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# **Deep Learning Application for Image Enhancement**

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# About me

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# Agenda

- Overview
- Image Enhancement.
- Deep learning background.
- Deep Learning Applications on Image Enhancement .
  - Image Denoising.
  - Image Deblurring.
  - Image Super-resolution.

# Overview:

Recently, deep learning has obtained a central position toward our daily life automation and delivered considerable improvements as compared to traditional algorithms of machine learning. Enhancing of image quality is a fundamental image processing task and. A high-quality image is always expected in several tasks of vision, and degradations like noise, blur, and low-resolution, are required to be removed. The deep techniques approaches can significantly and substantially boost performance compared with classical ones. One of the main research areas where deep learning can make a major impact is imaging. This work presents a survey of deep learning on image enhancement and describes its potential for future research.

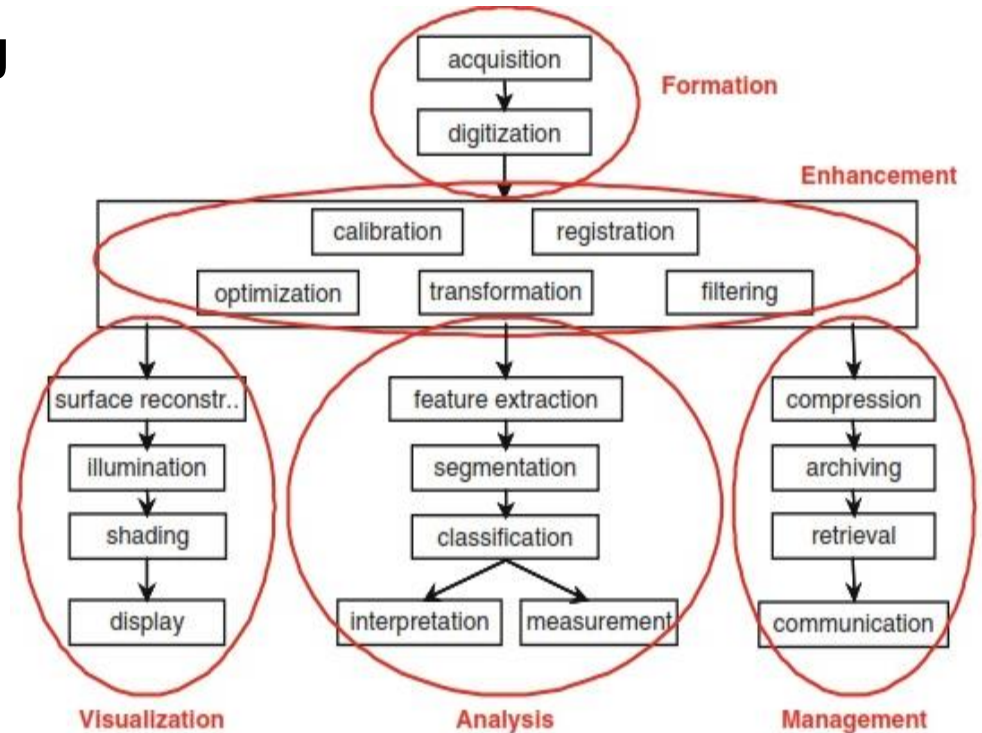
# Image Enhancement:

## Modules of Image Processing

In general, image processing covers four main areas:

Image **formation**, **visualization**, **analysis**, and **management**.

The algorithms of image **enhancement** can be assigned as pre- and post-processing in all areas.



# Image Enhancement:

- ❑ Image quality enhancing is a fundamental problem in image processing that has received great attention over several decades.
- ❑ A high-quality image is always expected in different tasks of vision, and degradations like low-resolution, blur, and noise, are required to be removed.
- ❑ Image enhancement is adjusting process of digital images so that the results are more appropriate for display or additional image analysis.



(a)



(b) Low-resolution



(c) Noisy

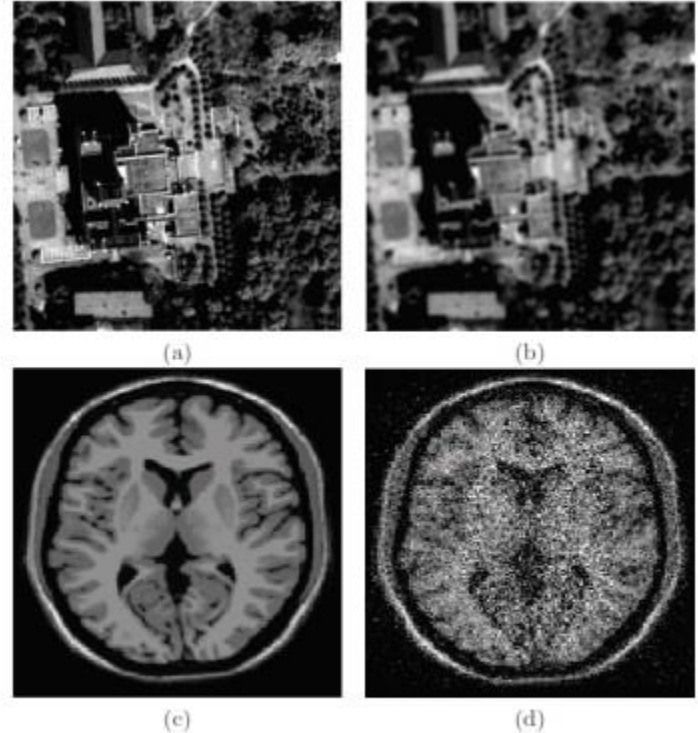


(d) Blurry

Examples of photography. (a) The image we want to see. (b)(c)(d) The images we may capture.

