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A REVIEW ON IMAGE SUPER-RESOLUTION USING CONVOLUTION NEURAL NETWORKS AND AUTO-ENCODERS

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ABSTRACT

Images are often shared across the internet. A common problem we might have faced with images at some point is with the quality of the images. Images are compressed to save space and time for transfer. But low-resolution images are hard to work with when it comes to various applications like biometric recognition, character recognition and any other which uses images as a main source. It becomes harder to work on a low-resolution image and understand it than a high-resolution image. Image super-resolution aims at recovering a high-resolution image from a low-resolution image. We use a deep learning powered autoencoder to significantly enhance the quality of images. That is, our neural network will create high-resolution images from low-res source images. This is an underdetermined problem, meaning its solution is not unique. This is because a multiplicity of solutions exists for any given low-resolution pixel. We aim to create a model which can efficiently enhance the resolution of images. The model will be adaptive making it suitable for all types of images.

Keywords: Image Super-Resolution, Deep Learning, Autoencoder, Low-Resolution, High-Resolution

INTRODUCTION

Single image super-resolution (SR) , which aims at recovering a high-resolution image from a single lowresolution image, is a classical problem in computer vision. This problem is inherently ill-posed since a multiplicity of solutions exist for any given low-resolution pixel. In other words, it is an underdetermined inverse problem, of which solution is not unique. Such a problem is typically mitigated by constraining the solution space by strong prior information. To learn the prior, recent state-of-the-art methods mostly adopt the example-based strategy. These methods either exploit internal similarities of the same image, or learn mapping functions from external low- and high-resolution exemplar pairs.

The external example-based methods can be formulated for generic image super-resolution, or can be designed to suit domain specific tasks, i.e., face hallucination , according to the training samples provided. The sparse-coding-based method is one of the representative external example-based SR methods. This method involves several steps in its solution pipeline. First, overlapping patches are densely cropped from the input image and pre-processed (e.g.,subtracting mean and normalization). These patches are then encoded by a low-resolution dictionary. The sparse coefficients are passed into a high-resolution dictionary for reconstructing high-resolution patches. The overlapping re-constructed patches are aggregated (e.g., by weighted averaging) to produce the final output.

This pipeline is shared by most external example-based methods, which pay particular attention to learning and optimizing the dictionaries or building efficient mapping functions. However, the rest of the steps in the pipeline have been rarely optimized or considered in an unified optimization framework.

LITERATURE SURVEY

1. Lowcomplexity single-image super-resolution based on nonnegative neighbor embedding:

This paper describes a single-image super-resolution (SR) algorithm based on nonnegative neighbor embedding. It belongs to the family of single-image example-based SR algorithms, since it uses a dictionary of low resolution (LR) and high resolution (HR) trained patch pairs to infer the unknown HR details. Each LR feature vector in the input image is expressed as the weighted combination of its K nearest neighbors in the dictionary; the corresponding HR feature vector is reconstructed under the assumption that the local LR embedding is preserved. Three key aspects are introduced in order to build a low-complexity competitive algorithm: (i) a compact but efficient representation of the patches (feature representation) (ii) an accurate estimation of the patches by their nearest neighbors (weight computation) (iii) a compact and already built (therefore external) dictionary, which allows a one-step upscaling. The neighbor embedding SR algorithm so designed is shown to give good visual results, comparable to other state-of-the-art methods, while presenting an appreciable reduction of the computational time.

2. Super-resolution through neighbor embedding

In this paper, we propose a novel method for solving single-image super-resolution problems. Given a low-resolution image as input, we recover its high-resolution counterpart using a set of training examples. While this formulation resembles other learning-based methods for super-resolution, our method has been inspired by recent manifold teaming methods, particularly locally linear embedding (LLE). Specifically, small image patches in the lowand high-resolution images form manifolds with similar local geometry in two distinct feature spaces. As in LLE, local geometry is characterized by how a feature vector corresponding to a patch can be reconstructed by its neighbors in the feature space. Besides using the training image pairs to estimate the high-resolution embedding, we also enforce local compatibility and smoothness constraints between patches in the target high-resolution image through overlapping. Experiments show that our method is very flexible and gives good empirical results.

3. A soft edge smoothness prior for color image superresolution

Designing effective image priors is of great interest to image super-resolution (SR), which is a severely under-determined problem. An edge smoothness prior is favored since it is able to suppress the jagged edge artifact effectively. However, for soft image edges with gradual intensity transitions, it is generally difficult to obtain analytical forms for evaluating their smoothness. This paper characterizes soft edge smoothness based on a novel SoftCuts metric by generalizing the Geocuts method . The proposed soft edge smoothness measure can approximate the average length of all level lines in an intensity image. Thus, the total length of all level lines can be minimized effectively by integrating this new form of prior. In addition, this paper presents a novel combination of this soft edge smoothness prior and the alpha matting technique for color image SR, by adaptively normalizing image edges according to their alpha-channel description. This leads to the adaptive SoftCuts algorithm, which represents a unified

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treatment of edges with different contrasts and scales. Experimental results are presented which demonstrate the effectiveness of the proposed method.

