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

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



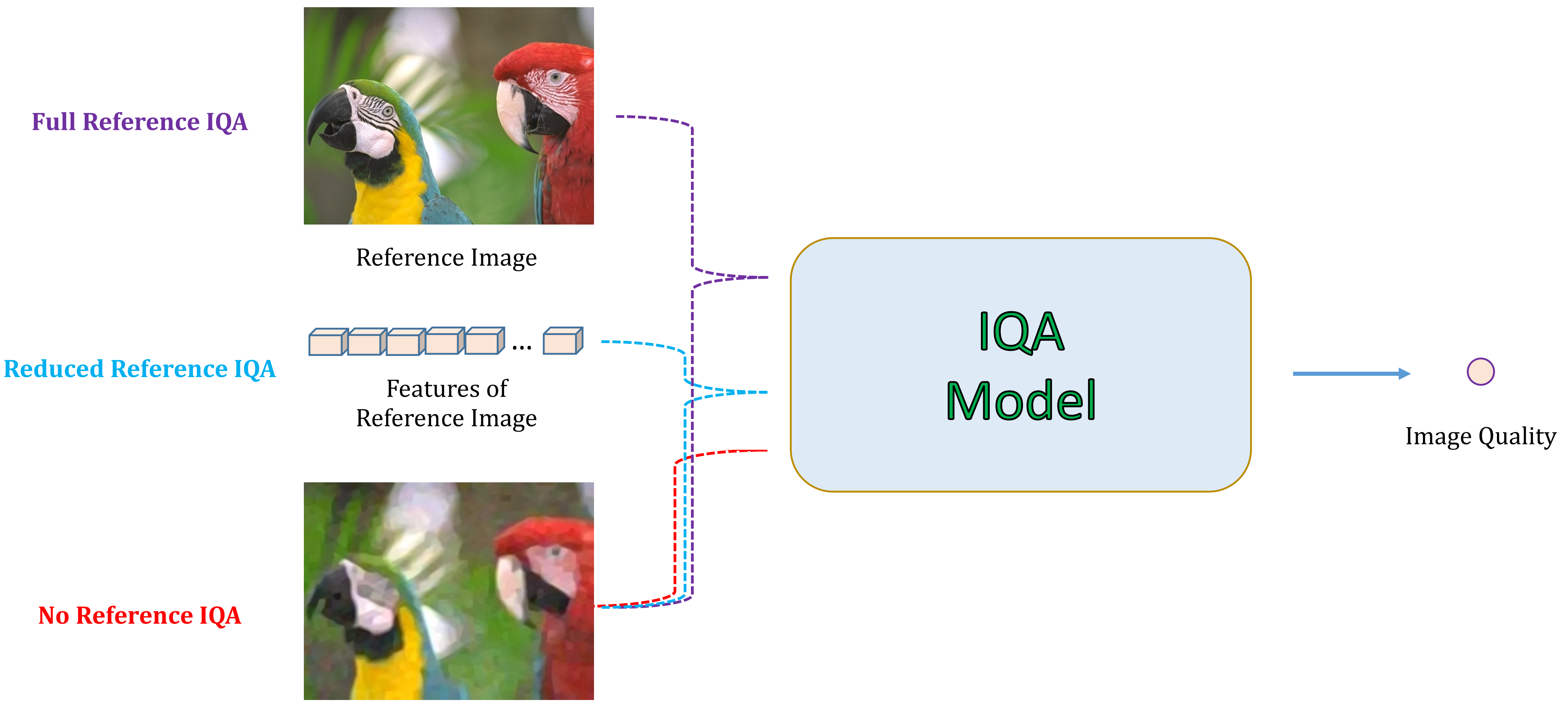
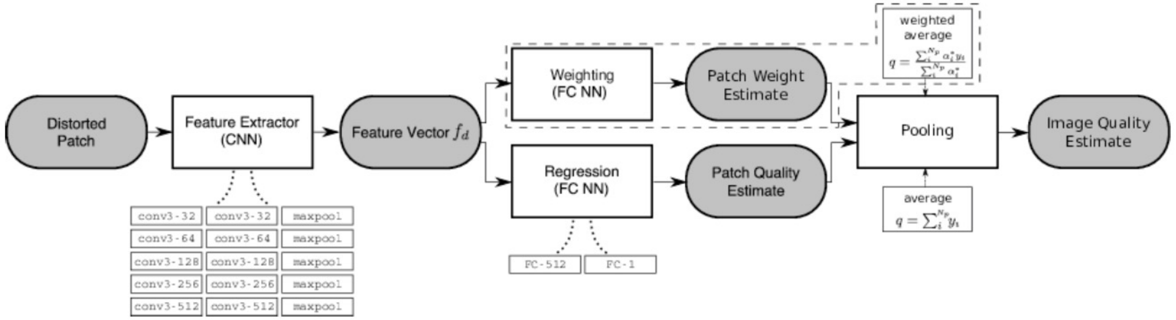
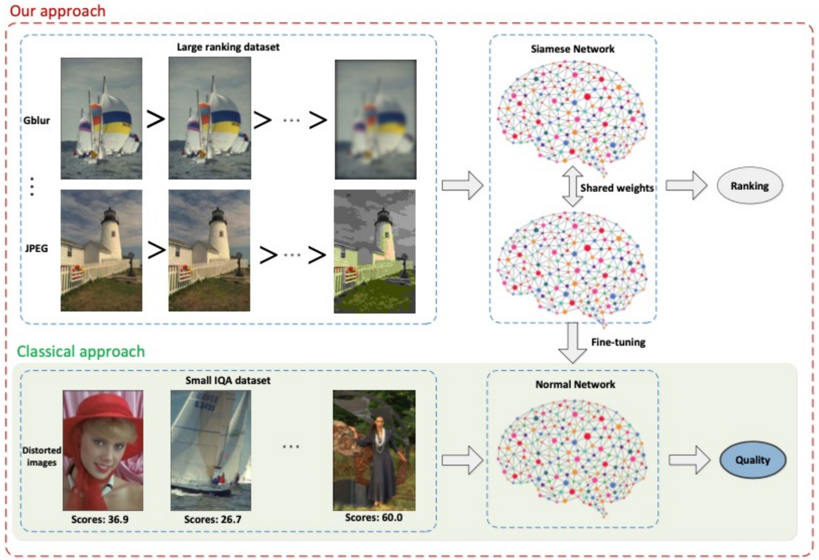



