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

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

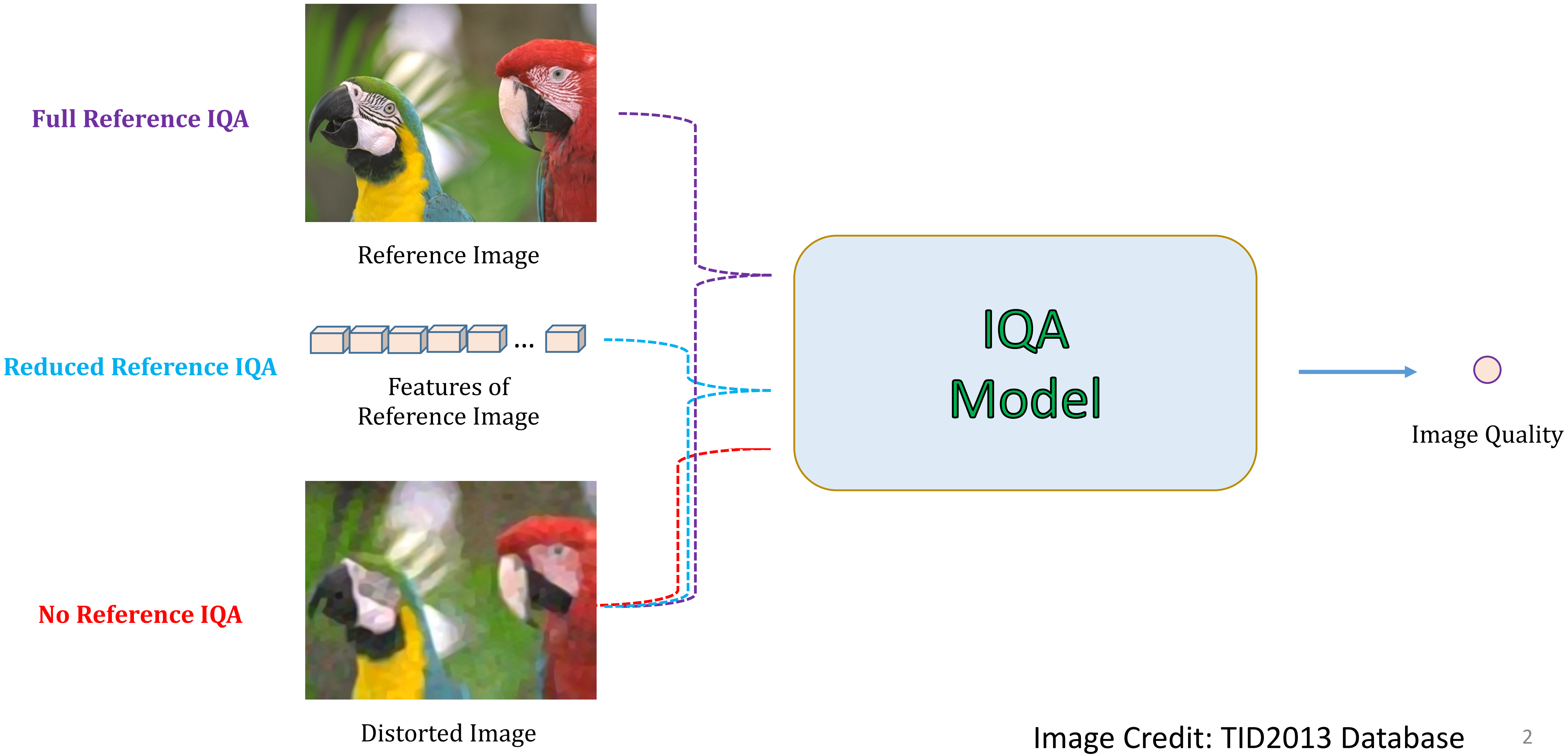
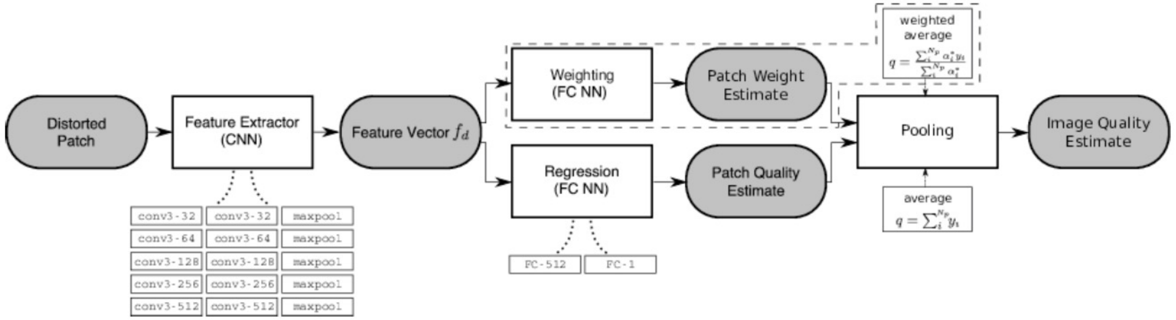
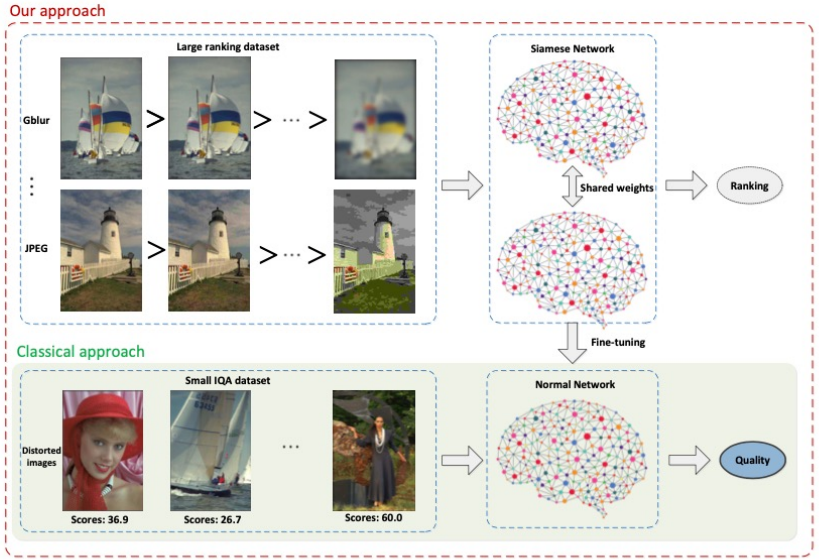


