deimeq – A Deep Neural Network Based Hybrid No-reference Image Quality Model

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Motivation



- number of posted photos increases daily[1]
- no-reference image quality methods: hand-crafted features or DNNs
- end user's expectation: high quality, high resolutions, small filesize

→ a brief analysis of current image/video quality models

[1] for Flickr: average 1.63 million photos per day for 2017, see [fli]

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models using . . .

- hand-crafted features, e.g., brisque [MMB12], niqe [MSB13]
  - rely on analyzed distortions → develop features/models independent on distortions
- using DNNs, e.g., VeNICE [DWM17], patch quality prediction [Wie+18]
  - using patches, smaller input resolutions → higher resolutions, avoid pure patching
- diversity of image quality databases, e.g., TID2013 [Pon+15], Live-2 [SSB06], KonIQ-10k[LHS18], LIVEWILD [GB16]
  - specific distortions or 'content diversity' → generalizability of models

→ how to handle such problems?

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How to solve the identified problems?

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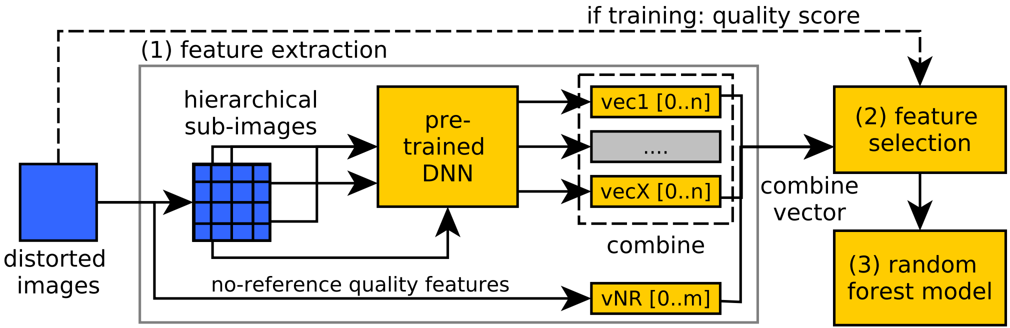
- avoiding of hand-crafted features
  → use pre-trained DNNs as feature extractor
- higher resolutions, pure patching
  → use hierarchical sub-imaging approach
- content diversity vs specific distortions
  → describe approach as meta-concept
- generalizability of models
  → train and validate on different databases

→ introduce our model **deimeq**

Our general approach



- create hierarchical sub-images
- use pre-trained DNN as feature extractor, with summarization
- calculate state-of-the-art no-ref features
- train & validate random forest model; with feature selection

→ which pre-trained DNN is most suitable for image quality?

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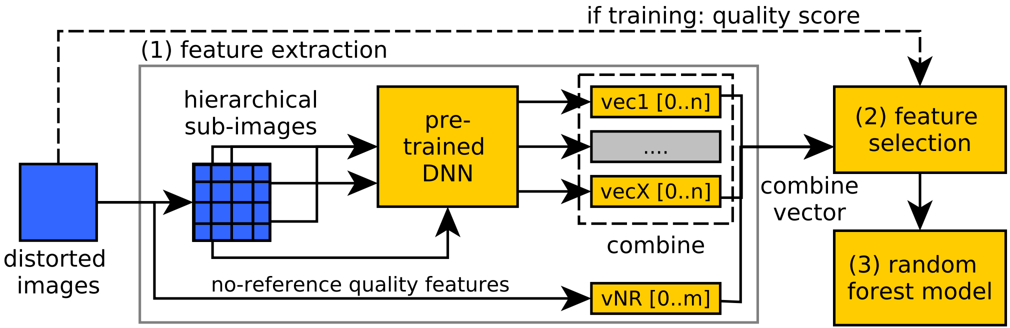

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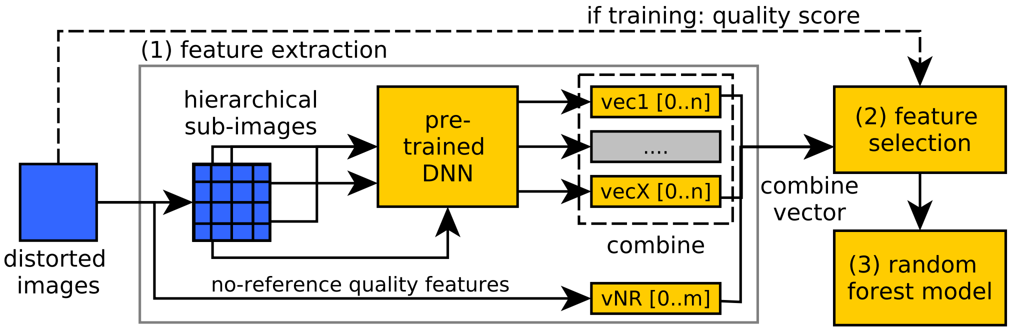

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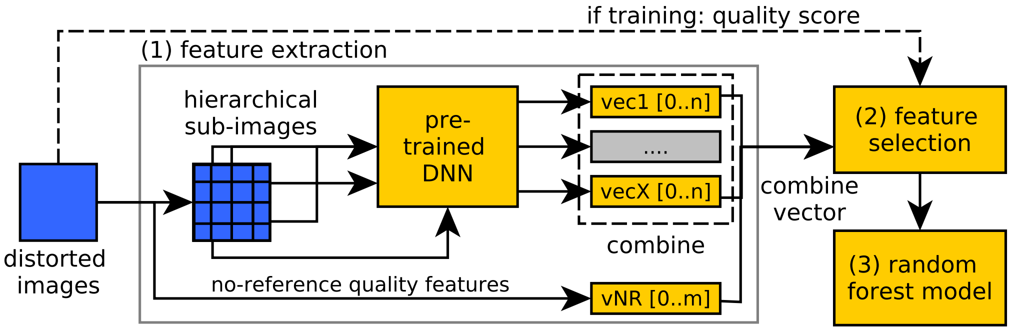