Image Credit: TID2013 Database

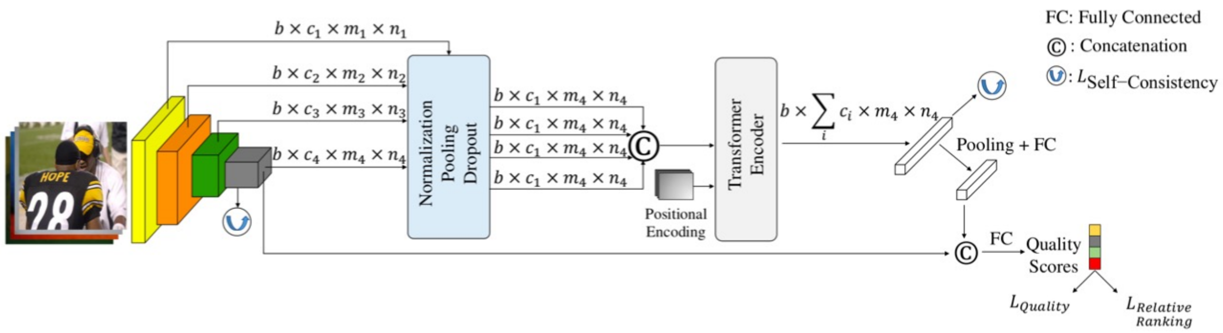
# Recent Progress on No-reference IQA




Learning-based Methods [1]




Rank-based Methods [2]




Transformer-based Methods [3]

