Task-Focused Knowledge Transfer from Natural Images for CT Image Quality Assessment

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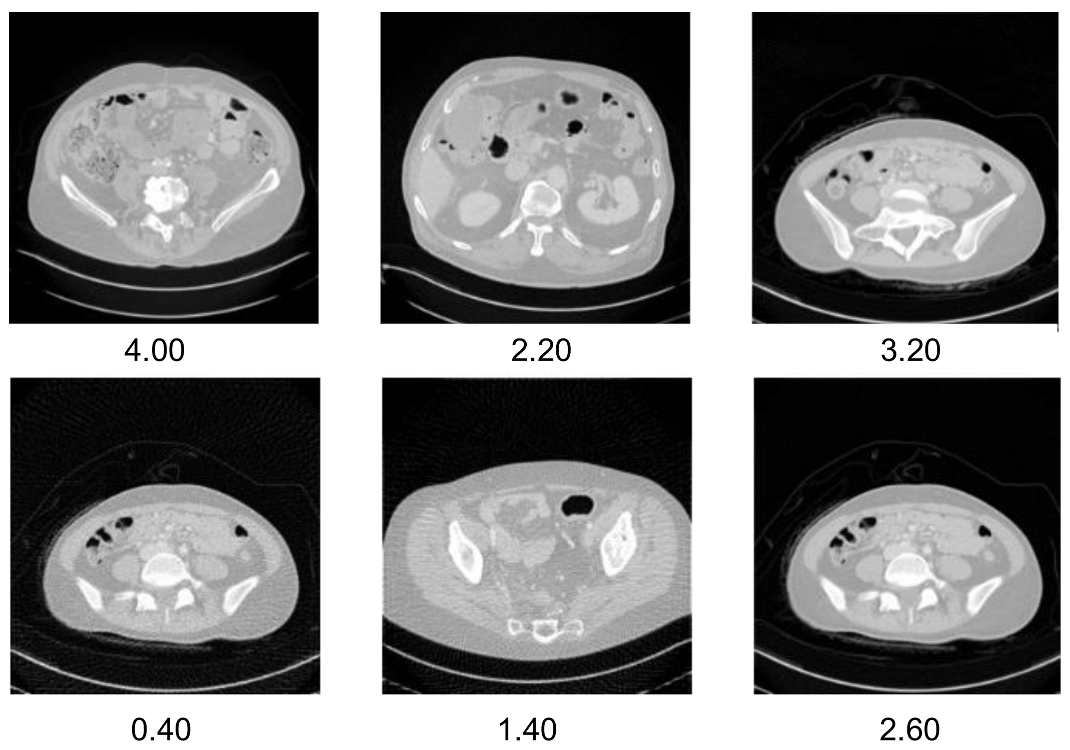
PROBLEM

- ❑ Advanced reconstruction techniques like Iterative Reconstruction and Deep Learning-based Reconstruction have transformed CT image quality assessment (IQA).
- ❑ A standardized metric is urgently needed to objectively assess CT image quality, ensuring diagnostic accuracy while minimizing unnecessary radiation exposure.

CONTRIBUTIONS

- ❑ TFKT: A novel task-specific transfer learning approach with hybrid CNN-Transformer for no-reference assessment of CT image quality leveraging natural images.
- ❑ Extensive experimentation demonstrating the effectiveness of TFKT in predicting radiologists' assigned scores both from in-domain (LDCTIQA) and out-of-domain (in-house) CT images.

KADID[1] images and mean opinion scores (MOS)