EXISTING SYSTEM

There are existing methods which are traditional methods to convert a low res image to high res image. Traditional methods often work poorly. Traditional methods include classical interpolation, linear upscaling, cubic and bicubic interpolation and many others. All these are various algorithms which perform in different ways. Methods like Guassian smoothening, Weiner, Median filters are good at denoising but they also have downsides like loss of details of image due to blurring.

Over the years, many methods have been developed and these range from smooth interpolation methods to deconvolution methods.

DISADVANTAGES

- Often relies on naive assumptions

- Even the assumptions are only adapted to only a certain type of environment and wont work in a general setting

- Most seen in practice interpolation methods require complex calculations.

- Greater time needed to generate output.

PRPOSED SYSTEM

In the proposed system, we build an autoencoder which is a solution to this problem is based on artificial neural networks in a subset of AI called as deep learning. Autoencoders are a specific type of feedforward neural networks where the input is the same as the output. They compress the input into a lower-dimensional code and then reconstruct the output from this representation. They can be trained and functioned to do many things.

In our case, we make them to improve the resolution of an image by training it to deconstruct and then reconstruct to produce high resolution images. We'll be able to feed this neural network, images of any resolution and have it output a high resolution version of the same image.

Advantages:

- AI based methods are powerful because they're generalizable

- Autoencoders are considered as unsupervised learning technique so we just need to give some raw input to it without doing much.

- Improves the performance of the data in some cases.

- Helps in dimentionality reduction

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MODULES

Compressing Images with Encoder: Encoder maps the input into the code. It is a network (CNN, RNN etc) that takes the input, and output a featured map/vector/tensor. It compresses the image which is taken as input and the compressed image is given as output.

Reconstructing Image with Decoder: Decoders maps the code to a reconstruction of the input. It is again a network (usually the same Network Structure as Encoder but in opposite orientation) that takes the featured vector from the encoder and reconstructs the input matching the original input but in a different functionality. The functionality can be changed according to the need and in our case, we reconstruct the image as a high resolution image.

It gives the best closest match to the actual or intended output.

Loss Function: Loss functions measure how far an estimated value is from its true value. It maps decisions to their associated costs. Loss functions are not fixed, they change depending on the task in hand & the goal to be met.

License Plate Recognition: It is a process of recognizing number plates using Optical Character Recognition (OCR) on images. One of the applications of image super resolution is license plate recognition. In this, the images used to recognize a license plate number should be clear in order to get the number correctly. If the images are in low resolution or poor quality, there’s a chance to obtain false outputs. In such cases a high resolution images makes the job more easier. This module contains the process to achieve this from the high resolutions images we obtained as output from previous steps.

CNN PSNR

In the context of Convolutional Neural Networks (CNNs), Peak Signal-to-Noise Ratio (PSNR) is a metric used to evaluate the quality of a reconstructed or compressed image compared to a reference image. A higher PSNR value indicates better image quality. CNNs often leverage PSNR to optimize their training and performance in tasks like super-resolution, denoising, and image compression.

CNN SNR

CNN (Convolutional Neural Network) is a type of neural network used in various applications, including signal-to-noise ratio (SNR) estimation and other signal processing tasks. SNR is a measure of the signal's power compared to the noise level. CNNs can be trained to accurately estimate SNR by analyzing different features of the signal, such as its spectrogram or power spectral density.

CNN MSE

In the context of Convolutional Neural Networks (CNNs), MSE (Mean Squared Error) is a loss function used to evaluate the difference between the predicted output and the actual target value. Specifically, it measures the average squared difference between the CNN's predictions and the true values. A lower MSE indicates a better fit of the CNN to the data.

