IJITCE

ISSN 2347- 3657

International Journal of Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 1, 2025

IMAGE ENHANCEMENT USING DJANGO AND ML

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Abstract:

Image super-resolution is one of the vital image processing methods that improve the resolution of an image in the field of computer vision. In the last two decades, significant progress has been made in the field of super resolution, especially by utilizing deep learning methods. Image super resolution plays an important role in several fields such as, computer graphics, medical imaging, security, space, and satellite. The main objective of this project is to enhance and improve the resolution of an image, so it can be used beneficially in the fields mentioned before. In this we aim to use pioneers of convolutional neural networks to enhance the resolution of the image, with a focus on comparing the performance of the CNN models to that of a previously established method, sparse coding. The model utilizes a neural network architecture that incorporates convolutional layers to learn and extract features from the low-resolution input image, and then uses these features to reconstruct a high-resolution output image. The sparse coding approach, on the other hand, utilizes a sparse representation of the image to reconstruct the high-resolution output. The results of this study will provide insight into the effectiveness of CNN models for enhancing the resolution of the image and its potential as an alternative to traditional sparse coding methods.

Keywords: Deep learning methods, Convolutional Neural Networks (CNN), Sparse Coding, Image super resolution, Computer Graphics, Medical Imaging, Security, Space, and Satellite.

1. Introduction

Image processing is a term that describes the methods used to manipulate, analyze, and interpret digital pictures. It includes using mathematical techniques to a picture in order to analyze it and improve its quality, increase feature extraction, or analyze its data. Techniques used often in image processing include filtering, detection of edges, segmentation, and extraction of features. Satellite imagery, computer vision systems, and medical imaging are just a few of the many uses for image processing.

Image super-resolution, or the technique of recovering high resolution pictures from low resolution photos, is a prominent family of image processing methods in computer vision and image processing. It may be used for safety and monitoring in medical imaging, among other useful applications. Along with improving picture perception quality, it aids in a number of computer vision tasks. Since there are frequently many HR photographs that correlate to a single LR image, the problem is essentially ill-posed and highly challenging to solve. Many super-resolution technologies, such as modern learning-based approaches and early classical approaches, are proposed as remedies for this problem. Traditional approaches include those that rely on regularization and interpolation. Recently, many methods based on convolutional neural networks have been suggested to handle the image SR problem.

Applications

Super Resolution has several real-world applications in industries including security, surveillance, and medical imaging, as was before mentioned. This section provides examples of super resolution applications in several disciplines.

2. Literature review

Z. Xu, Q. Ma and F. Yuan [1] The paper provides single color image super-resolution using sparse representation and color constraint. The paper highlights the importance of color image super-resolution in various applications such as high-definition digital TV, remote sensing monitoring, mobile internet, medical, cultural relic protection, and display. Author proposed a blended sparse super-resolution reconstruction method for color images **He, J., Yu, L., Liu, Z. et al [2]** The author proposed single image super-resolution (SISR), aiming at recovering the high- resolution (HR) output from a given low-resolution (LR) input. It is based on an end-to-end trainable unfolding network that combines deep learning and prior-based methods. The system is composed of two main components: a convolutional sparse coding (CSC) model and a super- resolution (SR) model **Kim, S.; Jun, D.; Kim [3]** the paper proposes two lightweight neural networks for single image super-resolution (SISR). These networks are called SR-ILLNN and SR-SLNN. The proposed networks are designed to achieve a good trade-off between the accuracy of SR (PSNR and SSIM) and the network complexity. The first network, SR-ILLNN, learns the feature maps, which are derived from both low-resolution and interpolated low-resolution images. **Maral, B. C. [4]** The paper provides a comprehensive overview of the field of single image super-resolution (SISR). This includes a discussion of the different types of SISR methods, the challenges involved in SISR, and the applications of SISR. The paper categorizes SISR methods into four main categories: spatial domain methods, frequency domain methods, learning-based methods, and hybrid methods. **L. Jiang, M. Zhong and F. Qiu [5]** the paper proposes a novel deep neural network for single image super-resolution. The SADNN consists of convolutional layers, pooling layers, and self-attention layers. The self- attention mechanism to capture the global relationships between different positions in an image. This allows the SADNN to reconstruct high-resolution images with better texture details and image hierarchy. **William Symolon, Cihan Dagli [6]** The paper focuses on improving the resolution of low-quality satellite images captured by CubeSats. CubeSats are small satellites with limited imaging capabilities, leading to low-resolution images. The researchers used a deep learning method called Convolutional Neural Network (CNN) to upscale these images and make them sharper and more useful.