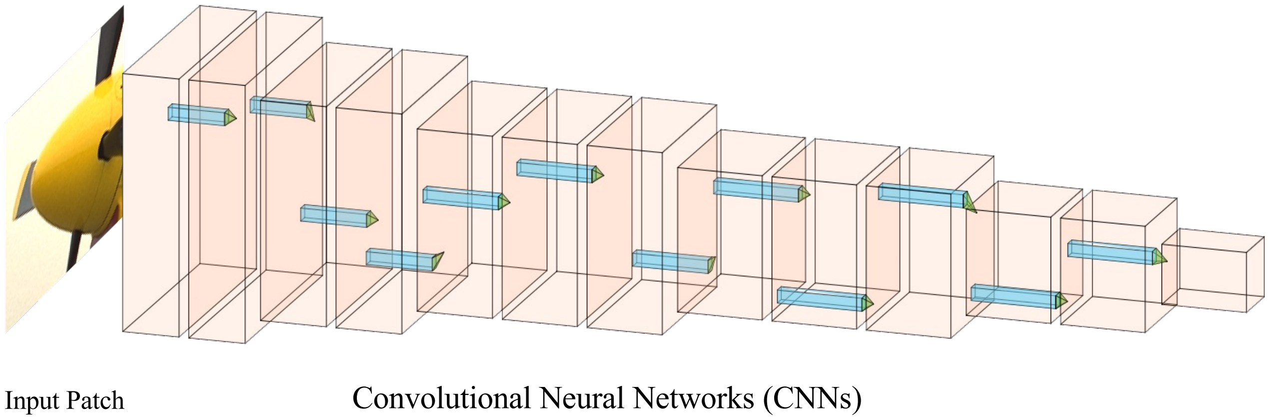

Credit:

[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**):

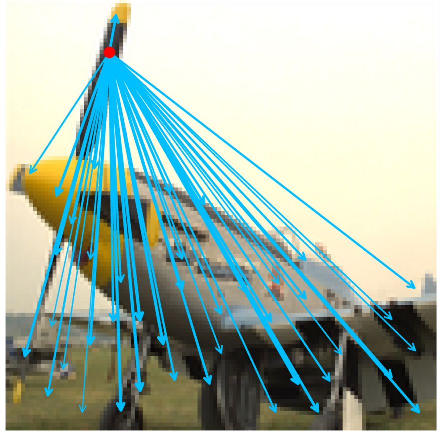
  1. Translation invariance (Pooling)
  2. Translation equivalence (Convolution)
  3. Fewer trainable parameters (Weights sharing)