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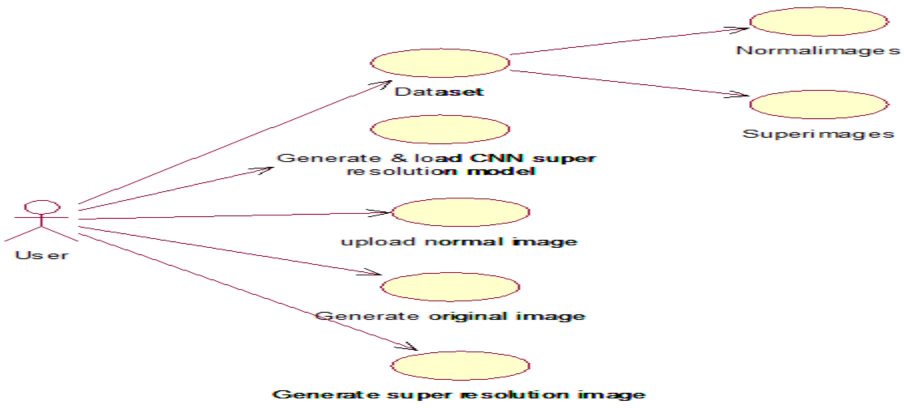
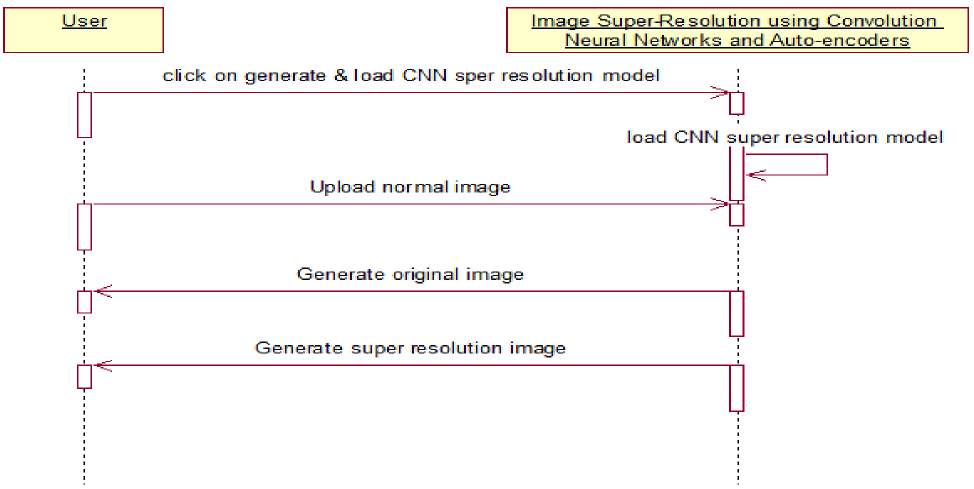
USE CASE DIAGRAM