# Image Enhancement

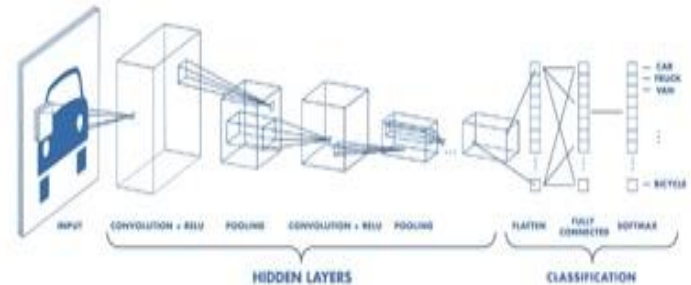
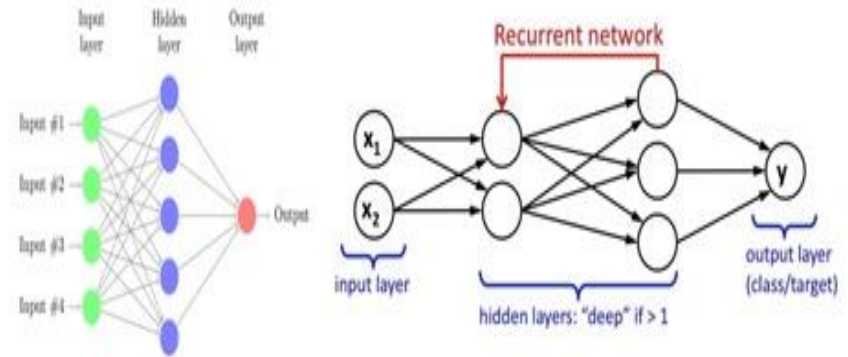
- ❑ Medical imaging suffers from issues occurred by heterogeneous composition of the medium in body, which disturbs the phase and wave amplitude as well as its reflections
- ❑ Remote sensing imaging are used to monitor changes to the earth's surface. But during sensing process through the atmosphere, transmission through telecommunicate, captured images often degraded by atmospheric scattering improper focusing, target motion.



Examples of remote sensing and medical imaging. (a)(c) The images that are expected. (b)(d) The images that are degraded.

# Deep learning background:

- Increasingly, deep learning techniques are utilized to recognize objects in images; match news items, speech transcribe into text, and select the search relevant results.
- Neural networks has got a rapid development until 1990s, producing a series of basic network units such as auto-encoders, convolutional neural network, restricted Boltzmann machines, and recurrent neural networks.





# Deep learning background:

- ❑ “*Traditional neural networks*” are feed-forward neural networks with a single hidden layer, where each input neuron is connected to every neuron in the hidden layer, and each neuron in the hidden layer is connected to every neuron in the output layer.
- ❑ “*Convolutional neural networks*” (CNNs) are a form of deep, feed-forward artificial neural network that is commonly used to analyse visual imagery. Layer by layer, information flows from the input to the output in "CNNs."
- ❑ “*Recurrent neural networks*” (RNNs) are a type of neural network for sequential data in which nodes form a directed graph along a sequence of connections. This enables it to display temporal behavior for a time sequence.

# Deep Learning Applications on Image Enhancement: (Image Denoising)

- ❑ In image denoising, the basic concept of learning in image denoising is to use training data to refine a module of the designed model.
- ❑ Deep learning is an example, in which the goal is to learn a discriminative restoration function. The first attempts to use (CNNs) and stacked auto-encoders to denoising natural image are promising, demonstrating that these deep models can work like or better than traditional wavelet or Markov random field-based denoising approaches.



clean (name: 008934)



noisy ( $\sigma = 25$ )PSNR:20.16dB



BM3D: PSNR:29.65dB



ours: PSNR:30.03dB



clean (name: barbara)