3. METHODOLOGY

The unsupervised learning, dimensionality reduction, and generative modelling, a neural network design known as an autoencoder is employed. In Figure 3.1, an encoder and a decoder are depicted as the two primary parts of the system. A lower-dimensional representation known as a bottleneck or latent space is created by the encoder by compressing an input. Following that, the decoder uses the lower-dimensional representation to try and recreate the original input. In order to reduce the reconstruction error between an autoencoder's reconstructed output and original input, the autoencoder must be trained. Backpropagation, a method for accomplishing this, involves changing the network's weights. Consequently, the autoencoder learns to keep the crucial information in the input while removing the noise and the unnecessary information.

ISSN 2347–3657

Volume 13, Issue 1, 2025

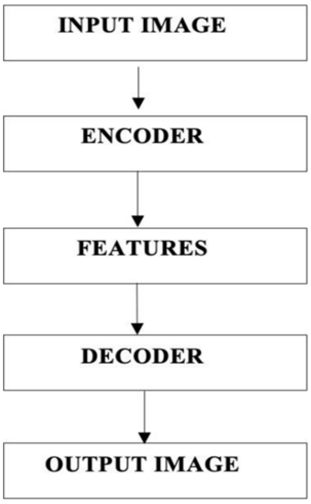

Figure: Autoencoder Block Diagram

By mapping the input data into a lower-dimensional space, autoencoders can reduce the dimensionality of the data while maintaining its key characteristics They can also be used for generative modelling, which involves encoding the bottleneck representation as random noise and decoding it into a high-dimensional image. Finally, autoencoders can be used to create new samples.

Architecture

An encoder and a decoder are the two primary parts of an autoencoder's architecture. The encoder converts the input data into a bottleneck or latent space, a lower-dimensional representation. A feedforward neural network with a number of dense (completely connected) layers that minimize the input's dimensionality is often used to implement the encoder. The lower- dimensional representation's dimensionality depends on the size of the bottleneck layer. The decoder converts the representation from high dimensions to lower dimensions. Additionally, the decoder is designed as a feedforward neural network with numerous dense layers that raise the representation's dimensions. To accurately recreate the input data, the decoder should be the inverse of the encoder.

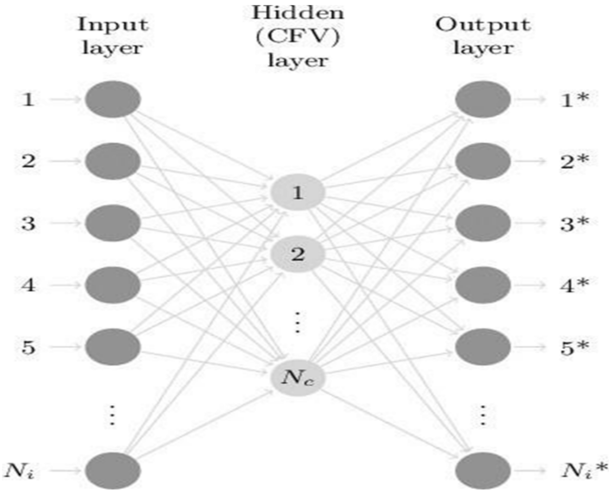

Figure: Vanilla Autoencoder architecture

Convolutional Autoencoder:

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 1, 2025

For image compression and denoising, a typical form of neural network design is a convolutional autoencoder. Convolutional layers, which are ideal for handling picture data, are used in conjunction with the encoder and decoder architecture of a conventional autoencoder. A convolutional autoencoder's encoder typically consists of a number of convolutional and pooling layers that increase the number of feature maps while decreasing the spatial dimensions of the input picture. Then, the decoder part reduces the number of feature maps while increasing the spatial dimensions of the encoded image back to its original size using transposed convolutional layers.

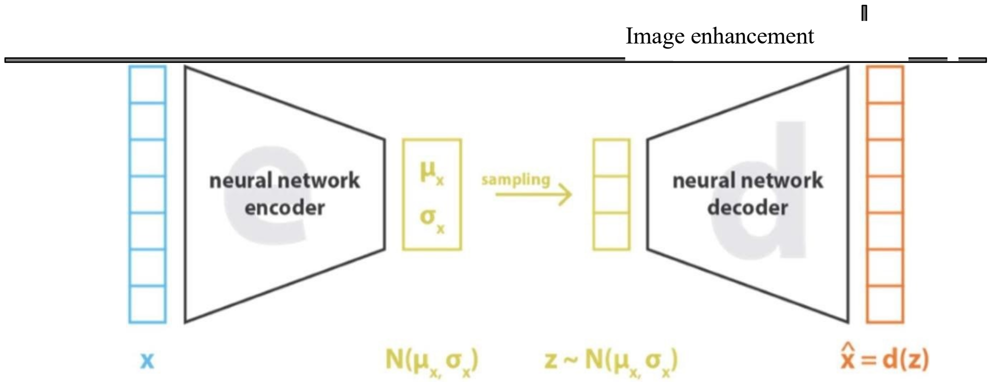

Figure: Variational autoencoder architecture

After the network has been trained, the encoder may be used to map the input data to the latent space, and the decoder can then be used to produce new data by sampling from the latent space and re-mapping it to the initial input space. VAE is regarded as a generative model that may be used to a number of tasks, including feature extraction, text production, and picture synthesis. When compared to a conventional autoencoder, a VAE has the advantage of producing fresh, unused data by sampling from the latent space

