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# A study on Just Noticeable Difference (JND) Using DeepConvection Network (DCNN)

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**Abstract**
The prediction approach obtained from the unique brain theory known as deep convolution network is just a noticeable difference (JND) (DCNN). Various compression techniques are used in images to reduce image size while maintaining image quality and resolution. The screen content image (SCI) is unique in that it includes textual and illustrated areas, which causes several difficulties in image quality assessment (IQA). The Human Visual System (HVS) is used to predict order- based information, which prevents residual irregular unreliability for image insight and comprehension. Deep Learning is used extensively in JND images. JND is enormous and is based on optical data and emotional factors that are not fullyrecognized. The primary goal is to compare the distorted image to the original image. Any DL or ML approach cannot accurately analyse the distorted image. DCNN isused in this paper to find the JND among the given images. The proposed model centred on detecting accurate distortions after applying image compression techniques and analysing image quality. This type of distortion can be used to deceive the DL or ML approaches. The quality of the distorted image is used to determine performance.

**Key words:** Just Noticeable Difference (JND), Deep Learning, DCNN, screen content image (SCI), Image Quality Assessment (IQA). Human Visual System (HVS).

## Introduction

JND (Just Noticeable Difference) in images shows very little difference in the image that cannot be seen by humans and can be seen by various algorithms. When using streaming services, processing large images and videos becomes more difficult [1]. Various image formats, including Ultra-High-Definition (UHD), Three Dimensional (3D) [2], and Virtual Reality (VR) images and videos, can provide a much more immersive and practical experience than traditional multimedia. To analyse the qualitative effects of visual data, various image and video coding techniques [3] are currently used.

JND explains the less known HVS threshold on visual contents, which is most commonly used for ocular overflow estimation. JND models are classified into two types: pixel-wise and subband-domain JND models. The original image/video is extracted using the first model. The second model is the one most commonly used to compute the compressed domain. There are two components in pixel-based estimation: luminance adaptation (LA) and spatial masking (SM) [4], [5], [6], [7]. Background is used to implement LA, which is based on Weber's law. The available dataset, such as VGG-16, is trained efficiently. The D-CNN is used to develop an improved distortion approach in this paper. The most common application of DCNN is to identify patterns in images and videos. DCNN will attempt to demonstrate the distortion between the input and original images. Figure 1 depicts the step-by-step analysis of the distorted images. The JND is visible among the images in the output image.

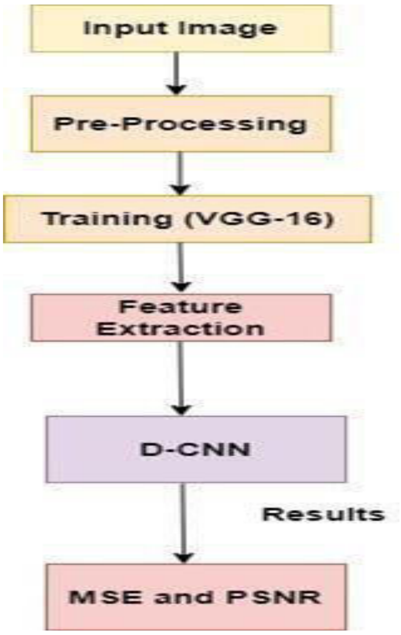


Figure 1 Process of Proposed Approach (D-CNN)

**Literature Survey**

Several JND datasets for image and video compression are available in the literature, each with a different pre-processing approach to obtain accurate and representative JNDs. The MCL-JCI dataset [10] is made up of 50 source images (SRC) with varying numbers of JND points based on JPEG compression levels. Following the collection of raw JND points, a Gaussian mixture model was used to generate a staircase quality function from a set of JND points [11]. The MCL-JCV dataset was released by [12], and it contains JND data collected from 50 observers using a similar staircase quality function designed for H.264/AVC. JND samples for 40 reference panoramic images at various JPEG compression levels are included in the JND-PANO dataset [13]. VideoSet is a large-scale dataset that contains JND samples for various H.264 compression levels and resolutions [14]. PWJNDInfer is made up of JND samples from 202 reference images at various compression levels.

The explosion of JND subjective studies in recent years has sparked a lot of interest and sparked a lot of interesting ideas for the development of JND prediction models. By defining JND prediction as a multi-label classification task and reducing it to a series of binary classification problems, Liu et al. proposed a picture-wise binary JND prediction model [15]. Zhang et al. proposed a ratio prediction model for video compression distortions based on content [16]. To the best of our knowledge, this is the first study to use the first JND points to predict overall image quality on a continuous scale for various distortion types in the sub-threshold and supra-threshold ranges.

