IRAQI Academic Scientific Journals
العراقية المجلات الأكاديمية العلمية
University of Kut Journal
ISSN (E): 2616 - 7808 II ISSN (P): 2414 - 7419
js.uokut.edu.iq
k.u.c.j.sci@alkutcollege.edu.iq
Vol. 11 , Issue 1 , June 2026

Estimating a High-resolution Image from a Single Low-resolution Image, Using Deep Learning Algorithm

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Abstract

Single-image super-resolution (SISR) is an advanced and highly significant technique in computer vision and artificial intelligence fields. It aims to reconstruct high-resolution (HR) images from their low-resolution (LR) counterparts, presenting considerable challenges due to the loss of fine details during image downscaling. Applications of SISR range from medical imaging and satellite imagery to consumer photography and video streaming. Over recent years, the advent of deep learning has revolutionized the SISR domain, with convolutional neural networks (CNNs) emerging as the most promising approach. These networks have demonstrated remarkable accuracy, outperforming traditional image processing methods.

This paper focuses on the Very Deep Super-Resolution (VDSR) model, a specialized CNN architecture designed to improve the quality of single-image super-resolution. VDSR excels by learning the intricate relationships between low- and high-resolution images, particularly the mapping of the high-frequency details lost in LR images. This capability is achieved through a deeper network structure and the use of residual learning, which facilitates faster convergence and enhances performance. The paper conducted experiments to estimate HR images from LR inputs using the VDSR model and compared the results with traditional methods such as bicubic interpolation.

The findings reveal that the VDSR model delivers superior performance, producing HR images with greater accuracy and preserving finer details compared to bicubic interpolation. These results highlight the potential of VDSR in real-world applications where high-quality image reconstruction is critical. This study underscores the ongoing importance of deep learning in addressing challenges in SISR and paves the way for further advancements in the field.

Keywords: High-resolution images, Super-resolution techniques, Deep learning, Network training, Low-resolution images and Bicubic interpolation.

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Paper Info.
Published: Jun. 2026

تقدير صورة عالية الدقة من صورة منخفضة الدقة باستخدام خوارزمية التعلم العميق

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المستخلص

إعادة تحسين الصورة الأحادية هي تقنية متقدمة وذات أهمية في مجال الرؤية الحاسوبية والذكاء الاصطناعي. تهدف هذه التقنية إلى إعادة بناء صور عالية الدقة (HR) من نظيراتها منخفضة الدقة(LR) ، وهي عملية تواجه تحديات بسبب فقدان التفاصيل الدقيقة أثناء تقليل الدقة. تُستخدم هذه التقنية في تطبيقات متعددة تشمل التصوير الطبي وصور الأقمار الصناعية وتعزيز التصوير الفوتوغرافي للمستهلكين وبث الفيديو. في السنوات الأخيرة، أحدث ظهور التعلم العميق ثورة في مجال تحسين الصور الأحادية، حيث برزت الشبكات العصبية الالتفافية (CNNs) كأكثر الطرق تحقيقا للكفاءة والدقة، متفوقة على الطرق التقليدية لمعالجة الصور.

في هذه الورقة البحثية، نسلط الضوء على نموذج **Very Deep Super-Resolution (VDSR)**، وهو بنية متخصصة للشبكات العصبية الالتفافية صُممت خصيصًا لتحسين جودة الصور الأحادية. يتميز نموذج

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معلومات البحث
تأريخ النشر : حزيران 2026

VDSRبقدرته على تعلم العلاقات المعقدة بين الصور منخفضة الدقة والعالية الدقة، لا سيما من خلال تتبع التفاصيل الدقيقة المفقودة في الصور منخفضة الدقة. يتحقق هذا من خلال بنية شبكة عميقة واستخدام التعلم المتبقي، مما يساهم في تسريع عملية التقارب وتحسين الأداء. أجرينا تجارب لتقدير الصور عالية الدقة من المدخلات منخفضة الدقة باستخدام نموذجVDSR ، وقمنا بمقارنة النتائج مع الطرق التقليدية مثل طريقة الاستيفاء المكعب.
أظهرت النتائج أن نموذج VDSR يوفر أداءً متفوقًا، حيث ينتج صورًا عالية الدقة بدقة أكبر ويحافظ على التفاصيل الدقيقة بشكل أفضل مقارنة بطريقة الاستيفاء المكعب. تسلط هذه النتائج الضوء على الإمكانات الكبيرة لنموذج VDSR في التطبيقات العملية التي تتطلب إعادة بناء صور بجودة عالية. تؤكد هذه الدراسة على الأهمية المستمرة للتعلم العميق في مواجهة تحديات تحسين الصور الأحادية، مما يمهد الطريق لتحقيق مزيد من التطورات في هذا المجال.

