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Title **DEEP IMAGE QUALITY METRICS ON IMAGE ENHANCEMENT**

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# DEEP IMAGE QUALITY METRICS ON IMAGE ENHANCEMENT

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**ABSTRACT**
Image metrics based on Human Visual System (HVS) play a remarkable role in the evaluation of complex image processing algorithms. However, mimicking the HVS is known to be complex and computationally expensive (both in terms of time and memory), and its usage is thus limited to a few applications and to small input data. All of this makes such metrics not fully attractive in real-world scenarios. To address these issues, we propose Deep Image Quality Metric (DIQM), a deep-learning approach to learn the global image quality feature (mean-opinion score). DIQM can emulate existing visual metrics efficiently, reducing the computational costs by more than an order of magnitude with respect to existing implementations
.

## 1. INTRODUCTION

**Digital Image Processing:**

An image may be defined as a two-dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point.

When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer.

Note that a digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, pels, and pixels. Pixel is the term most widely used to denote the elements of a digital image.

**Fundamental Steps in Digital Image Processing:**

It is helpful to divide the material covered in the following chapters into the two broad categories defined in Section 1.1: methods whose input and output are images, and methods whose inputs may be images, but whose outputs are attributes extracted from those images. The diagram does not imply that every process is applied to an image.

Rather, the intention is to convey an idea of all the methodologies that can be applied to images for different purposes and possibly with different objectives. Image acquisition is the first process acquisition could be as simple as being given an image that is already in digital form. Generally, the image acquisition stage involves preprocessing, such as scaling.

Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image. A familiar example of enhancement is when we increase the contrast of an image because “it looks better.” It is important to keep in mind that

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enhancement is a very subjective area of image processing.

**STEPS IN DIGITAL IMAGE PROCESSING**

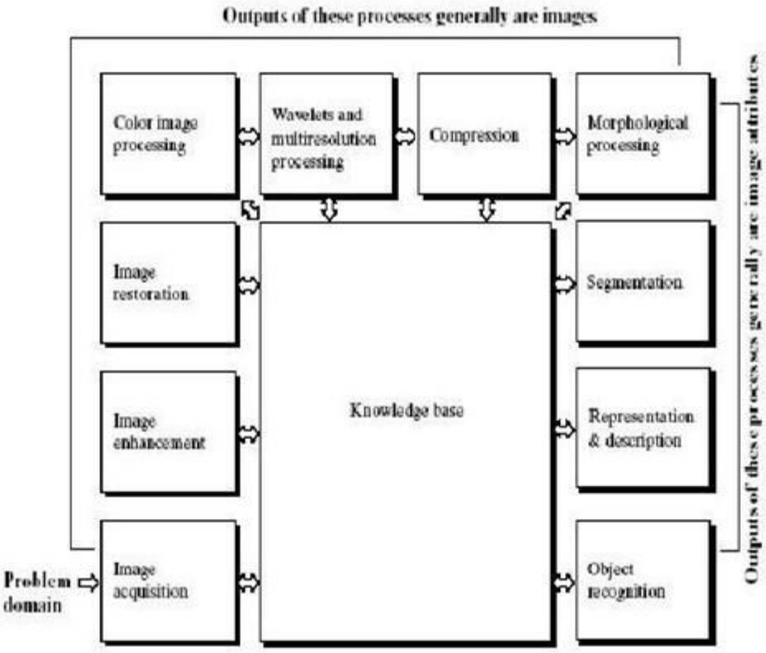


**Fig 1.1: Steps in digital image processing**

**Image restoration:**

It is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation. Enhancement, on the other hand, is based on human subjective preferences regarding what constitutes a "good" enhancement result. Color image processing is an area that has been gaining in importance because of the significant increase in the use of digital images over the Internet.
Fundamental concepts in color models and basic color processing in a digital domain. Color is used also in later chapters as the basis for extracting features of interest in an image.

**Wavelets:**

These are the foundation for representing images in various degrees of resolution. In particular, this material is used in this book for image data compression and for pyramidal representation, in which images are subdivided successively into smaller regions.
This is true particularly in uses of the Internet, which are characterized by significant pictorial content. Image compression is familiar (perhaps inadvertently) to most users of computers in the form of image file extensions, such as the jpg file extension used in the JPEG (Joint Photographic Experts Group) image compression standard

**Compression:**

As the name implies, deals with techniques for reducing the storage required to save an image, or the bandwidth required to transmit it. Although storage technology has improved significantly over the past decade, the same cannot be said for transmission capacity.
This is true particularly in uses of the Internet, which are characterized by significant pictorial content. Image compression is familiar (perhaps inadvertently) to most users of computers in the form of image file extensions, such as the jpg file extension used in the JPEG (Joint Photographic Experts Group) image compression standard.

