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Analysis of Image Quality Assessment Methods and Metrics: A Comprehensive Review

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The evaluation of metrics, the effects of machine learning, and the use of preprocessing techniques for image enhancement constitute the essence of image quality. Through a thorough investigation, this study seeks to identify the core components of image quality. First, various measures for gauging image quality are compared to see how well they work. These metrics offer precise evaluations of aspects of a picture such as sharpness, contrast, and color integrity. The effect of machine learning techniques on the quality of images is then examined. The study investigates the use of machine learning approaches to improve image quality by training models on substantial datasets and tailoring them for certain tasks. In addition, the function of preprocessing methods in picture enhancement is investigated. Before further processing or analysis, the image quality is improved using various techniques, including noise reduction, image denoising, and local entropy filtering. The findings of this work offer important new perspectives on the assessment of image quality measurements, the potential of machine learning for image enhancement, and the significance of preprocessing methods in producing higher image quality.

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1. Introduction

In the domains of computer vision and image processing, the assessment of image quality is crucial. The caliber of the photos used can have a big impact on how well different image-related applications work, like image compression, picture restoration, and image recognition. Image quality evaluation, however, is always subjective and depends on personal tastes and perceptions[1]. Researchers have created a wide range of image metrics that offer quantitative measurements of many facets of image quality to overcome this subjectivity and reach evaluations that are more objective. The idea of image quality and its importance in various image-processing applications are discussed in this examination[2]. There are many different types of proposed image metrics in the literature, such as perceptual-based, structural similarity, and pixel-based metrics[3]. By assessing many properties, such as pixel-level differences, structural similarity, and perceptual resemblances to human perception, these metrics seek to evaluate image quality. It also explored how image quality affects machine-learning models[4]. The quality of the input images is crucial

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to machine learning algorithms, particularly those employed for computer vision tasks. Low-quality images, such as those with noise, blurring, or compression artifacts, can hurt how well machine learning models function, producing unreliable results. To get the best results from machine learning models in tasks like object identification, image classification, and image segmentation, excellent image quality is, therefore, essential[5]. Techniques for preprocessing are frequently used to enhance image quality. Before feeding the images into machine learning models, these strategies entail applying various filters, transformations, and augmentation algorithms to the images. Preprocessing can help improve the overall quality of the photos and the performance of the ensuing machine-learning models by lowering noise, boosting contrast, sharpening edges, and correcting distortions[6]. This study offers a thorough introduction to the evaluation of image quality, image metrics, the influence of image quality on machine learning models, and the function of preprocessing in enhancing image quality. Researchers and practitioners in the field of computer vision can create more precise and dependable image-processing algorithms and applications by recognizing the significance of image quality and using the right image metrics and preprocessing approaches[7]. The impact of image quality on machine learning models is discussed in detail in this work, along with a thorough introduction to image quality and image metrics[8]. The preprocessing methods used to enhance image quality are also covered.

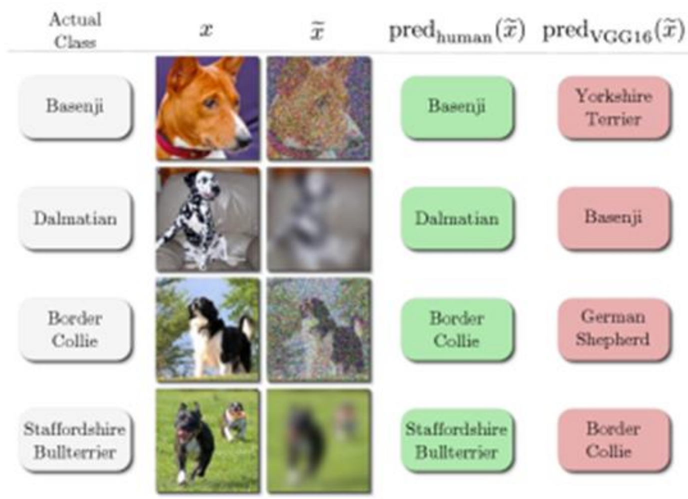

Fig. 1: Human vs. DNN predictions on distorted data [9].