الكلمات المفتاحية: صور عالية الدقة، تقنيات الدقة الفائقة، التعلم العميق، تدريب الشبكة، صور منخفضة الدقة، الاستيفاء التكعيبي

Introduction

An image processing approach called (Single Image Super-Resolution) to reconstruct an image with (High Resolution Image) from a (Low Resolution Image) one. Many techniques to improve image resolution have been developed over time. Such an approach employs fixed mapping techniques to establish a stable relationship based on specific prior knowledge.

Other techniques employ machine learning strategies that make use of a dictionary, seeking to understand how to transform low-resolution images into high-resolution equivalents. Moreover, certain algorithms utilize neighborhood embedding, where they learn high-resolution images from a set of stored prior high-resolution patches in a dictionary. These patches can be blended in a manner that corresponds with the low-resolution images.

Extraction of visual characteristics from an image to create a higher-resolution edition of the same image is the aim of super-resolution techniques. These qualities might be as basic as Shapes, Shades, and Outlines, or they can be as intricate as Texture and Lighting.

In this work, we demonstrate the outcomes produced in the MATLAB environment as we investigate the application of deep learning techniques to extract high-resolution pictures from low-resolution inputs. This method takes advantage of highly abstract features to extrapolate details, creating high-resolution images without requiring any modifications to the image capture equipment.

Literature Review

To acquire high-resolution photographs, a number of earlier studies and algorithms will be reviewed in this part.

a) Upscaling Methods

Improving an initial picture to produce an output with high resolution is a basic step towards increasing image fidelity. The enhancing strategies used in the various suggested works will be covered in this section. In essence, low-resolution images can either be resized to the desired dimensions before being fed into a deep learning model or improved during the final layer of the model itself. [1]

1. Bicubic Interpolation

To create the high-resolution image, the original values of pixels are subjected to bicubic interpolation. As compared to earlier methods like bilinear and nearest neighbor interpolation, it is an improvement. As a first step, bicubic interpolation was used to improve resolution in a number of models, treating the low-resolution image prior to it being processed by the network. The improved low-resolution image is then transformed into its larger high-resolution version as the model learns filters which fill in the features that are missing [2],[3].

[4] described a sparse coding network in their published study with the goal of enhancing the supplied image quality. This method's strength is its capacity to learn an additional intricate regression function that isn't comprehensible by a sparse coding model of the same kind. In addition, the network under discussion in this work is a CNN model (Convolutional Neural Network) that is employed to attain the best resolution through pixel extraction and restoration.

Figure (1) shows the block diagram of achieving a super resolution image from a low-resolution image using Bicubic interpolation.