**Morphological processing:**

It deals with tools for extracting image components that are useful in the representation and description of shape. The material in this chapter begins a transition from processes that output images to processes that output image attributes, Segmentation procedures partition an image into its constituent parts or objects.

In general, autonomous segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually. On the other hand, weak or erratic segmentation algorithms almost always guarantee eventual failure. In general, the more accurate the segmentation, the more likely recognition is to succeed.

**Representation and description:**

Almost always follow the output of a segmentation stage, which usually is raw pixeldata, constituting either the boundary of a region (i.e., the set of pixels separating one image region from another) or all the points in the region itself.

In either case, converting the data to a form suitable for computer processing is necessary. The first decision that must be made is whether the data should be represented as a boundary or as a complete region. Boundary representation is appropriate when the focus is on external shape characteristics, such as corners and inflections.

Regional representation is appropriate when the focus is on internal properties, such as texture or skeletal shape. In some applications, these representations complement each other. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. A method must also be specified for describing the data so that features of interest are highlighted. Description, also called feature selection, deals with extracting attributes that result in some quantitative information of interest or are basic for differentiating one class of objects from another.

**Recognition:**

So far, we have said nothing about the need for prior knowledge or about the interaction between the knowledge base and Knowledge about a problem domain is coded into an image processing system in the form of a knowledge database.

This knowledge may be as simple as detailing regions of an image where the information of interest is known to be located, thus limiting the search that has to be conducted in seeking that information. The knowledge base also can be quite complex, such as an interrelated list of all major possible defects in a materials inspection problem or an image database containing high-resolution satellite images of a region in connection with change-detection applications.

In addition to guiding the operation of each processing module, the knowledge base also controls the interaction between modules. This distinction is made in Fig. 1.23 by the use of double headed arrows between the processing modules and the knowledge base, as opposed to single-headed arrows linking the processing modules.

Although we do not discuss image display explicitly at this point, it is important to keep in mind that viewing the results of image processing can take place at the output of any stage.

## 2. LITERATURE REVIEW

### COMPONENTS OF IMAGE PROCESSING SYSTEM

A convolutional neural network is a feed-forward neural network that is generally used to analyze visual images by processing data with grid-like topology. It’s also known as a ConvNet. A convolutional neural network is used to detect and classify objects in an image. Below is a neural network that identifies two types of flowers: Orchid and Rose.

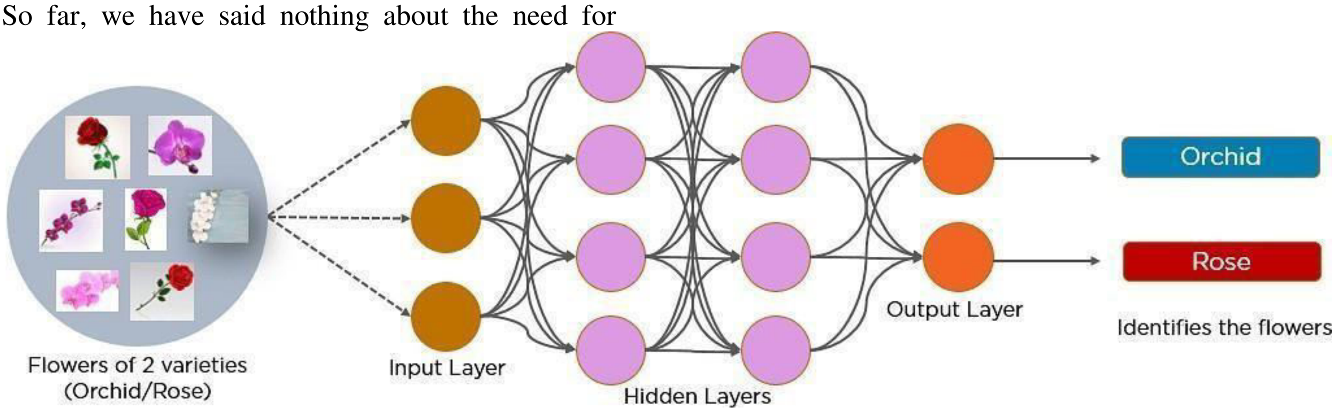


**Fig 3:** Diagram for literature survey

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In CNN, every image is represented in the form of an array of pixel values.