SYSTEM DESIGN

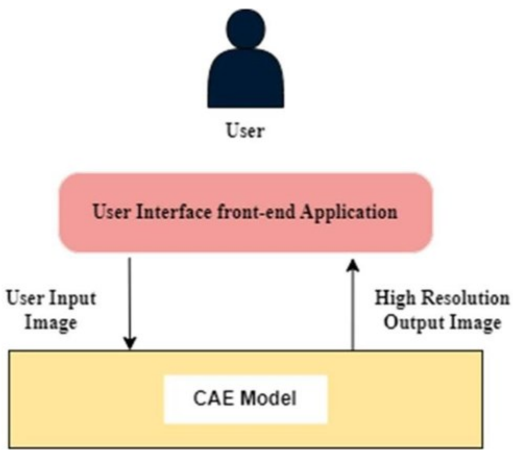

Figure: Overview of System Architecture

Data Flow Diagram

The DFD is also known as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of the input data to the system, various processing carried out on these data, and the output data is generated by the system. It maps out the flow of information for any process or system, how data is processed in terms of inputs and outputs. It uses defined symbols like rectangles, circles and arrows to show data inputs, outputs, storage points and the routes between each destination. They

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 1, 2025

can be used to analyses an existing system or model of a new one. A DFD can often visually "say" things that would be hard to explain in words and they work for both technical.

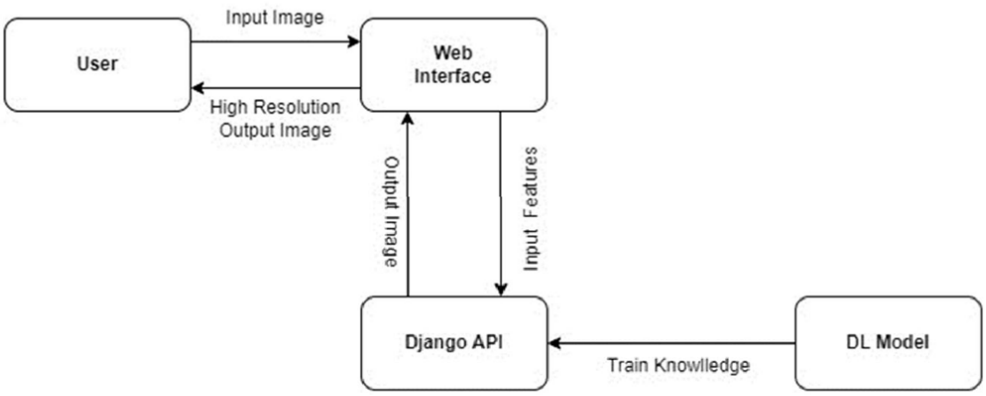

Figure: Data Flow Diagram

RESULTS:

These are the final results of 3 models we trained based on convolutional auto encoder technique

Auto-Encoder Model_1

In the first model we are using only 1 convolution layer after every max-pooling or up- sampling layer. Here we are using filters: 64, 128, 256, kernel_size : 4 , padding = same , pool_size : 2 (inside max-pool layer). From Table 5.1 we can observe that total trainable parameters are 1,319,556 and initially shape of our input is (256,256,4) since we applied 64 filters at beginning it becomes (256,256,64) then due to max-pooling layer the shape changes to (128,128,64) each and every time we apply a max-pooling layer dimensions becomes half.