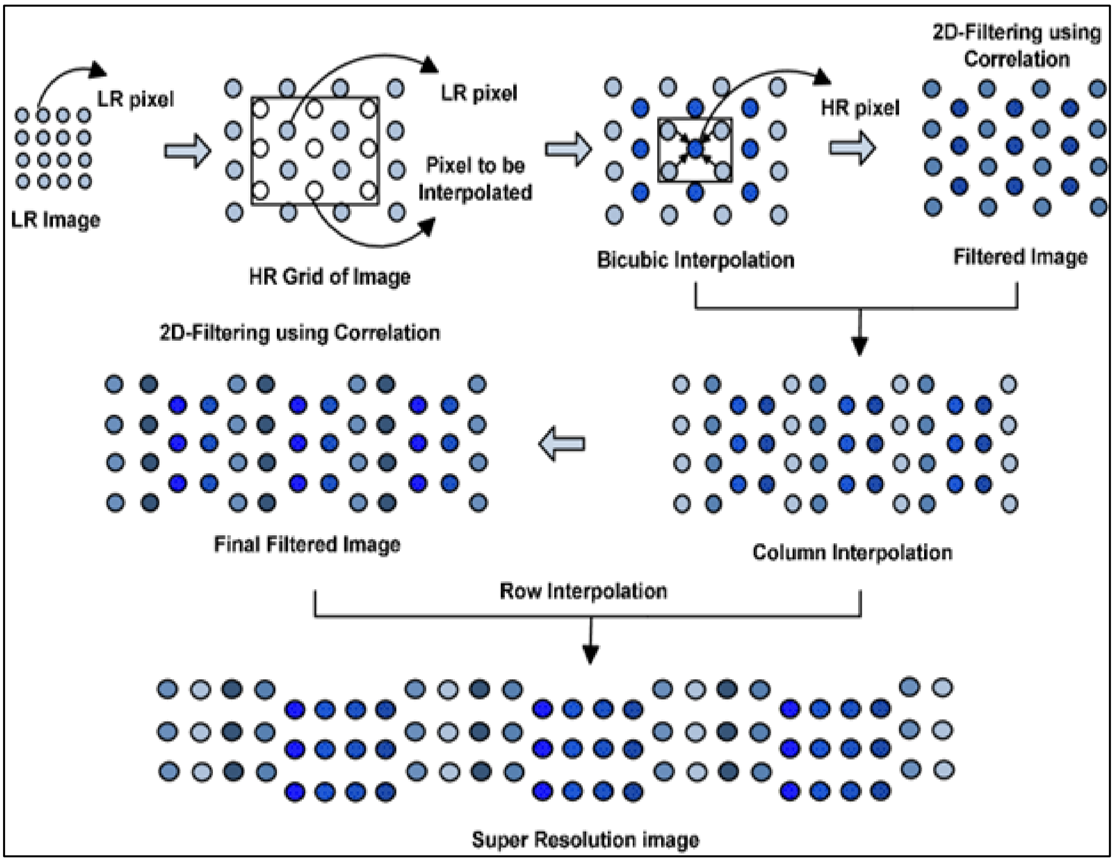

Figure (1:) Block diagram of achieving a super resolution image from a low-resolution image using Bicubic interpolation

2. Deconvolution Layer

By producing inputs that result in a specific feature map, the deconvolution layer functions as the convolution layer's inverse process. Deconvolution layers can be added at the final stage of a model developed using deep learning to improve the quality of low-quality images, as seen with the bicubic interpolation strategy. However, doing so may result in an increase in the total amount of convolution operations.

By utilizing learnable filters that adapt during the backpropagation process, this layer outperforms static bicubic interpolation and delivers improved results across various models. In subsequent work, the SRCNN model was further refined to incorporate a transposed convolution layer, enabling faster execution. [5][6].

Figure 2 shows the usage of a deconvolution layer for the preliminary up-scaling undertaking approach that the version is extra data-adaptive than other networks which used constant filters for the equal undertaking. Its deep structure permits for extra accuracy in the estimations because of the extra non-linearities

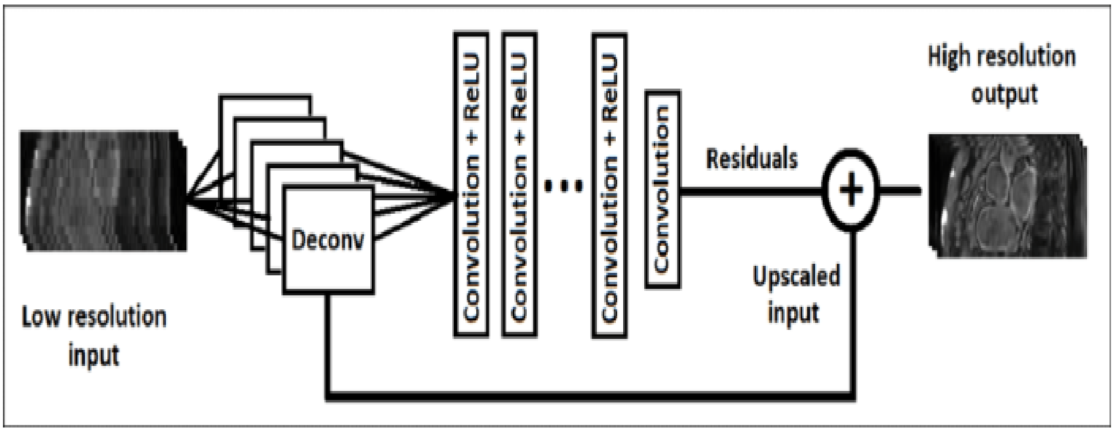

Figure (2:) Block diagram of achieving a super resolution image from a low-resolution image using deconvolution Layer