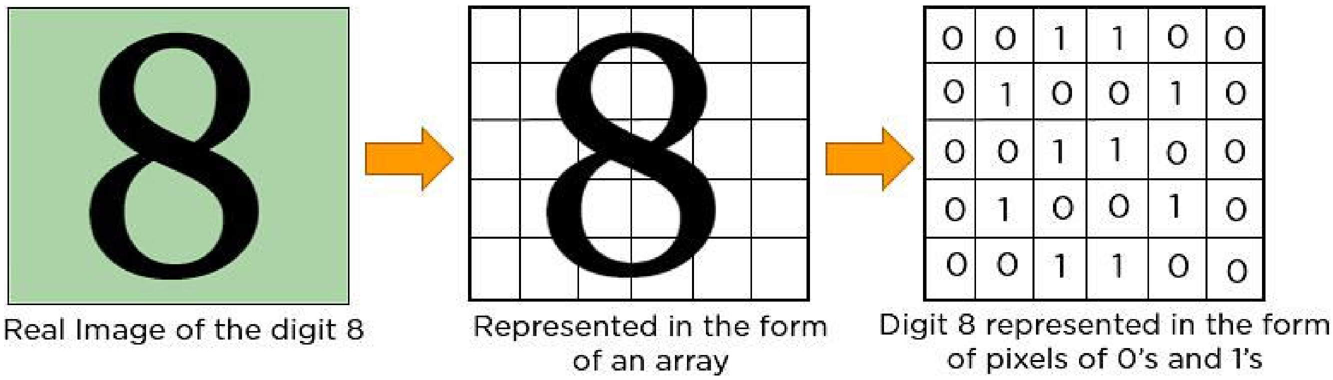
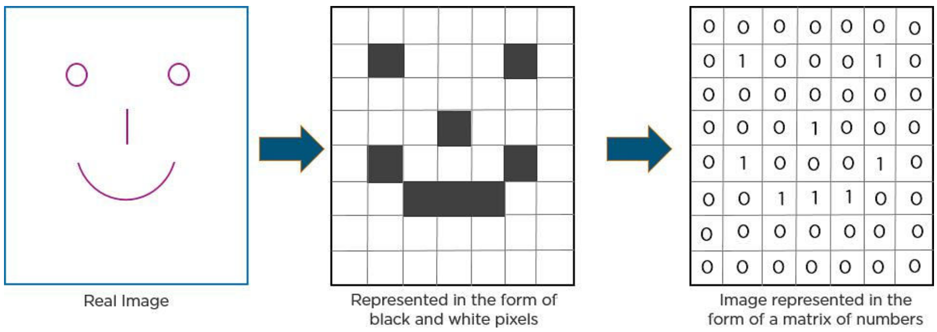



**Fig 3.2:** Diagram for pixel values

Here is example to depict how CNN recognizes an image:




As you can see from the above diagram, only those values are lit that have a value of 1.

## 3. PROPOSED SYSTEM

High Dynamic Range Visual Differences Predictor (HDR-VDP) in this section, we define two different settings to test the Q score in representative scenarios, encompassing both HDR and SDR contents, for which HDR-VDP is well suited. The first scenario reproduces standardization in HDR content (Section IV-A1), while the second scenario is devoted to representing distortions in SDR content (Section IV-A2) 1)

Scenario 1: In the last few years, academia and industry have been actively working on the definition of standards for the emerging HDR features added to several digital products. Valuable objective metrics have thenceforth become a fundamental tool for the standard evaluation.

We used the recently proposed JPEG-XT standard coding system [2], [3] for still HDR images as a representative example. Starting from the initial dataset of 2, 709 HDR images, we simulated the compression artifacts produced by JPEGXT, leaving all encoding parameters set as specified in [2]. We decided to use a local TMO [38] since, as shown in [2], the compression capability of JPEG-XT is not strongly influenced by a specific tone mapping operator. The compression factor for the tone mapped image was fixed to 80; while the residual compression factor was varied from 1 to 100 at steps of 20 (we did not observe significant changes at smaller steps). We used all the three profiles available in the Part-7 of the standard, where each profile is selected randomly for all possible combinations. 2)

Scenario 2: HDR-VDP can likewise be used to evaluate distortions for SDR content. Therefore, we selected four common types of distortions that are representative of various image processing tasks and randomly applied them to our set of SDR images. The distortions we considered are listed below: • Blur - we selected Gaussian Blur distortion, where the sigma parameter is randomly chosen within the range [0.5, 4]

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• Quantization - we randomly applied two types of quantization distortion: JPEG compression with random quality values in the range [10, 75], and bit reduction applied to each color channel of the input image by reducing encoding bits in the range [2, 6].

• Noise - we used two types of noise: Gaussian noise and salt-and-pepper noise (or Impulse Noise). For the Gaussian noise, we considered the sigma parameter in the range [0.0001, 0.005]. For the salt-and-pepper noise, the intensity parameter is varied in the range [0.001, 0.01]. The type of noise to be applied and its parameters are decided randomly.