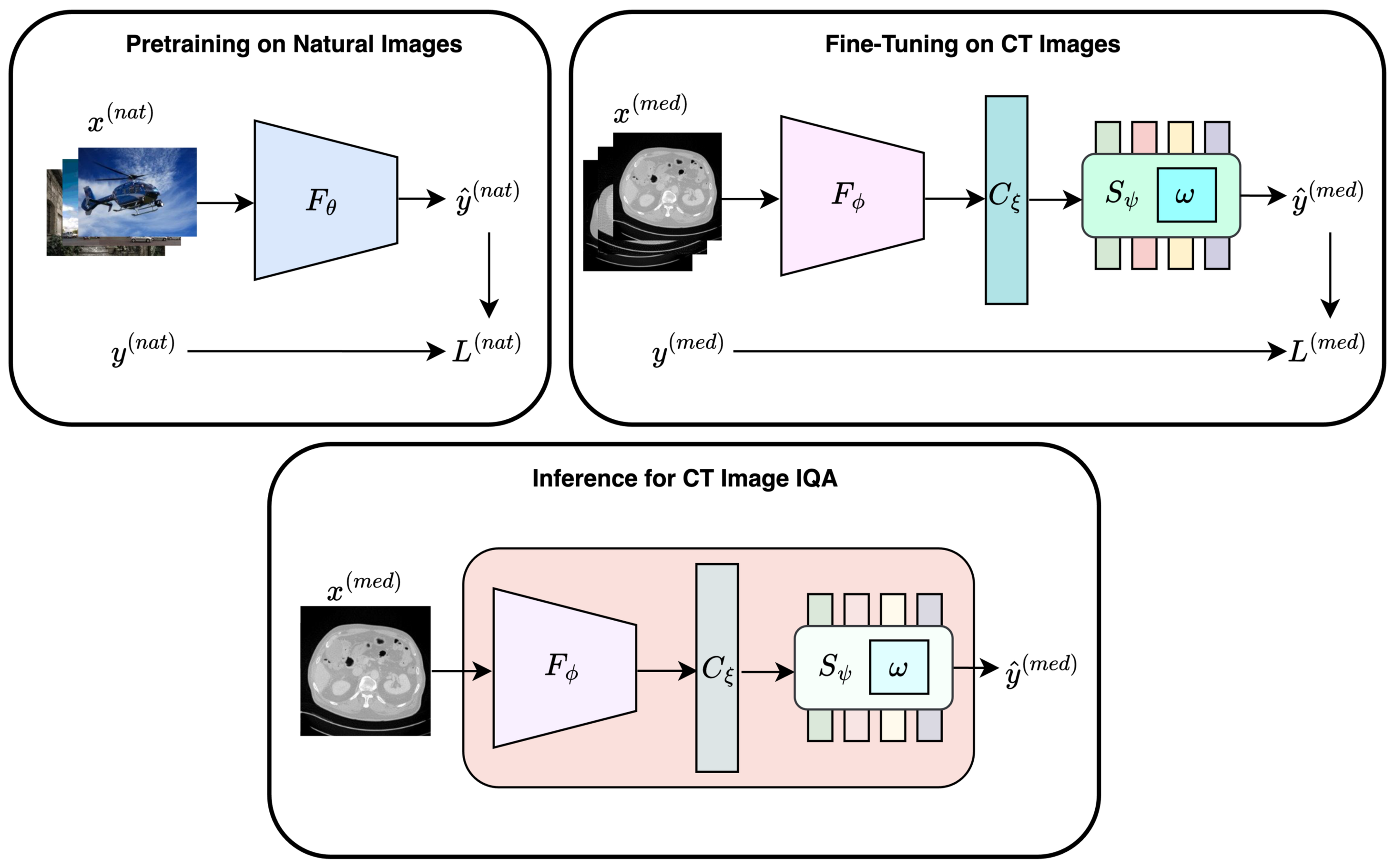
LDCTIQA[2] images and IQA scores

LDCTIQA Scoring Criteria[2]

Score	Quality	Diagnostic Quality Criteria
0	Bad	Desired features are not shown
1	Poor	Diagnostic interpretation is impossible
2	Fair	Suitable for compromised interpretation
3	Good	Good for diagnostic interpretation
4	Excellent	Anatomical features are clearly visible

METHODS

- ❑ Pretraining: Leveraging EfficientNet[3] *(F)*, TFKT is trained to predict the MOS scores (1-5) from input natural images.
- ❑ Finetuning:
  - LDCTIQA dataset is used to predict diagnostic quality of CT images.
  - ImageNet pretrained Swin Transformer[4] *(S)* to exploit both local and global features in medical images.
  - A connector module *(C)* to bridge between the *F* and *S*