Image Credit: TID2013 Database

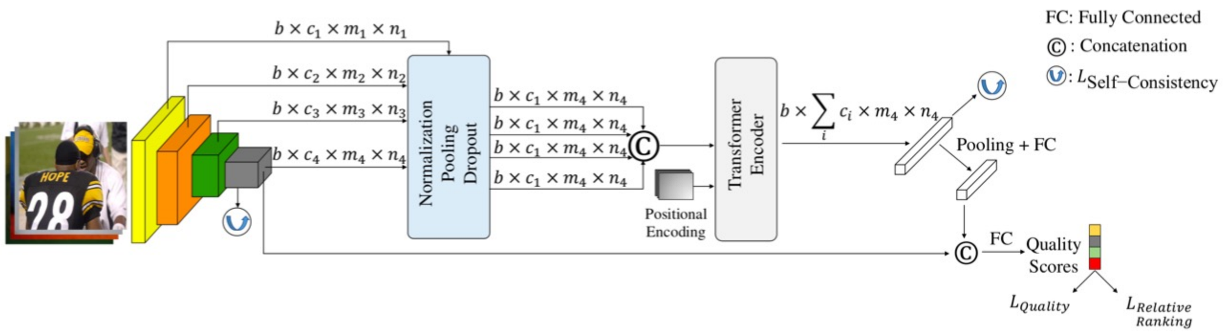
Recent Progress on No-reference IQA



CNN-based Methods [1]



Ranking-based Methods [2]



Transformer-based Methods [3]

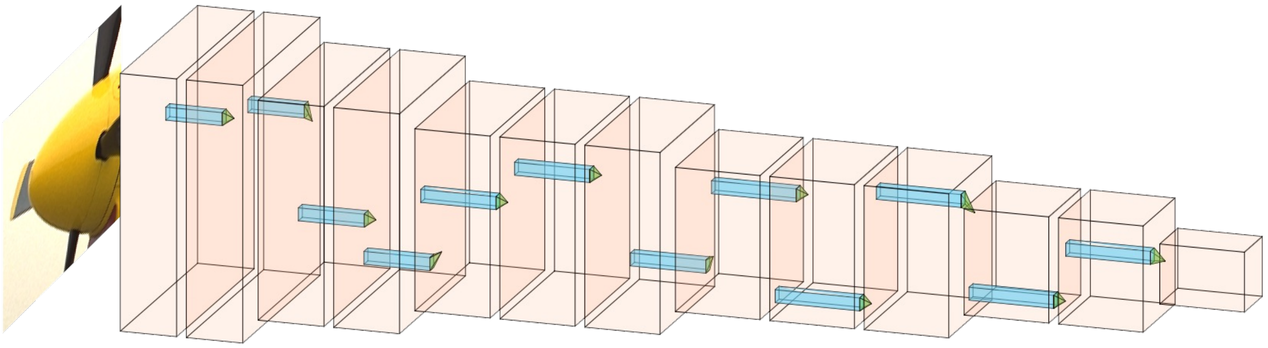
Credit:

[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)

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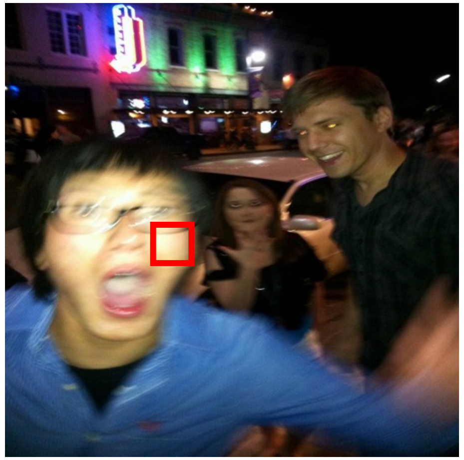
- Convolutional Neural Networks (**Local Modeling**):

    1. Translation invariance (Pooling)
    2. Translation equivalence (Convolution)
    3. Fewer trainable parameters (Weight sharing)

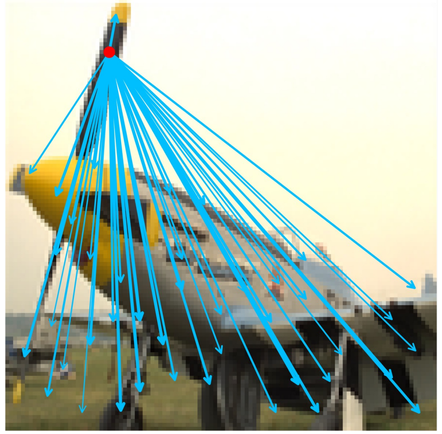
- **Limitations** of the local-modeling method:

    1. Small-sized receptive field → Extracted features are too local
    2. Parameters fixed across the whole image → Image content is equally treated
    3. Lack of geometric and relational dependency modeling → Missing complex relations and layouts