2. *Quality of images:*

A thing's quality might be rated as "poor," "good," or "great" depending on how many of its features it possesses (such as a car or a phone) or how well it meets our needs (a printer). So, if you hope to reply to the query what is the image quality, needed to reply the queries: (1) What is the meaning of images in general? (2) How can you take advantage of images? The answers to these queries Images "transfer visual information about the outside world and are used as input to human visual perception," according to one theory. The three stages of perception, cognition, and action that make up how a person interacts with their environment are visual perception in particular"[10][11].

Subjective and objective quality assessment (IQA) are two general categories for image quality assessment (QA)[12]. People's job in subjective quality assurance is to evaluate the visual appeal of the material, and the mean of their subjective evaluations is known as the Mean Opinion Score (MOS)[13]. In recent years, the design of objective QA methodologies has advanced, and three structural kinds are now firmly established in IQA studies. (1)Full-Reference (FR) IQA, (2) Reduced-Reference (RR) IQA, and (3) No Reference (NR) or Blind IQA[14].

The capacity to fully reproduce the reference image's pure quality replica is a prerequisite for FR methods when evaluating the quality of distorted images, whereas, for RR methods, specific features must be extracted from the reference image[15]. The quality evaluation by comparing the difference between the distorted image and the reference image is the NR method.

The better measure of objective quality must reflect the image distortions so well, such as blurring, noise, compression, and find incompletion[16]. The effective performance of tasks requiring vision-based algorithms, such as feature extraction, image-based measurements, error uncovering, backtracking, and divisions, among others, is predicted by expectant measures of the sort.

2.1 Quality Attributes:

- Prediction accuracy: The model is said to be accurate if the projected values coincide with the target field's actual values within the uncertainty caused by statistical irregularities and noise in the input data[17].

- Prediction monotonicity: objective quality measures must be capable of determining the relation between two or more values in the ML model [18].

- Prediction consistency: a test of the equivalence assumption for all input images (images) in the ML model across several indicators of the same construct. Thus, the objective quality metrics must be able to be reliable [19].

2.2. Impact of image quality on a machine learning model:

Machine learning models, especially those that rely on computer vision tasks like image classification, object recognition, or segmentation, can be significantly impacted by the quality of the images [20]. Following are some significant ways that machine learning model performance might be impacted by image quality:

- Accuracy: The model can more easily tell apart various classes or objects since high-quality photos typically have more information, features, and higher contrast. Lower accuracy may result from models that have difficulty extracting pertinent information from poor-quality or fuzzy photos[21].

- Robustness: Models that are trained on high-quality images are typically more resilient and generalize to real-world situations better. Models may perform badly on unseen data if they are trained on noisy or low-quality images because they may become too sensitive to any artifacts or flaws in the training data[21].

- Feature extraction: Image quality influences a model's capacity to extract pertinent characteristics during feature extraction. When analyzing low-quality photos, the model may struggle to recognize crucial patterns or structures due to missing or distorted information. As a result, the model can generate erroneous predictions or have trouble extrapolating to new examples[22].

- Preprocessing: Image quality affects the procedures that must be taken before the data is fed into the model. Poor-quality photos could need extra preprocessing processes like denoising, scaling, or contrast enhancement, which can increase pipeline complexity and introduce potential errors[23].

- Efficiency in training: Converging models that have been trained on high-quality images often takes fewer iterations and resources. On the other hand, training on poor-quality photos can call for more extended training periods and more data augmentation methods to make up for the low quality. This may affect how effective and scalable the training process is[24].

- Data bias: The caliber of the photos utilized for model training may create bias. The model may fail to generalize to lower-quality photos or various contexts, producing biased predictions, if the training data is predominantly made up of high-quality photographs from particular sources or environments[25].

- The task at hand, the dataset, and the model architecture all play a role in how the influence of image quality is determined. It is important to balance the quality of the photos with the available computational resources even though high-quality photographs typically result in greater model performance.