**Visual Saliency Model for Just Noticeable Difference Estimation**

Humans can automatically detect distortion in the given input image in every image. Humans can automatically detect distortion in the given input image in every image. Users from various fields want to find their own interests based on vision space of various variation data such as games, edges, and default object information. The HVS that dynamically creates a saliency map to target the image or video uses selective approaches and vital discernment to solve topologically tedious issues. This method has the disadvantage of causing low-frequency properties to be assigned to regions with high frequency properties.

**Convolutional neural network (CNN) for Just Noticeable Difference Estimation**

CNN has been successfully used to detect various objects, items, and human detection applications such as image classification [17], object detection [18], and scene parsing [19]. CNN-based DL is a powerful domain that can solve a variety of problems in visual recognition tasks. DL models, in particular, are widely used in highly accurate human detection. However, after the video or image has been distorted, this detection becomes difficult. As a result, these approaches are exhausting in terms of accurately beating the images.

**Training for Data using VGG-16**

VGG16 is a CNN model that provides effective training on a variety of complex datasets. This provides training for large datasets and image datasets. This training model is made up of 16 different types of filters and several layers. This model makes use of 13 hidden layers and three fully connected layers.

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### Dataset Description

The dataset was compiled from Flickr images, which included 25k labelled images from 38 different categories. 5k images are chosen for experiments from a pool of 25k images. Three thousand images are used for training, and two thousand images are used for testing. Figure2 depicts a few images.

Figure 2 Flickr Dataset Images

### Proposed Model

The proposed method is CNN, also known as feed-forward neural network (FFNN), which is used to observe visual images by processing data with a grid-like topology. CNN is also known as ConvNet. CNN is capable of classifying the various objects in the images. D-CNNis a significant deep learning approach that consists of multiple hidden layers that process compressed images to find accurate distortion. The JND model with DCNN is commonly used to analyse the least detectable distortion from given images. The proposed model is primarily concerned with determining the precise difference between the input image and the distorted image.

### Layers in DCNN

The convolutional layer, for example, contains a nxn square neuron layer. If you use the mxm filter with, the convolutional layer output will be (Nm+1)(Nm+1). To compute the pre- nonlinearity input to some unit xl in our layer, add the contributions (weighted by the filter components) from the previous layer cells:

$$x^l_{i,j} = \sum_{x=0}^{m-1} \sum_{y=0}^{m-1} \omega_{xy} y^{l-1}_{(i+x)(j+b)}$$

### Deep-CNN

In this paper, a hybrid deep learning algorithm (DCNN) is used to analyse the Just Noticeable Difference (JND) in images from a given dataset. This is an innovative deep learning algorithm that examines every attribute in the dataset. To improve the results, an efficient pre-processing technique is used.

Step 1: Prepare the dataset for training by initialising it.
Step 2: Preparation is the second step (noise removal)
Step 3: Instruction
Step 4: Develop a New Deep Learning Algorithm The following is the algorithm:

- Improved feature extraction from given input.
- Enhanced Filters were applied to the given sample.
- Finally, the outcome is displayed.

Step 5: Results

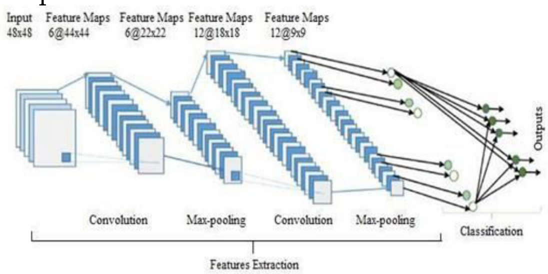


Figure 3 Processing of D-CNN

### Experimental Results

Python programming language is used to conduct experiments. Python is the most powerful programming language, producing the best results for all types of applications. The system requires 8 GB of RAM and a hard drive with a capacity of 20 GB from the overall system hard drive. The image's performance is explained in tables 1 and 2.

### Mean Squared Deviation (MSD)

MSD is an image quality estimator that calculates the average square of errors. The error in this measure represents the difference between predictor and predicted output. The risk function takes into account the expected value of the squared error loss.