Motivation of NLNet



Local Feature Extraction is critical



Non-local Dependency
Learned by the NLNet

1. HVS is **adaptive to the local content**:

→ 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

Image Credit: TID2013 and LIVEC Databases

NLNet Architecture

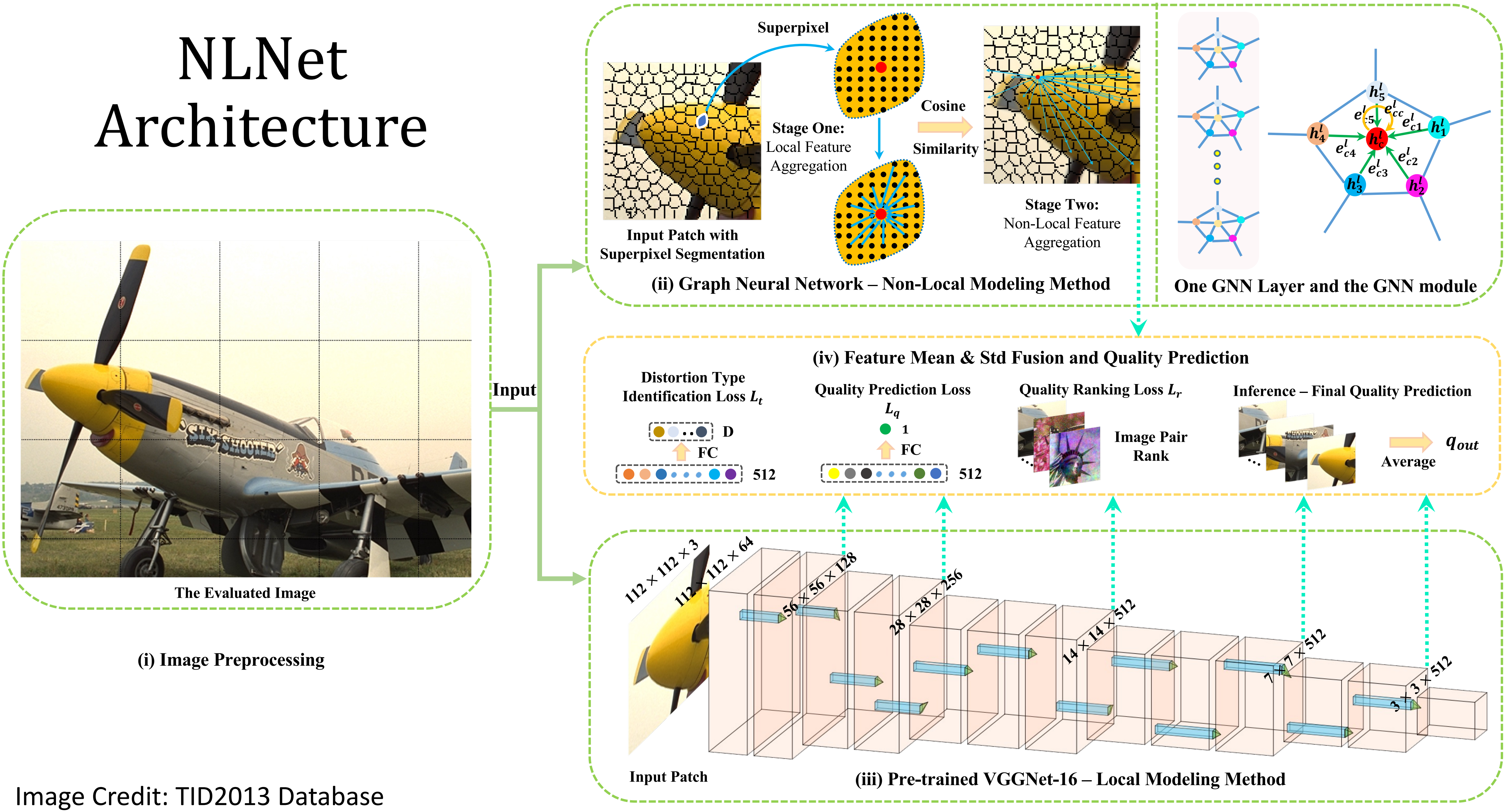
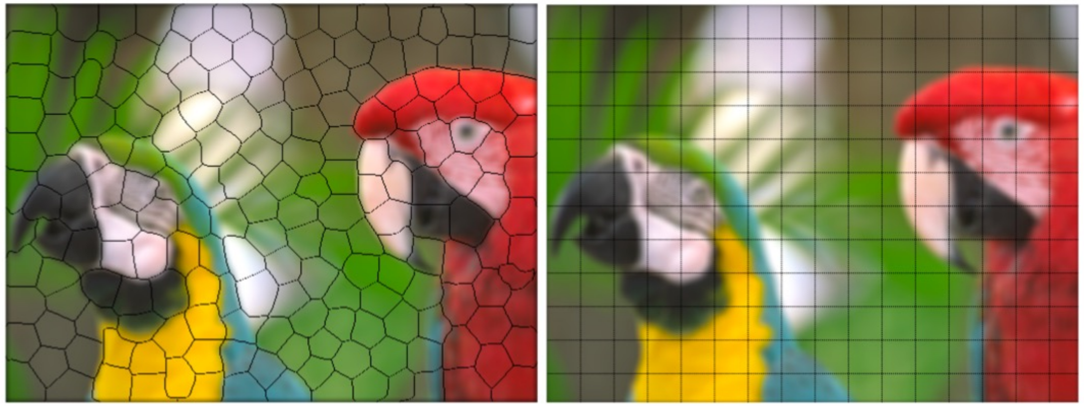


Image Credit: TID2013 Database

SLIC Superpixel Segmentation

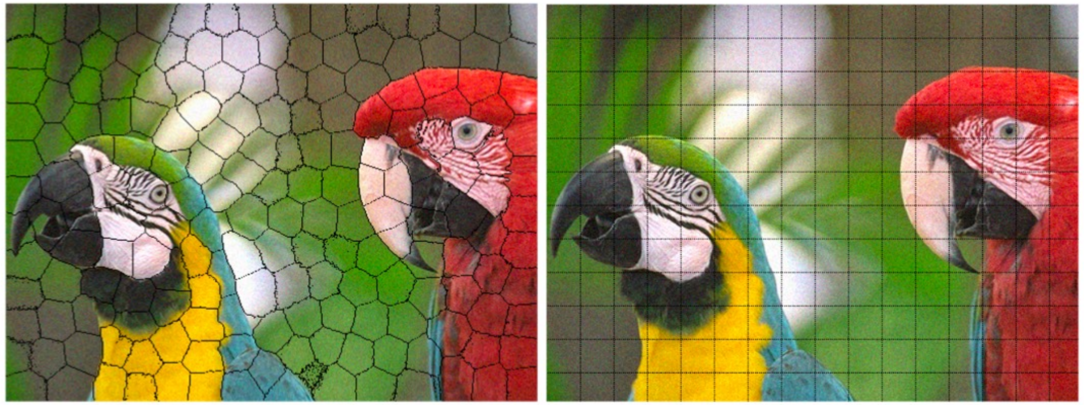
Superpixel *versus* **Square Patch**

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.

Image Credit: TID2013 Database

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	$5 \sim 8$	$3 \sim 5$	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	LIVE		CSIQ		TID2013	
Testing	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.

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THANK YOU!

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

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