2.3. Image preprocessing to improve image quality:

- Before supplying images to machine learning models, image-preprocessing techniques can be used to improve the quality of the images. Here are a few typical methods for improving image quality during image preprocessing:

- Resizing: Resizing an image can simplify computations and assist standardize its dimensions. To avoid distortion, it's crucial to keep the aspect ratio when resizing. An example of resizing algorithms "Aspect Ratio Preserving Resizing" algorithm:

Given an original image with width W and height H, and a target width TW and target height TH: Calculating the scaling factor:

$$\text{ScaleFactor} = \min(TW/W, TH/H). \quad \textbf{(1)}$$

- By dividing the smaller of the goal width ratio (TW/W) and target height ratio (TH/H), the scaling factor is calculated. The new dimensions are calculated: Scale factor times width, NewWidth Scale factor times H yields NewHeight. By adding the scaling factor to the original width and height, you may get the new width and height [26].

- Normalization: Normalizing an image's pixel values ensures that they are contained inside a given range (for example, 0 to 1). This may lessen the impact of extreme pixel values and improve model stability while being trained[27].

- Denoising: Denoising methods can be used to lessen noise and artifacts in the image, such as median filtering or Gaussian filtering. Using these methods, the image is smudge-free while still retaining key details[28].

- Enhancing Contrast: By redistributing pixel intensities, contrast enhancement techniques like histogram equalization or adaptive histogram equalization (AHE) can make details in a picture more visible[29].

- Sharpening: Sharpening filters can improve the edges and features in an image, such as the unsharp mask or the Laplacian filter. These filters enhance high-frequency elements and sharpen the image as a whole[30].

- Color Correction: Color distribution in a picture can be changed using color correction techniques like gamma correction or white balancing. By doing this, lighting-related color biases and fluctuations are reduced.

- Image Augmentation: Image augmentation methods can be used to produce more training samples, such as rotation, flipping, or adding noise. By adding changes to the training data, augmentation can aid in the model's ability to generalize[13].

  Based on the unique qualities of the photos and the specifications of the task at hand, it is crucial to select the proper preprocessing approaches. The best preprocessing approach combination for enhancing image quality and the performance of machine learning models must be identified through diligent testing and evaluation.

3. IMAGE METRICS:

- Numerous methods are given for assessing the quality of native photographs. The numerous facets of these techniques (methods) differ, especially when it comes to practical considerations and complexity [31]. The creation of full-reference image quality standards and metrics has continued over time. There was less research and development put into the reduced-reference image quality standards [32]. The lack of metrics development for the quality of no-reference images is evident [33].

- Image processing performance metrics: Computer algorithms were used to improve the properties of digital images. Among these techniques for digital images are classification, coding, and filtering. Performance metrics were used to evaluate these techniques in achieving expected results [34]. Pre-processing performance measurements, segmentation performance metrics, and classification performance metrics are all types of image processing metrics that are applied at different stages[35].

- Preprocessing Performance Metrics: Performance measures (quality score) are used to evaluate the liquidation process. There are specific techniques for reducing noise (distortion) in images, and the effectiveness of these techniques is assessed using filtering performance measures. Peak signal-to-noise ratio (PSNR) and mean square error are the most straightforward and fundamental metrics to employ (MSE)[36].

- Peak Signal-to-Noise Ratio: Peak Signal-to-Noise Ratio (PSNR) of a picture is the ratio of the maximum power of the signal to the maximum power of the noise distorting the image. are expressed in decibels [36].

$$PSNR = 10 * \log10((MAX^2) / MSE) \quad (2)$$

- Mean Square Error: The intensity differences between the filtered picture pixels and the reference (noiseless) image pixels are averaged to get the mean square error (MSE). According to the assumptions of the majority of measurements, seeing the error signal typically lowers the image's perceptual quality (metrics) [36][37].

$$MSE = (1/N) * \Sigma[\Sigma[(I(i,j) - \hat{I}(i,j))^2]] \quad (3)$$

- PSNR Gain: The value at which a new filter's PSNR exceeds that of an existing filter is known as the filter's PSNR gain. If the PSNR gain of the new filter is positive compared to the current one, but if it is negative, the latter is the best. Decibels are used to quantify performance gains [36].

$$PSNR\ Gain = PSNR\_new - PSNR\_current \quad (4)$$

- True Acceptance Rate: The percentage of times a system accurately confirms an authentic identification assertion is known as the true acceptance rate (TAR). The approach with the greatest TAR value will perform the best [38][39].