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted

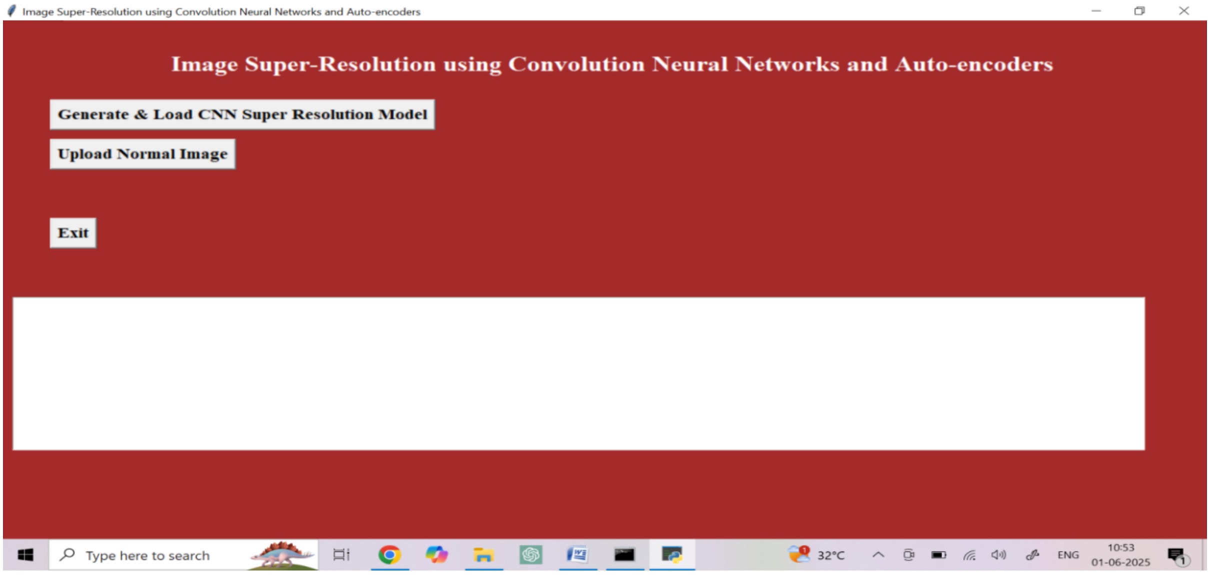


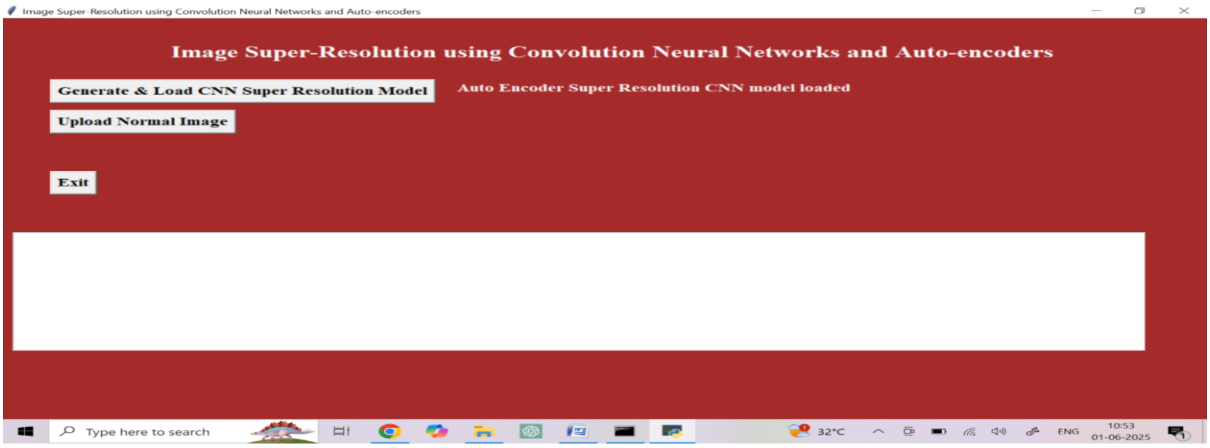
SEQUENCE DIAGRAM

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.



SCREEN SHOTS





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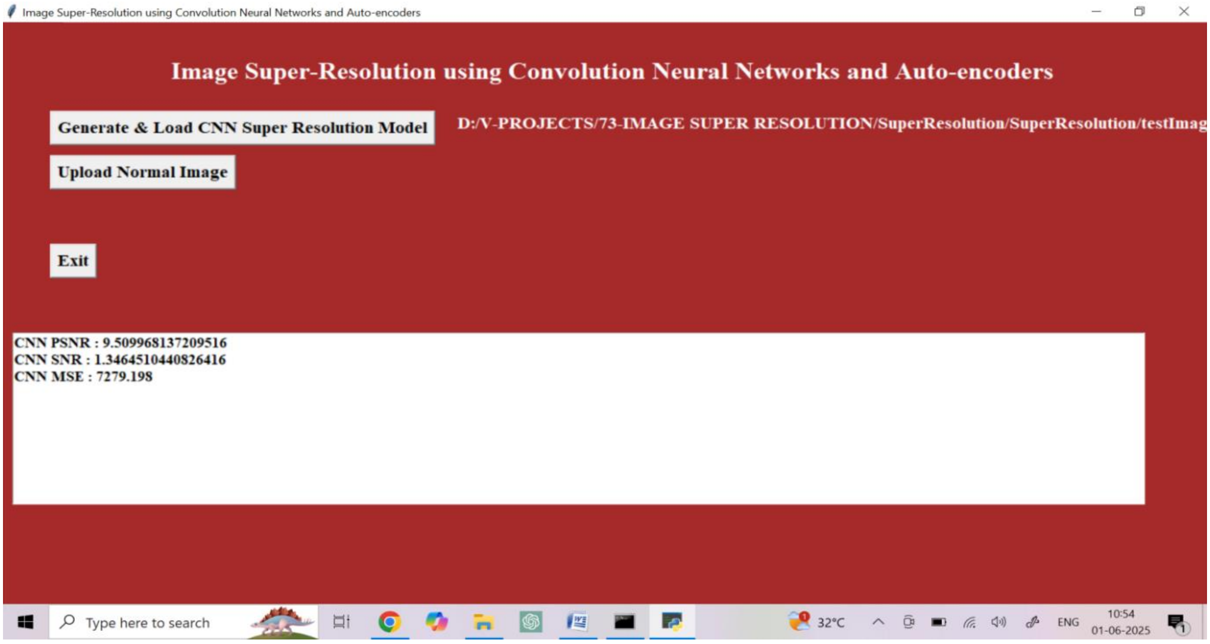

CONCLUSION

In this project we are designing CNN model with auto-encoder layers to increase image quality and this model will be called as super resolution model. This CNN model will be trained with low quality and high quality images and then this trained model can be applied on any low quality images so CNN model will learn from low quality images and then replace high intensity pixels with low intensity pixels to increase image quality and form a super resolution image.

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