MSE among two images such as g(a, b) and $\hat{g}$(a, b)

$$MSE = \frac{1}{MN}\sum_{a=0}^{M}\sum_{b=1}^{N}[\hat{g}(n,m) - g(n,m)]^2$$

### PSNR (Peak Signal to Noise Ratio)

Another quality metric that calculates the reconstruction of lossy image

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compression codecs is the PSNR. The signal represents the original data in this measure, while the noise represents the error caused by compression or distortion. In comparison to compression codecs, this measure is an approximation of human perception of reconstruction quality.

PSNR = 10log10(peakval2)/MSE

Table 1 Performance of Algorithms

| Algorithms | Image Quality (MSD) | PSNR | Perceptually-Lossy | Lossy |
|---|---|---|---|---|
| Visual Saliency | 61.64 | 30.80 | 25.18 | 0 |
| CNN | 66.28 | 36.65 | 21.15 | 0 |
| D-CNN | 70.88 | 39.65 | 17.15 | 1 |

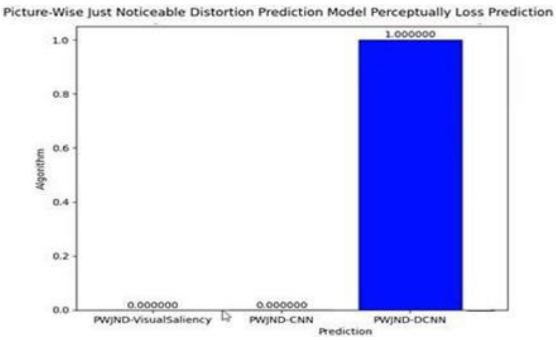


Figure 4 Prediction

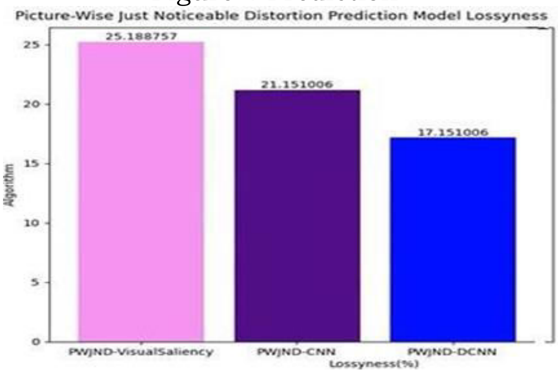


Figure 5 Loosynes

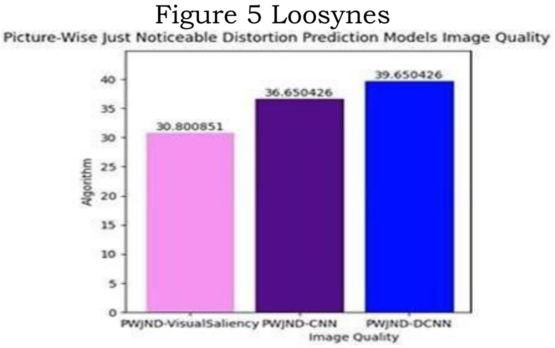


Figure 6 Image Quality

Table 2 Performance in terms of Time (Sec)

| Algorithms | Compression Time | Prediction Time | Total time |
|---|---|---|---|
| Visual Saliency | 5.27 | 2.3 | 7.64 |
| CNN | 6.72 | 3.3 | 10.09 |
| D-CNN | 7.00 | 3.4 | 10.44 |

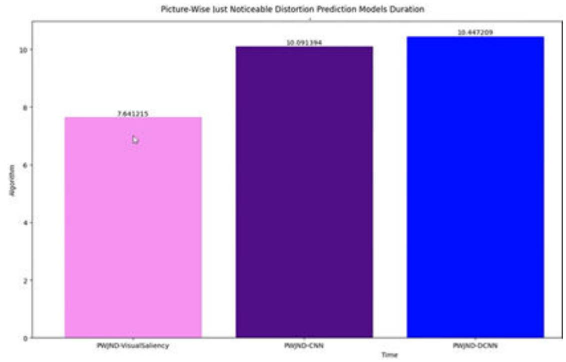


Figure 7 Overall Time (Sec)

## Conclusion

This paper created the advanced JND model D-CNN with the powerful training VGG16. VGG16 is important in training for complex datasets such as MIRFlickr. This is a very complex dataset, and training for this VGG16 pre-trained model is also very complex. With so many layers in thismodel, the JND with just noticeable distortion yields the best results. Pre-processing is also important for reducing noise in the given dataset. Pixel-based JND is also used to improve image distortion detection. The parameters include PSNR (Peak Signal to Noise Ratio) of 70.88 and Mean Squared Deviation (MSD) of 39.65.

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