$$TAR = (\text{Number of Correct Authentic Identifications} / \text{Total Number of Authentic Identifications}) * 100 \quad (5)$$

- False Acceptance Rate: FAR measures the proportion of times a system verifies an identity claim wrongly. The applicant should be classified using the method that results in the lowest FAR[38].

$$FAR = (\text{Number of False Acceptances} / \text{Total Number of Verification Attempts}) * 100 \quad (6)$$

- Pixel Error Rate: the proportion of noise-free pixels in an image (filtered). The discrepancy in the number of black pixels between the noiseless and filtered images after they have been converted to binary images is referred to as pixel error. The symbols M and N can be used to denote rows and columns, respectively. The method with the lowest PEER value is considered to be the best[11].

$$PEER = (\text{Number of Incorrectly Classified Pixels} / \text{Total Number of Noise-Free Pixels}) * 100 \quad (7)$$

- Recognition Accuracy: The features of an image can be precisely identified using RA. The candidate whose results have the greatest RA value is ranked as the best-performing candidate[40].

$$RA = (\text{Number of Correctly Identified Features} / \text{Total Number of Features}) * 100 \quad (8)$$

4. RELATED WORK

(**Z**hang et al., 2018) introduced a model for classifying urban land cover using extremely high-resolution satellite imagery; the novel multi-scale deep learning models ASPP-Unet and ResASPP-Unet were proposed. The models enhanced the accuracy of feature extraction and classification using residual units and the atrous spatial pyramid pooling (ASPP) method. WorldView-2 (WV2) and WorldView-3 (WV3) imageries were used in Beijing to train and assess the models. In comparison to well-known models like U-Net, CNN, and SVM, the proposed models gave precise and trustworthy results for identifying urban land cover [41].

(**A**thar & Wang, 2019) recommended that conducted the largest performance evaluation research to date on image quality assessment (IQA) using nine subject-rated datasets with various distortion types. Their findings identified the best full-reference (FR) and no-reference (NR) IQA techniques, with a significant finding that rank aggregation-based FR fusion outperforms other FR fusion approaches and even the best FR techniques. This suggests its potential use as a substitute for subjective assessments in large datasets where obtaining human opinions may be challenging [42].

(**M**ichalak & Okarma, 2019) create a technique for picture preparation leveraging local image entropy filtering is offered to get over the challenges of automatic word identification in natural photos taken under uncontrolled illumination circumstances. By accounting for shadows and uneven lighting in document images, the proposed method aims to improve commonly used thresholding techniques for photographs [43].

(**B**angaru et al., 2019) make a study to the impact of SEM image magnification on model accuracy and classifier training for degree of hydration measurement. The examination of microstructure using SEM images was shown to be adequate for the Random Forest classification algorithm. According to statistical analysis, magnification has little effect on the training and accuracy of the degree of hydration measurement model. As a result, it is possible to interpret images at various magnifications using a single classifier, saving time and effort during training[44].

(**W**u et al., 2019) create a model for real-time quality improvement system for esophagogastroduodenoscopy (EGD) procedures called WISENSE. The WISENSE system efficiently tracked blind spots, timed the procedure, and produced photo documentation by combining deep convolutional neural networks and deep reinforcement learning[45].

(**U**llah et al., 2020) Proposed a system for the examination of microstructure and estimation of degree of hydration using SEM images, a machine learning-based image segmentation technique was proposed. The impact of SEM photo magnification on model accuracy and classifier training for a degree of hydration measurement was examined. The results showed that using Random Forest classification for microstructure analysis was appropriate[46].

(**C**oe & Atay, 2021) suggested model to assess race-affected facial recognition using various algorithms. The accuracy, metrics, miss rates, and performances of machine learning and deep learning algorithms were compared. The results showed that VGG16 outperformed the other algorithms, including SVC as the top machine learning algorithm, in terms of reducing racial bias [47].

(**W**ang et al., 2021) build a model In order to classify images, contrast and compare deep learning, namely Convolutional Neural Networks (CNN), with traditional machine learning, particularly Support Vector Machine (SVM). According to the findings, normal machine learning outperforms deep learning on big sample datasets (as exemplified by CNN), but deep learning outperforms it on small sample datasets [48].