3. Sub-pixel Convolution Layer

Transposed convolution layers improve the efficiency of the network, but the output quality may suffer from checkerboard patterns. To solve this problem, a unique upscaling method was developed that involves randomly rearranging the network's produced features to generate a high-resolution image [7]. Figure (3) indicates the proposed green sub-pixel convolutional neural network (ESPCN), with convolution layers for characteristic maps extraction, and a sub-pixel convolution layer that aggregates the characteristic maps from LR area and builds the SR photograph in an unmarried step

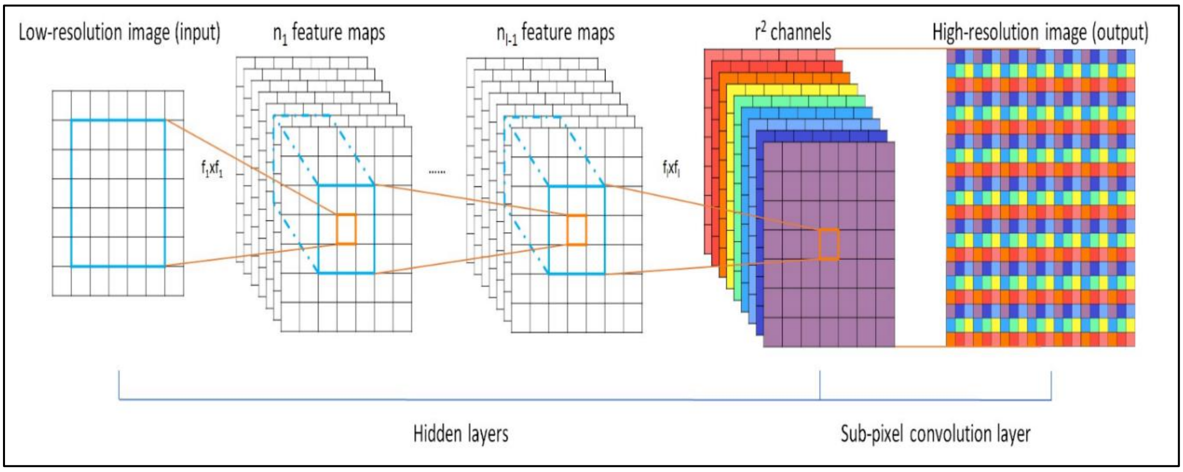

Figure (3): The proposed efficient sub-pixel convolutional neural network (ESPCN)

b) Network Architectures:

The way map features interact with each other is determined by a network's design, which is vital to the whole image processing process. A multitude of techniques have surfaced in the last five years that can be categorized according to common tactics or fundamental ideas. The primary classifications of various network architectures are covered in this section.

1. **Linear Networks:**

(CNNs) organized in a layered configuration is shown by this design.

To develop a straightforward mapping among low-resolution and high-resolution images, a three-layer CNN architecture were created. Conversely, as with the bicubic interpolation technique, deconvolution, which layers can be added at the final stage of the deep learning model in order to improve low-quality images; however, this could result in an increase in the general total of convolution operations.

Figure (4) illustrates the use of deep learning to demonstrate the applicability of image upscaling in the SRCNN study.