Schematic diagram of the proposed TFKT-based CT IQA method

EXPERIMENTS

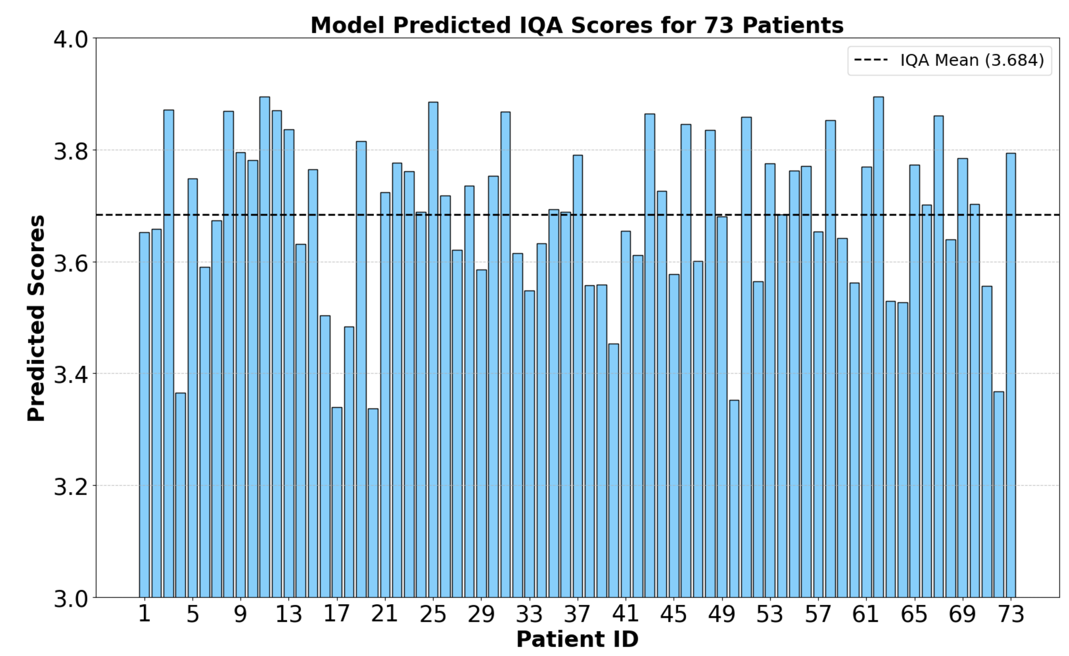
- ❑ Training
  - Phase 1: 10,000 natural distorted images from the KADID dataset
  - Phase 2: 800 images from the LDCTIQA train set
  - Loss: MSE loss is used in both phases
- ❑ Testing
  - Setting A: 200 CT images from the LDCTIQA train set
  - Setting B: LDCTIQA test set of 300 CT images
- ❑ Evaluation
  - Correlation coefficients:
    Pearson's linear correlation coefficient *(r)*,
    Spearman's rank correlation coefficient *(ρ)*, and
    Kendall rank correlation coefficient *(τ)*.
  - Overall model performance *(s)* by aggregating the three correlation coefficients $(r + \rho + \tau)$.

RESULTS

- ❑ TFKT outperforms all the baseline and state-of-the-art methods, demonstrating its effectiveness for CT IQA
- ❑ Ablation study justifies the task-similar knowledge transfer.

Quantitative comparison of TFKT against baseline and state-of-the-art CT IQA methods.

Methods	r	ρ	τ	s
DBCNN	0.9714	0.9734	0.8808	2.8255
MD-IQA	0.9771	0.9793	0.9106	2.8670
MANIQA	0.9768	0.9786	0.8891	2.8445
EfficientNetV2L	0.9569	0.9741	0.8772	2.8082
SSIQA	0.9784	0.9767	0.8905	2.8456
TFKT- frozen F	0.9724	0.9757	0.8852	2.8332
TFKT - w/o Pretraining Phase	0.9809	0.9840	0.9097	2.8745
TFKT	**0.9842**	**0.9846**	**0.9126**	**2.8814**
Results on LDCTIQAC Test Set				
TFKT - w/o Pretraining Phase	0.9221	0.9294	0.7746	2.6261
TFKT (LDCTIQAC Test Set)	**0.9434**	**0.9425**	**0.8017**	**2.6876**



- ❑ The TFKT model tested on 73 out-of-domain pediatric abdominal CT scans. Slice-wise predictions are averaged to obtain IQA score in a scan.
- ❑ As expected for clinical images, TFKT predicted scores are also in good agreement (IQA >3).

CONCLUSIONS

- ❑ TFKT model provides a no-reference, fully-automated, and reliable deep learning-based solution for CT image quality assessment.
- ❑ Our ongoing work is focused on large-scale clinical validation with different patient populations across various body parts.

REFERENCES

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Acknowledgement

This work was supported by the Igniting Research Collaborations (IRC) program and UNITE Research Priority Area at the University of Kentucky