(**S**arki et al., 2021) Make a study in order to accurately classify Diabetic Eye Disease (DED) from retinal fundus pictures, this study emphasizes the crucial role that image processing plays. DED is a serious worry for diabetic people, and early detection is crucial to avoid vision loss [49].

(**L**i et al., 2022) a novel method by a Gabor filter-based improved pix2pix color rendering technique presented to address problems with color overstepping, boundary-blurring, and unstable training. The preprocessing technique used Gabor filters to preserve image details while preventing feature loss [50].

(**R**ukundo, 2023) generate a measure, Myocardial Infarction (MI) using the EWA method using the automatically segmented LGE-MRI images. A variety of techniques, including arbitrary threshold, comparison of sums, and sums of differences, were utilized to quantify the relationship between semi-automatic/manual and fully automated quantification of MI outcomes [51].

I. Table for related work.

Author & Year	**Dataset**	**Proposed techniques**	**Accuracy**	**Disadvantages**
(Zhang et al., 2018)	WV2 imagery covers part of Haidian and Xicheng Districts with area of 17.22 km2 , and WV3	In this study the ASPP-Unet and ResASPP-Unet models for urban land cover classification from VHR imagery .	(87.1% for WV2 imagery and 84.0% for WV3 imagery	The models need a large number of high-quality ground truth samples as training data.

	imagery covers part of Chaoyang District with area of 3.06 km2			
(Athar & Wang, 2019)	A review on nine datasets DMOS (Differential Mean Opinion Score), MOS (Mean Opinion Score)	Computing the weighted average PLCC and SRCC values for each IQA method over different databases. The weight assigned to a database depends on its size in terms of the number of distorted images	—	Learning based fusion methods do not offer clear advantages over individual FR methods.
(Michalak & Okarma , 2019)	dataset of 140 differently illuminated document images	thresholding—one of the global binarization methods may be used for this purpose, in experiments the classical Otsu's thresholding	0.93%	Binarization of unevenly illuminated and degraded document images is still an open and challenging field of research
(Bangaru et al., 2019)	—	Machine learning based image segmentation technique for concrete SEM image analysis and degree of hydration measurement. The study determines the effect of magnification on the degree of hydration measurement using the machine learning based image segmentation technique.	The segmentation accuracy of the models in both Scenario-I (100%	The SEM imaging at different magnification involves high cost and time.
(Wu et al., 2019)	Three dataset used 12220 in vitro, 25222 in vivo and 16760 unqualified EGD. images for training the network to identify whether a scope was in or outside the body (DCNN1).	WISENSE, a real-time quality improving system based on the DCNN and deep reinforcement learning (DRL) for monitoring blind spots, timing the procedure and generating photo documentation during Esophagogastroduodenoscopy (EGD) was developed. The performance of WISENSE was Verified in EGD videos.	VGG-16 and DenseNet (97.55%±0.18% and 97.86%±0.19%, respectively) in DCNN1, VGG-16 DenseNet (88.70%±0.23% and 83.76%±(respectively) in DCNN2.	First: The results were obtained using Olympus and Fujifilm endoscopes, which have a 70%31 and 14%32 endoscope market share, Respectively. Second: it is recommended that the EGD should last for at least 7min on a patient without a previous gastroscopy for the last 3years.