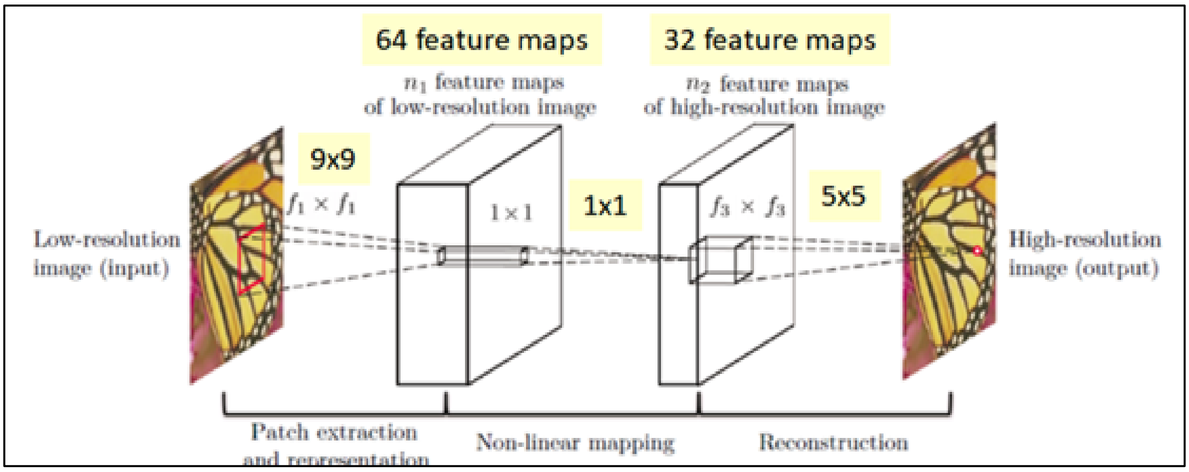

Figure (4) SRCNN Algorithm structure

2. **Residual Networks:**

A Deep Residual Learning work on Image Recognition were presented in[8],[9]. Recursive learning has been frequently used in the world of deep learning to build more easily trainable deep models. Instead, trying to directly learn the desired output, this concept entails understanding the distinction between input and the expected output. This refers to learning features from the high-resolution image then combining them with the features of the low-resolution image that are already accessible in the context of image improvement. Consequently, the following equation (1) can be used to show the disparities between the high-resolution image and the low-resolution image:

$$\textbf{Residual} = \{I_{HR} - I_{LR}\} \qquad (1)$$

By keeping the network from learning duplicate information present in low-resolution images, residual learning lessens the strain on the system. As seen in Equation (1), the network may focus on capturing the residual features because it doesn't need to preserve the previous data from the low-resolution image, which essentially stays constant during different convolutional procedures.

There are two main types of Residual Learning:

- **Global Residual Learning (GRL):**

In this procedure, element-wise addition is used to merge the low-resolution image with the feature maps generated by the last layer of the model. By giving the current features, a straight line to the network's output, this approach helps to cut down on pointless calculations inside the model. The VDSR method (Very Deep Super Resolution), illustrated in Figure (5), is one instance of this.

