# Feature Extraction of Image using Progressively Enhanced Convolutional Neural Networks

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#### Abstract

Deep convolutional neural networks (CNNs) have been extensively applied to image or video processing and analysis tasks. For single-image super resolution (SR) processing, previous CNN-based methods have led to significant improvements, when compared to the shallow learning-based methods. However, these CNN-based algorithms with simply direct or skip connections are not suitable for imagery SR because of complex imaging conditions and unknown degradation process. More importantly, they ignore the extraction and utilization of the structural information in images, which is very unfavorable for video satellite imagery SR with such characteristics as small ground targets, weak textures, and over-compression distortion. To this end, this letter proposes a novel progressively enhanced network for s image SR called PECNN, which is composed of a retraining CNN based network and an enhanced dense connection network. The retraining part is used to extract the low-level feature maps and reconstructs a basic high-resolution image from the low-resolution input. In particular, we propose a transition unit to obtain the structural information from the base output. Then, the obtained structural information and the extracted low-level feature maps are transmitted to the enhanced network for further extraction to enforce the feature expression.

*Keywords -* Dense connection, Residual network, Superresolution, Subpixel convolution, Video Satellite Imagery

## I. INTRODUCTION

The task of recovering a high-resolution (HR) image or video from its low-resolution (LR) counterpart is referred to as super resolution (SR). Recently, SR has been evolved to deal with image resolution enhancement in various applications, such as medical imaging, satellite imaging, face recognition, and video surveillance[1]. Remote sensing imagery finds the direct application of SR due to the requirement for high spatial observation precision. Video satellite is a new type of remote sensing satellite, which can capture continuous dynamic video rather than still imagery. Video satellites are thus particularly well suited for the observation of large dynamic targets, such as ships and aircrafts. Compared to traditional remote sensing satellites, video satellites improve the temporal resolution at the cost of spatial resolution, which thus calls for spatial enhancement through image SR[2].

## **II. LITERATURE SURVEY**

Literature survey is important because it helps to learn important authors and ideas related to the field of interest. This is useful part for the coursework and writing. Knowing key authors also helps to become acquainted with other researchers in the field. It compiles significant research published on a topic by accredited scholars and researchers. The survey examines contrasting perspectives, theoretical approaches, methodologies, findings, results, conclusions[2][5]. It also reviews critically, analyses, and synthesizes existing research on a topic and performs a thorough "review", "overview", or "look again" of past and current works on a subject, issue, or theory.

Sr no	Reference	Purpose	Merits
1	<i>Image Deblurring Using</i> <i>Convolutional Neural</i> <i>Network</i> Reshma Vijay V.J., Deepa P.L.	In this paper, they introduced. Different techniques are available to reconstruct images degraded by motion blur.	New method for image deblurring using the advantages of Convolutional Neural Network (CNN),
2	Blind Deblurring via a Novel Recursive Deep CNN Improved by Wavelet Transform GUOQUAN WEN, BINRUI LI, AND FEIFEI FAN	In this paper, wavelet transform is utilized to decompose and extract the low- and high-frequency information of the blurred image, which is taken as the first step of the presented deblurring methods in this paper.	
3	<i>Super-resolution through</i> <i>neighbor embedding</i> H. Chang, DY.Yeung, andY.Xiong,	In this paper, an algorithm for extracting blood vessels from fundus images has been proposed. The algorithm is based on two dimensional Gabor filter, local entropy thresholding and alternative sequential filter.	capable of extracting blood vessels.
4	<i>Fast and robust muti frame</i> <i>super resolution</i> S. Farsiu, M. D. Robinson, M. Elad, and P. Milanfar,	In this paper, a Stacked Sparse Auto encoder, an instance of a DL strategy, is presented for MA detection in fundus images. Small image patches are generated from the original fundus images.	
5	Hyper-spectralimagesuper-resolutionvianon-negativestructuredsparserepresentation,W. Dong et al.,	In this research article, a brief insight into the detection of DR in human eyes using different types of preprocessing segmentation techniques is being presented.	There are a number of methods of segmenting the blood vessels
6	Image super-resolution using deep Convolutional networks C. Dong, C. C. Loy, K. He, and X. Tang	In this research article, a brief insight into the detection of DR in human eyes using different types of preprocessing	There are a number of methods of segmenting the blood vessels

#### **III. EXISTING SYSTEM**

Previous system has led to significant improvements, when compared to the shallow learning-based methods. However, these systems with simply direct or skip connections are not suitable for Super Resolution images because of complex imaging conditions and unknown degradation process[2][6]. More importantly, they ignore the extraction and utilization of the structural information in satellite images, which is very unfavorable for Super Resolution images with such characteristics as small ground targets, weak textures, and over-compression distortion[7].

#### **IV. PROPOSED SYSTEM**

This system proposes a novel progressively enhanced network for processing on blur images, which is composed of a retraining CNN based network and an enhanced dense connection network[1]. The retraining part is used to extract the low-level feature maps and reconstructs a basic high-resolution image from the low-resolution input. In particular, we propose a transition unit to obtain the structural information from the base output. Then, the obtained structural information and the extracted low-level feature maps are transmitted to the enhanced network for further extraction to enforce the feature expression[2][3]. Finally, a residual image with enhanced fine details obtained from the dense connection network is used to enrich the basic image for the ultimate SR output.

#### **V. SYSTEM ARCHITECTURE**

A. Processing Techniques:

The color conversion model is very important to extract the required features. In this work, two conversion such as RGB to Gray and RGB to HSI are done and RGB, Gray and HSI color model are used as an input images for feature extraction module.

#### B. Feature Extraction:

Feature Extraction is the most important step in the analysis of images. It is a process of gathering distinguishable information from the image itself from an object or group of objects. At last step use CNN model and detect diabetic disease.



**Fig.1 Proposed Methodology** 

CNN (Convolutional Neural Networks) Algorithm:

In AI, Convolutional Neural Networks (CNN or ConvNet) are unpredictable feed forward neural systems. CNNs are utilized for picture arrangement and acknowledgment in light of its high exactness[4][5][6]. It was proposed by PC researcher Yann LeCun in the late 90s, when he was roused from the human visual impression of perceiving things.[4] The CNN pursues a various leveled model which takes a shot at structure a system, similar to a pipe, lastly gives out a completely associated layer where every one of the neurons are associated with one another and the yield is handled[5].

## **VI. FUTURE SCOPE**

- The system could also be extended to detect other retinal diseases like glaucoma, age-related macular degeneration.
- In future, the algorithm could however be developed for the detection of dark lesions such as hemorrhages in addition to micro-aneurysms detection.
- The system could be extended to segmentation of color fundus videos and optical coherence tomographic images.

#### VII. CONCLUSION

In this system, we propose a novel progressively enhanced network, for super resolving blur images. It is composed of a pertained network and a dense connection network. In particular, an effective transition unit is embedded in the middle of the network to catch the profile structure related information. We also promote the feature expression by adopting more effective dense connections and progressive feature learning fashion. Since the constructed network takes less depths and filters but more dense connections among layers, it enjoys pronounced SR performance within acceptable computational complexity and is therefore applicable for huge size satellite imagery.

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