(Ullah et al., 2020)	Harvard Medical School website (http://med.harvard. edu/AANLIB)	A medical decision support system using malignant and benignant classes. This system is designed by median filter, CLAHE, wavelet transform, color moments and feed-forward NN. The proposed system provide astounding results in categorizing the malignant and benignant MRI images. Considering this methodology, the physician can make the final decision without any hesitation, which is the main advantage of this system.	95.8%	The complexity of the system is reduced using a features reduction phase, color moments are used for feature selection. They reduced the dimension of feature vector from 1024 to 9 only.
(Coe & Atay, 2021)	FERET(Face Recognition Technology) NIST(dataset with access granted from the National Institute of Standards and Technology) Tuned datasets such as (FairFace) and (DemogPairs)	Evaluated racial bias across five machine learning algorithms using racially imbalanced and balanced datasets. The five machine learning algorithms explored were Support Vector Classifier (SVC), Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN), Decision Trees (DT), and Logistic Regression (LR). We evaluated racial bias across three deep learning algorithms using racially imbalanced and balanced datasets. The three deep learning algorithms explored were AlexNet, VGG16, and ResNet50.	100%	Calculating values for each pixel is a complex task that can involve thousands or millions of steps to complete depending on image size and quality, especially if you consider that each pixel comprises values representing the red, green, and blue values within itself.
(Wang et al., 2021)	MNIST(Modified National Institute of Standards and Technology) & COREL1000	Utilizes Support Vector Machines (SVM) to achieve image recognition, offering advantages on smaller datasets and demonstrating robust classification capabilities. (CNN) to enhance image recognition accuracy, particularly effective on large-scale datasets, thanks to their ability to capture intricate patterns and features in images.	MINST(SVM is 0.88 and CNN is 0.98) COREL1000 (SVM is 0.86 and the accuracy of CNN is 0.83)	solution effect on small sample data sets, and deep learning framework has higher recognition accuracy on large sample data sets.

(Sarki et al., 2021)	Messidor, Messidor-2, DRISHTI-GS, and Retinal Dataset from GitHub.	Study on the signifcance of image processing for DED classifcation. The proposed automated classifcation framework for DED was achieved in several steps: image quality enhancement, image segmentation (region of interest), image augmentation (geometric transformation), and classifcation.	Normal /mild DR: CNN 93.33 Normal /mild DME: CNN 91.43 Normal /mild GL: CNN 100	First, Data set acquired for this experiment were obtained from publicly available which limits number of high quality mild DED images, only limited-to-moderate data set sizes were employed. Second, the default model parameters were adopted for classification task. Finally, the 'black-box' nature of D.L-based solution is often criticized, causing Resistance in the broader approach adopted by practitioners.
(Li et al., 2022)	—	Gabor filter based improved pix2pix for robust image. Firstly, the multi direction /multi-scale selection characteristic of Gabor filter is used to preprocess the image to be rendered, which can retain the detailed features of the image while preprocessing to avoid the loss of features. also the ideal color image can be obtained. To reflect image color rendering quality of different models more objectively.	Average SSIM for: LSpix = 86.011	At present, the image resolution of image processing based on deep learning is limited, which leads to the limitation in the practical application of rendering Method.
(Rukundo, 2023)	LGE MRI (Late Gadolinium Enhancement Magnetic Resonance Imaging).	A novel strategy was introduced to handle interpolation masks and remove extra class labels in interpolated ground truth (GT) segmentation masks.	The relationship between semi-automatic and fully automated quantification of MI results was found to be closer in the case of bigger LGE MRI images (55.5% closer to manual results) than in the case of smaller LGE MRI images (22.2% closer to manual results).	Seeking to determine the best size and improve the segmentation accuracy required the use of extra-pixel category-based image interpolation algorithms instead of the traditional nearest neighbor of the non-extra pixel category.

5. CONCLUSION

Machine learning models, especially those designed for computer vision tasks, heavily rely on the quality of input images. Image quality can significantly impact accuracy, robustness, feature extraction capabilities, training effectiveness, and the potential for model bias. Higher-quality images typically contain more information and better contrast, enabling models to distinguish between different classes or objects more accurately. Various preprocessing techniques can be employed to enhance image quality. Commonly used preprocessing methods include resizing, normalization, denoising, contrast enhancement, sharpening, color correction, and image augmentation. These techniques aid in improving contrast and sharpness, correcting color biases, and augmenting the training data to enhance model generalization. They also help standardize image dimensions. However, it's crucial to strike a balance between image quality and available processing resources. Additionally, the choice of preprocessing techniques should be carefully considered, tailored to the unique characteristics of the images, and suitable for the specific task. The impact of image quality on machine learning models and the effectiveness of preprocessing methods ultimately depend on the task at hand, the dataset used, and the model architecture. Experimentation, evaluation, and continuous refinement of the preprocessing pipeline are essential to achieve the best results.

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