noisy ( $\sigma = 25$ )PSNR:20.19dB



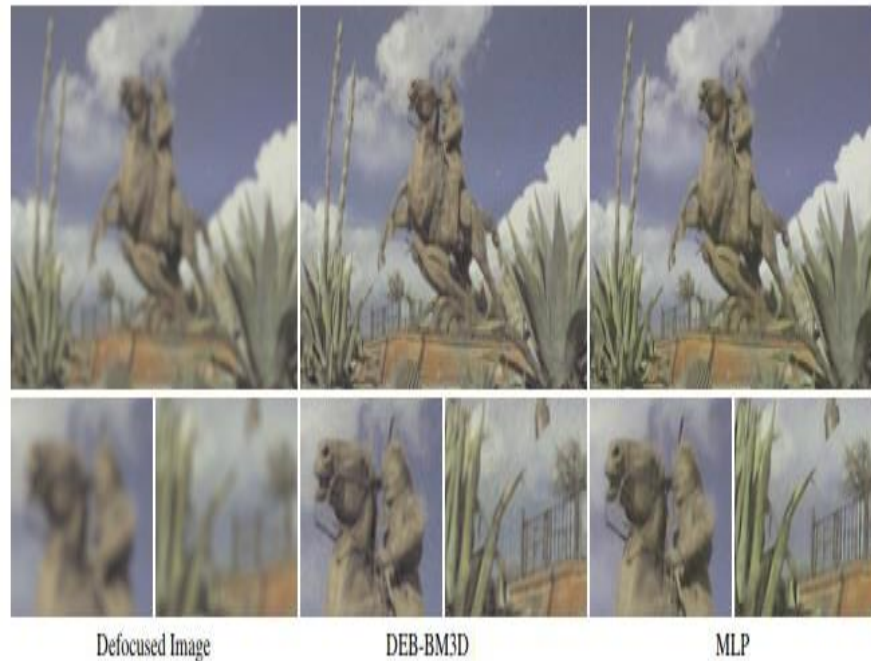
BM3D: PSNR:30.67dB



ours: PSNR:29.21dB

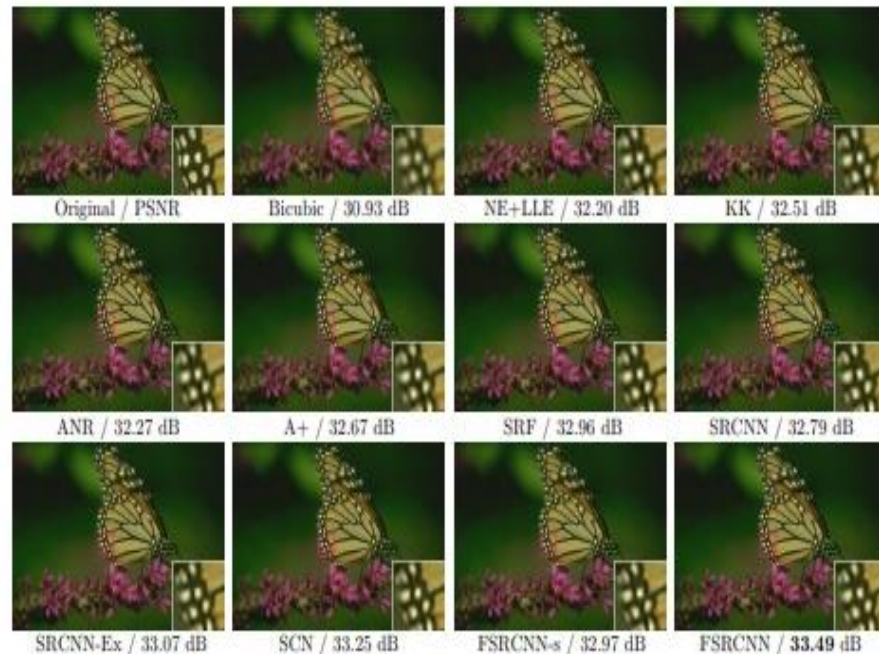
# Deep Learning Applications on Image Enhancement: (Image Deblurring)

- ❑ In image deblurring, the most critical issue is ill-posedness. The observed fuzzy images do not stably and uniquely evaluate as sharp images in the non-blind case, owing to the blur operator's ill-conditioned existence.
- ❑ Methods aim to learn a subspace in which the sharp picture can be found. A subspace can be created by extracting local patterns from multiple sharp images, where the sharp images and target images share similar information, allowing for an accurate representation of details in the target image



# Deep Learning Applications on Image Enhancement: (Image Super-resolution)

- ❑ In Image Super-resolution, the aim of super-resolution is to create a high-resolution image from one or more low-resolution images, recapturing high-frequency information that were lost during the imaging process.
- ❑ A belief network is a type of learning technique that can be expressed in terms of a Markov network. The images are analyzed with patch representation using a Markov network.
- ❑ An observation function connects the low-resolution patches and their corresponding high-resolution patches, defining how well one fits the other. A transition function connects the neighbor patches in the reconstructed image. The model uses the belief propagation algorithm to restore the high-resolution image after the parameters of the functions have been well trained.



# Conclusion:

- ❑ We highlighted several aspects of image enhancement. Providing a compendium of the advances made in the new and exciting sub-field of deep learning for image enhancement.
- ❑ The work discusses image enhancement categories in spatial domain and frequency domain.
- ❑ A brief introduction of popular techniques of image enhancement such as histogram, convolution, mathematical morphology, and calibration are presented.
- ❑ Deep learning technology and background is discussed. Furthermore, Applications of deep learning on image enhancement are analysis in most important tasks like image super-resolution, deblurring and denoising.

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