- **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



Image Credit: TID2013 and LIVEC Databases

# NLNet Architecture

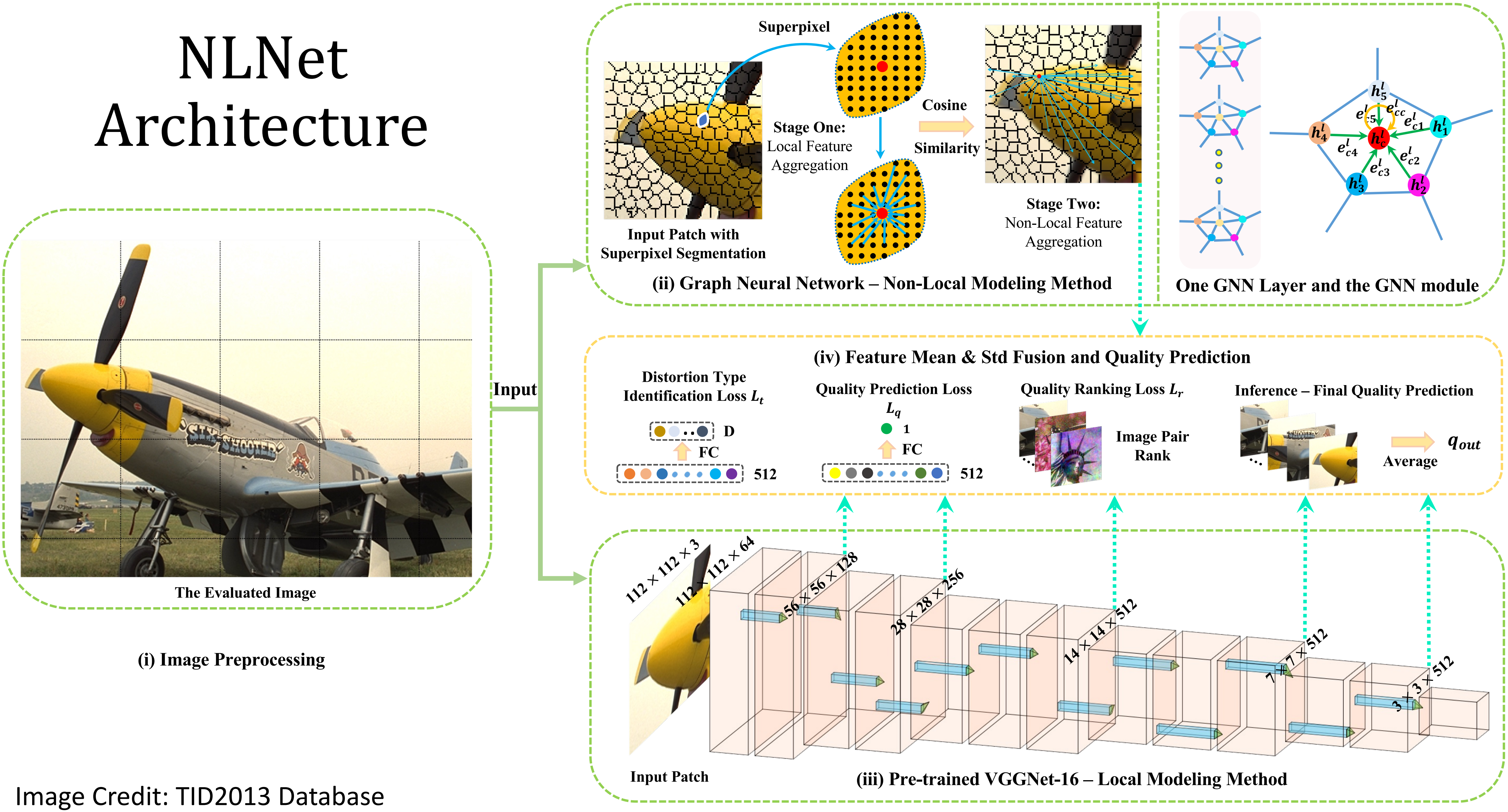



Image Credit: TID2013 Database

# SLIC Superpixel Segmentation

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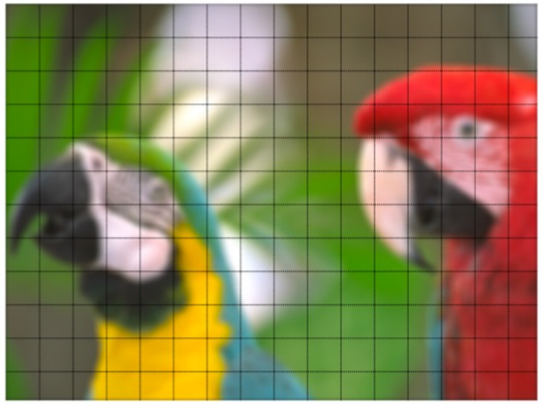
**Superpixel** *versus* **Square Patch**

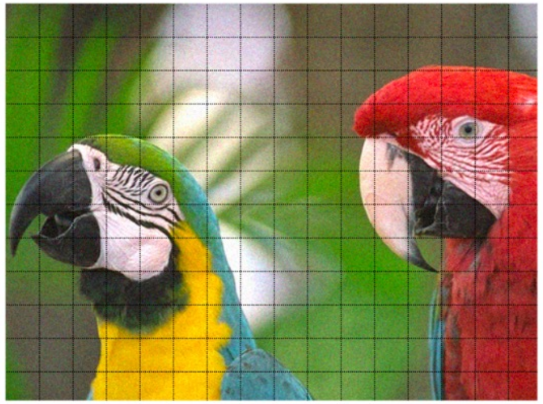
1. Adherence to boundaries and visually meaningful
2. Accurate feature extraction

(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 | $5 \sim 8$ | $4 \sim 5$ | 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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