• Sine gratings - we randomly applied either a vertical or horizontal sine grate using a randomly selected intensity in the range [0.005, 0.01] and a randomly selected frequency in the range [0.008, 0.65].

An example of these distortions is depicted in Figure 2. Typical image datasets used in the development of quality image metrics, such as TID20132 [45], Live IQA3 Release 2 [46], and the ESPL Synthetic Image 24 could be used as training data for our model.

However, as pointed out in the recent work of Kim et al. [47], they are too small for being used to train CNN-based models. We have thus decided to enlarge our original datasets by integrating the aforementioned datasets.
These common datasets consist of 4,492 distorted images. In particular, the first dataset has 25 reference images at 512 × 384 resolution with 3,000 distorted images. The second dataset has 29 reference images at different resolutions (from 640 × 512 to 768 × 512) with 992 distorted images.
Finally, the third dataset has 21 reference images at full HD resolution (1920×1080) with 500 distorted images. Note these images, which were larger than 512 × 512, were randomly cropped. B. Dynamic Range Independent Metric (DRIM) to evaluate the ability of our approach in approximating the contrast changes prediction of the DRIM, we defined four different scenarios that, also, in this case, include both HDR and SDR content.

Given that DRIM is robust to differences in dynamic range, we distributed the scenarios of interest across two main categories: different dynamic range (Section IV-B1), and similar dynamic range (Section IV-B2). 1) Different Dynamic Range: We identified two possible scenarios where SDR content is evaluated against its corresponding HDR content

## 4. RESULTS

**FIG-1.bmp:**

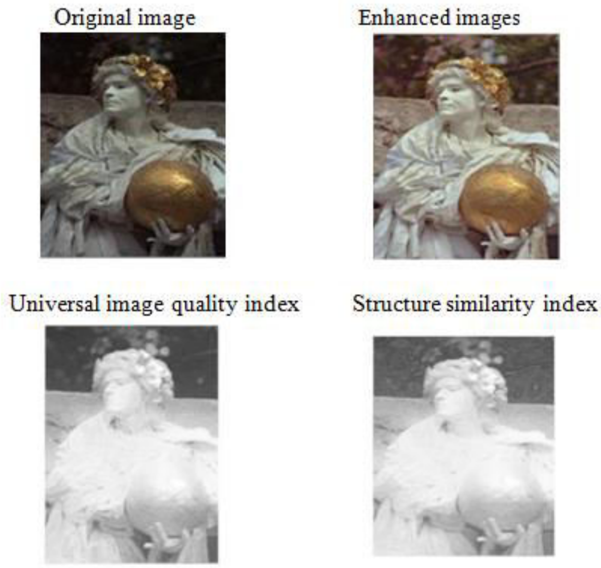
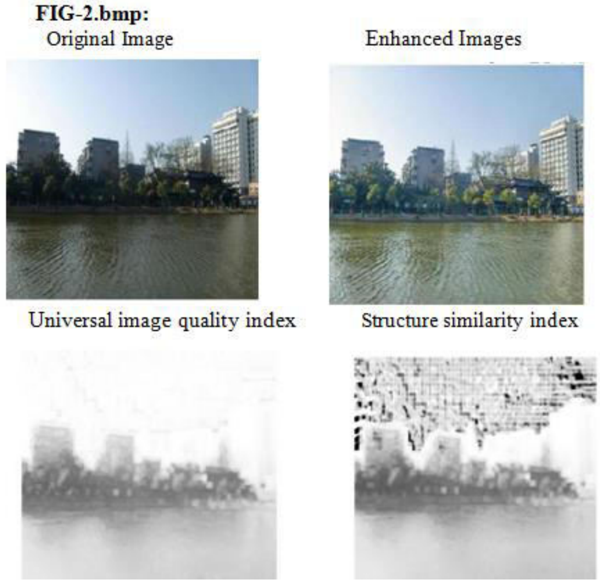



**FIG-2.bmp:**




## 5. CONCLUSION

Object visual metrics based on the HVS mechanisms provide a useful tool in the quality assessment of image/video processing techniques. However, their usage is precluded or limited in certain relevant applicative scenarios due to their high computational costs.

To overcome this problem, we have presented DIQM, a deep-learning-based objective metric which can predict scalar quality values comparable to those obtained by the traditional HDR-VDP and DRIM algorithms. DIQM has been tested on a large dataset covering 6 different representative scenarios, including standardization and distortions, both for HDR and SDR contents. We have empirically demonstrated DIQM can predict the quality value Q and the probability index with high accuracy. DIQM is also significantly computationally cheaper, thus making it feasible to apply such visual metrics to scenarios that remained out of reach up to date. Examples of applications that can benefit from the use of DIQM include optimization processes for selecting optimal parameters for TMOs, iTMOs, and JPEG-XT.

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