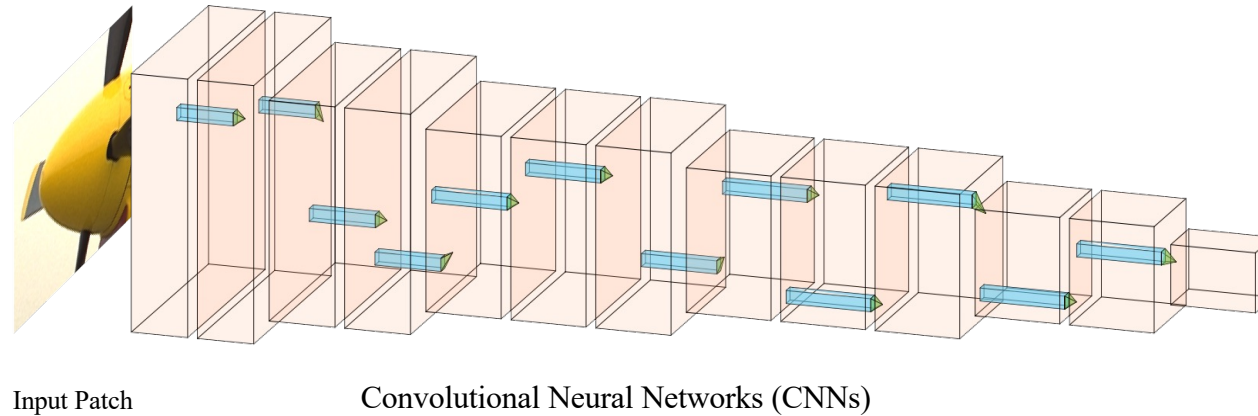
Credit:

[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

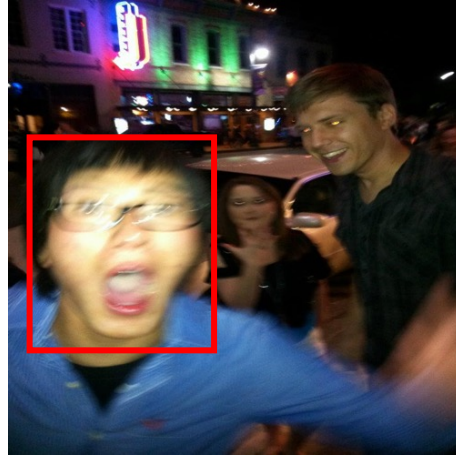
[3] Golestaneh *et al.*, No-Reference Image Quality Assessment via Transformers, Relative Ranking, and Self-Consistency, In WACV 2022

Challenges

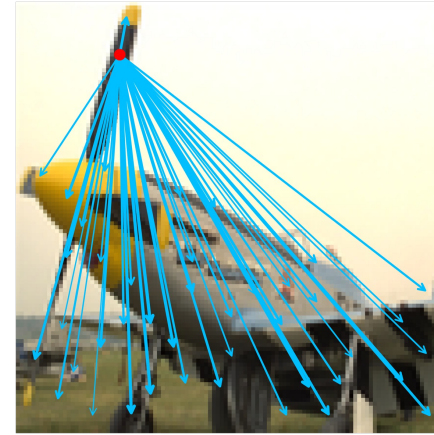


- Convolutional Neural Networks (**Local Modeling**):
 1. Translation invariance (Pooling)
 2. Translation equivalence (Convolution)
 3. Fewer trainable parameters (Weights sharing)
- **Limitations** of the local-modeling method:
 1. Small-sized receptive field → Extracted features are too local
 2. 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