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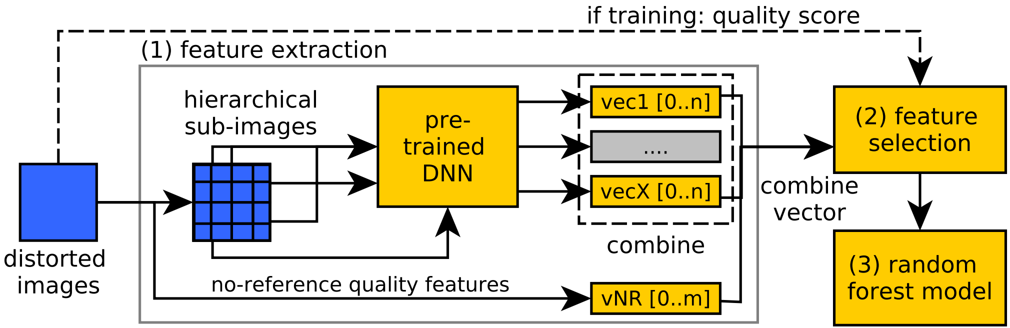

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Evaluation Approach and used Datasets

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- use brisque, niqe baseline models as reference
- deviq, deviq + {brisque, niqe}, with all possible DNNs
- cross validation on TID2013, Live-2: good and similar results,
- LIVEWILD: deviq+xception+brisque better than brisque+niqe
- main approach: cross-dataset evaluation
- hard task: train on Live-2, evaluate on TID2013
- TID2013: superset of distortions

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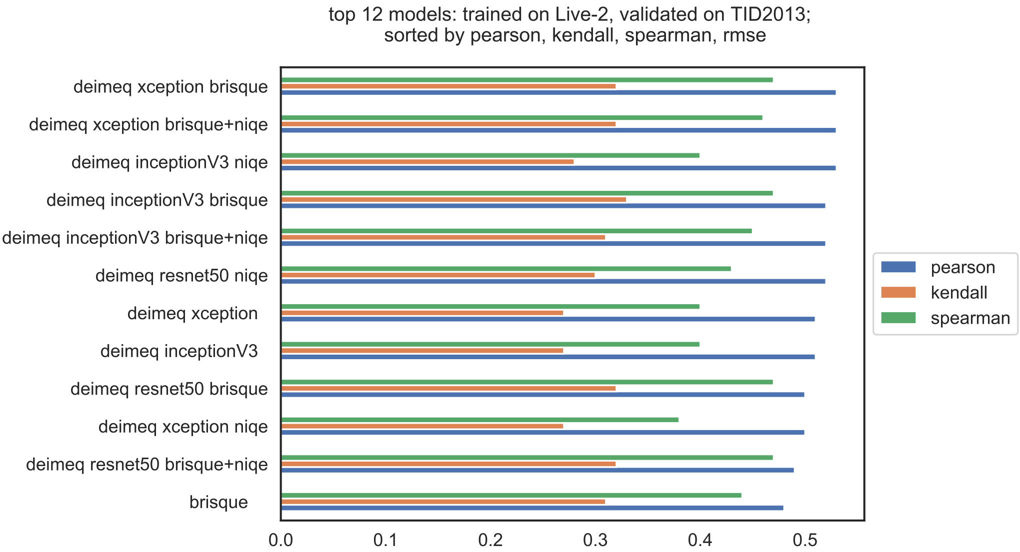

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- best: Xception > inceptionV3 > resnet50
- worst: vgg16 > mobilenet > incept-res
- improvements in combination with brisque+niqe
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- introduced a meta-concept for building no-reference image quality models
  - pre-trained DNNs $\rightarrow$ avoids large new training datasets
  - avoiding of pure-patching $\rightarrow$ using hierarchical sub-images
  - extendable by classical features $\rightarrow$ hybrid DNN, RF model
- performed evaluation of our model
  - cross validation per database $\rightarrow$ good results
  - cross-database validation $\rightarrow$ still a hard task
  - 3 out of 7 classification DNNs suitable $\rightarrow$ Xception best
- open points, possible extensions:
  - include other features, e.g., image aesthetic
  - databases with larger resolutions (>4K)

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Thank you for your attention

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LIVEWILD

Table: Top 10 performance of *deimeq* model variants and *brisque*, P=pearson, K=kendall and S=spearman correlations and RMSE values; **B**=brisque/**N**iqe as additional features; sorted by correlations; crossvalidation on LIVEWILD

model	used dnn	+feat.	P	K	S	RMSE
deimeq+	xception	**B**	0.62	0.42	0.6	14.98
deimeq	xception	**B**+**N**	0.62	0.41	0.59	15.02
deimeq	inceptionV3	**B**+**N**	0.6	0.4	0.58	15.29
deimeq*	xception		0.6	0.4	0.57	15.32
brisque		**N**	0.6	0.39	0.57	15.38
deimeq	xception	**N**	0.6	0.4	0.57	15.4
brisque			0.59	0.39	0.56	15.44
deimeq	mobilenet	**B**+**N**	0.59	0.4	0.57	15.43
deimeq	inceptionV3	**N**	0.59	0.39	0.57	15.49
deimeq	inceptionV3	**B**	0.59	0.39	0.57	15.53

LIVE 2, TID2013

Table: Image Quality Assessment Datasets

	Live-2	TID2013
# source images	29	25
# distortion types	5	24
# total distorted images	779	3000
image resolution (mostly)	768x512	512x384
quality score min/avg/max	0/51.5/100	3.4/62.1/100