Table: Summary of auto encoder model_1

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 256, 256, 4)]	0	[]
conv2d (Conv2D)	(None, 256, 256, 64)	4160	['input_1[0][0]']
max_pooling2d (MaxPooling2D)	(None, 128, 128, 64)	0	['conv2d[0][0]']
conv2d_1 (Conv2D)	(None, 128, 128, 128)	131200	['max_pooling2d[0][0]']
max_pooling2d_1 (MaxPooling2D)	(None, 64, 64, 128)	0	['conv2d_1[0][0]']
conv2d_2 (Conv2D)	(None, 64, 64, 256)	524544	['max_pooling2d_1[0][0]']
up_sampling2d (UpSampling2D)	(None, 128, 128, 256)	0	['conv2d_2[0][0]']
conv2d_3 (Conv2D)	(None, 128, 128, 128)	524416	['up_sampling2d[0][0]']
add (Add)	(None, 128, 128, 128)	0	['conv2d_3[0][0]', 'conv2d_1[0][0]']
up_sampling2d_1 (UpSampling2D)	(None, 256, 256, 128)	0	['add[0][0]']
conv2d_4 (Conv2D)	(None, 256, 256, 64)	131136	['up_sampling2d_1[0][0]']
add_1 (Add)	(None, 256, 256, 64)	0	['conv2d_4[0][0]', 'conv2d[0][0]']
conv2d_5 (Conv2D)	(None, 256, 256, 4)	4100	['add_1[0][0]']

When we started applying up-sampling layers it shapes changed from (64,64,256) to (256,256,64). At the end we added a conv2d layer with 4 filters because our input and output image number of channels should be same In Figure we can see the detailed structure of first variation of autoencoder.

ISSN 2347–3657

Volume 13, Issue 1, 2025

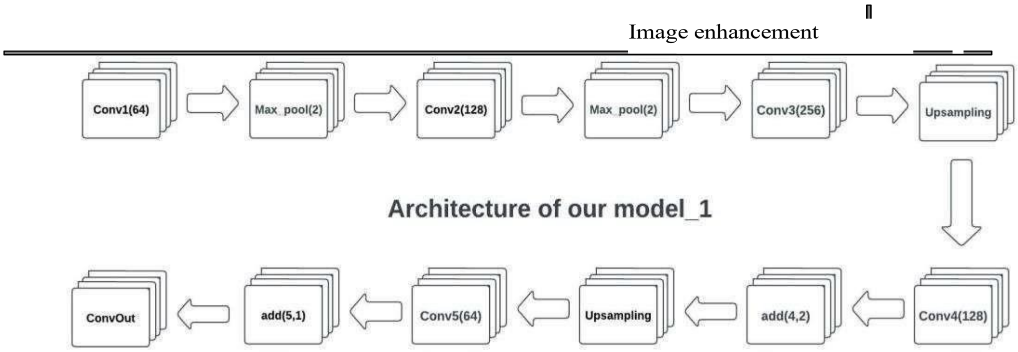

Figure: Architecture of model_1

The low-resolution image we passed as input and in Figure we can observer the reconstructed image using auto encoder model_1.

Figure: Input_1 to encoder model_1

Figure: Output_1 of auto- encoder model_1

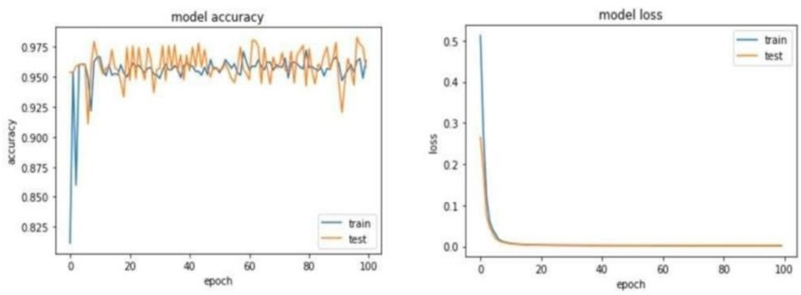

Figure: Accuracy and loss graph of auto-encoder model_2

Conclusion

Convolutional Autoencoder architecture has been proposed to restore a low-resolution image to a better-quality image with higher resolution. Our study provides insight into the effectiveness of Convolutional Autoencoder for image super resolution and its potential as an alternative to traditional sparse coding methods. The Convolutional autoencoder model requires 2 convolution layers after every max-pooling or up-sampling layer. It provides a cleaner image with higher resolution. To achieve best reconstructed image with high PSNR ratio and high SSIM value even on low performance centric device. By adding more convolutional layers and changing the filters we can get more accurate results i.e., high resolution in output of the images.

Future Scope

Any machine learning model that is being trained requires data to be used. The use of autoencoders for super resolution of pictures is a hot topic of research, and in the future, there will be enough of data accessible to train the model with in order to obtain more accurate results. The employment of generative models like GANs (Generative Adversarial Networks) in conjunction with autoencoders to enhance the realism of the produced high-resolution pictures is one potential future approach. Furthermore, more effective super resolution could result from the architecture of the autoencoder taking into account preexisting information about the particular sorts of pictures being processed (such as face images). Applying similar methods to 3D and video pictures, which are more complicated than 2D photos, is another field of research. Overall, the field is continuously evolving and new developments are likely to emerge in the future

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