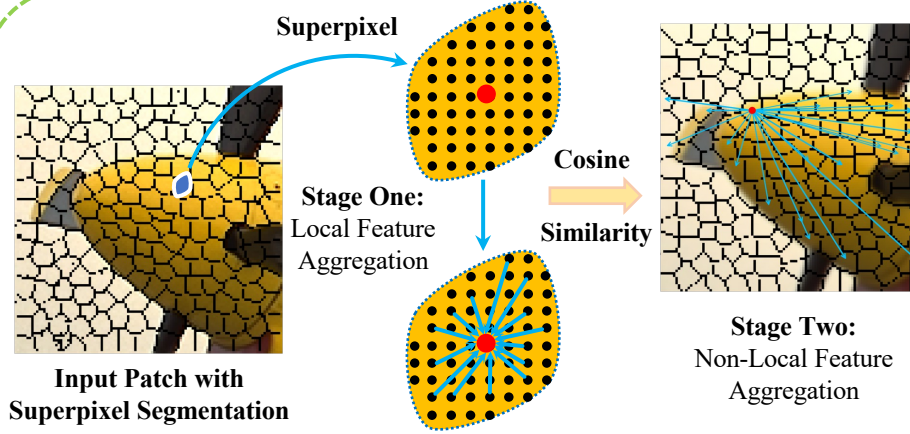
NLNet Architecture



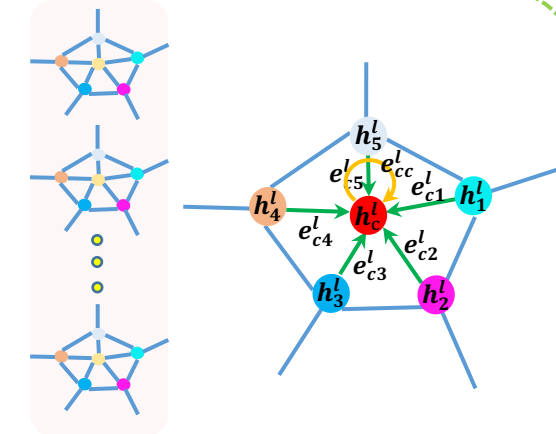
The Evaluated Image

(i) Image Preprocessing

Input

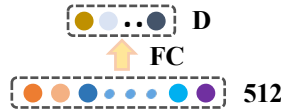


(ii) Graph Neural Network – Non-Local Modeling Method



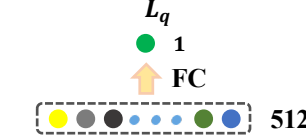
One GNN Layer and the GNN module

Distortion Type Identification Loss L_t



(iv) Feature Mean & Std Fusion and Quality Prediction

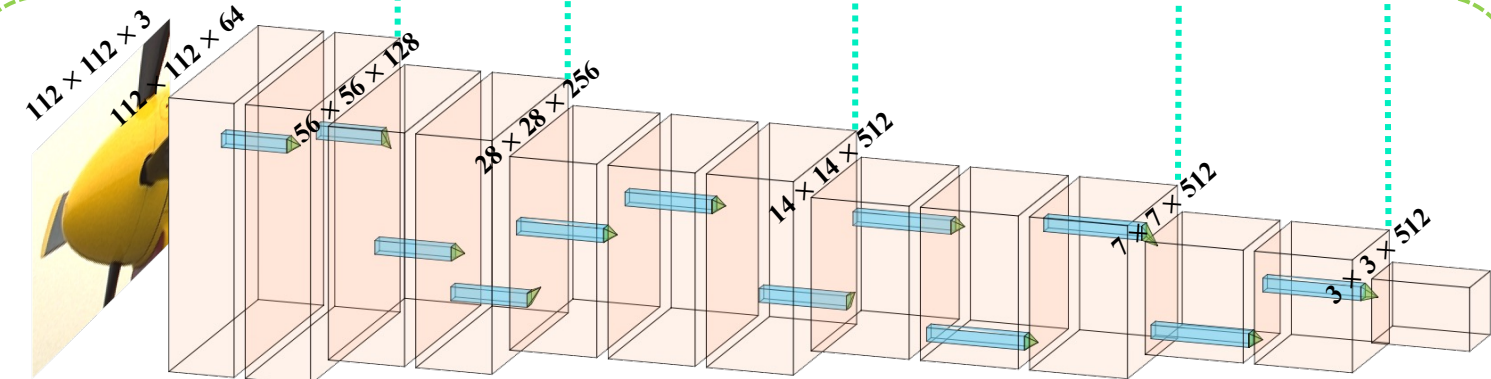
Quality Prediction Loss L_q



Quality Ranking Loss L_r



Inference – Final Quality Prediction



Input Patch

(iii) Pre-trained VGGNet-16 – Local Modeling Method

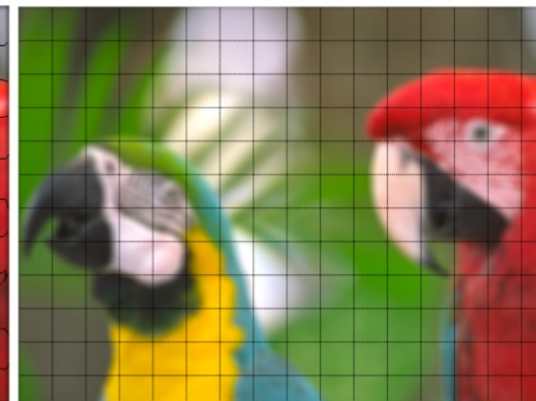
SLIC Superpixel Segmentation

Superpixel *versus* Square Patch

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



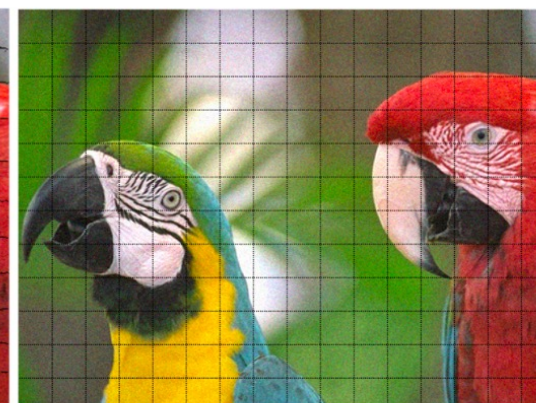
(a) The superpixel segmentation of the parrot image distorted by the Gaussian blur.



(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	0.972	-	-	0.835	0.855
DB-CNN (2020) [11]	0.968	0.971	0.946	0.959	0.816	0.865
HyperIQA (2020) [12]	0.962	0.966	0.923	0.942	0.729	0.775
GraphIQA (2022) [14]	0.968	0.970	0.920	0.938	-	-
TReS (2022) [15]	0.969	0.968	0.922	0.942	0.863	0.883
NLNet (Proposed)	0.962	0.963	0.941	0.958	0.856	0.880

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]	0.758	0.524	0.877	0.540	0.891	0.807
HyperIQA (2020) [12]	0.697	0.538	0.905	0.554	0.839	0.543
NLNet (Proposed)	0.771	0.497	0.923	0.516	0.895	0.730

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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