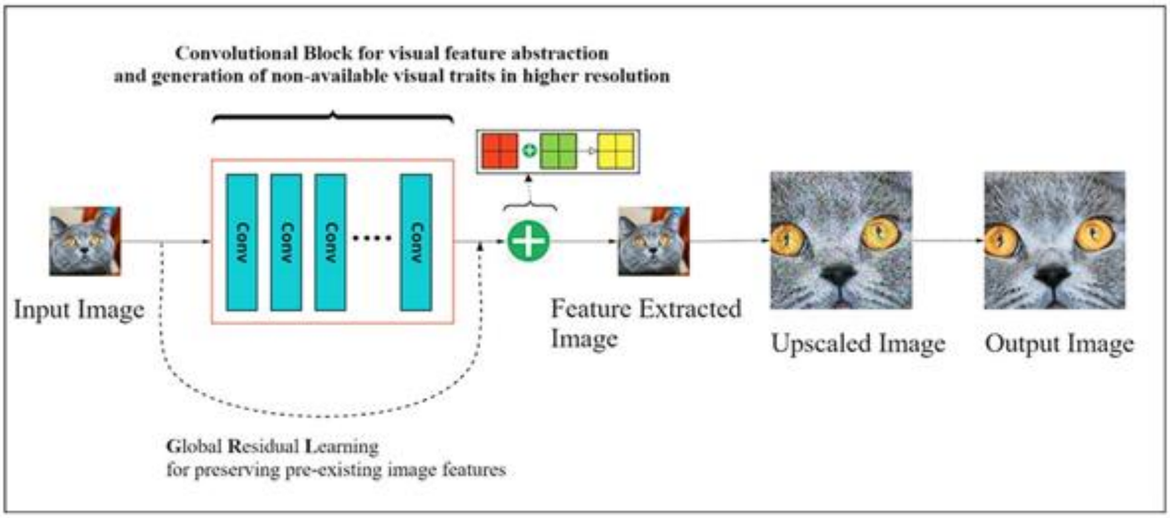

Figure (5) VDSR algorithm

- **Local Residual Learning (LRL):**

In order to do this, feature maps from several model layers must be combined element by element. In contrast to the Gradient Residual Learning (GRL) method, which commences with the original image and finishes at the network's last layer, the connections that start with the low-resolution image happen at different points along the network. As a result, Figure 6 illustrates how the model's early feature maps have higher activations than the latter portions of the network[10]

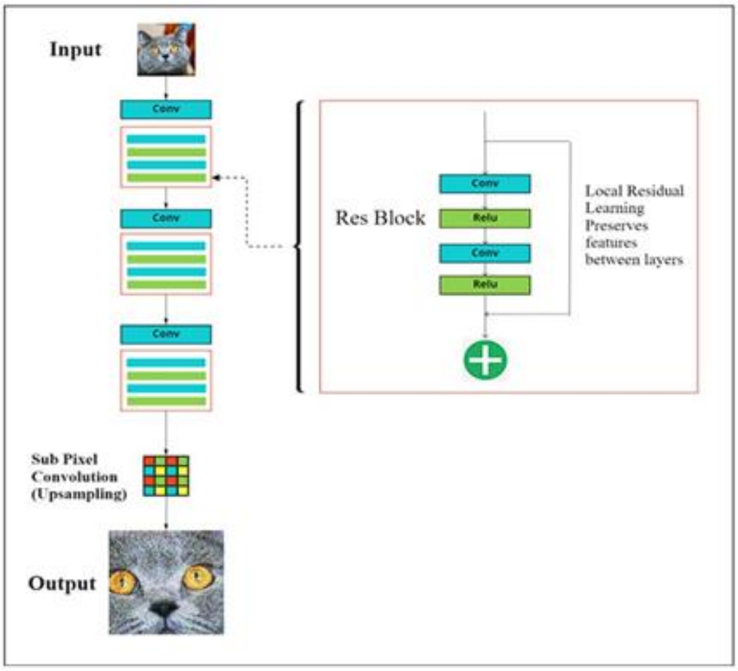

Figure (6): Flowchart of EDSR algorithm

Importance of the Research and Its Objectives:

The prediction of high-resolution images from their low-resolution counterparts is considered one of the more difficult issues in the image processing domain. This work faces several difficulties, such as the demand for substantial data and training resources, along with the uncertainty presented by multiple high-resolution photos that may correlate to a one low-resolution image.

Moreover, the notion of super-resolution may be intrinsically arbitrary and contingent upon the intended application of the picture. This makes the process more prone to mistakes and artifacts, including oversmoothing or halo effects, that could negatively impact the final image's quality.

Therefore, the importance of this study is in its intention to improve the clarity and quality of photographs, especially with regard to the more accurate refinement of textures, edges, and outlines. To enhance the entire visual experience, the research also attempts to minimize noise produced by gradients, compression, or image degradation.

Research Methodology

This section will introduce the proposed deep network, called DNCSC, that uses convolutional sparse coding (CSC) to solve the single-image super-resolution problem more successfully. Typically, this entails two primary procedures: the network architecture design and the task-specific training phase [11].

2-1 Network Architecture Design:

When constructing our network, it is imperative to consider the advantages of both conventional Sparse Coding (SC) as well as deep structures. Traditionally, instead of using the initial low-resolution observation Y, one would use a low-resolution image enhanced using interpolation techniques as input to forecast the final high-resolution output X by learning a transformation function. We argue that this approach is not optimal because, in the single-image super-resolution setting, there is a substantial relationship between the low-resolution input Y, the intermediate product I, with the final output X. While the three depict distinct spatial resolutions of the same picture, they share a significant amount of information, especially in the smoother areas of the image.

This analysis suggests that residual modeling can be used as a simple and natural replacement for the previously indicated standard procedure. This method is consistent with the work [12], which instead of estimating the full high-resolution image, concentrated on forecasting the high-resolution lost features for every patch, as it shown in figure (7).

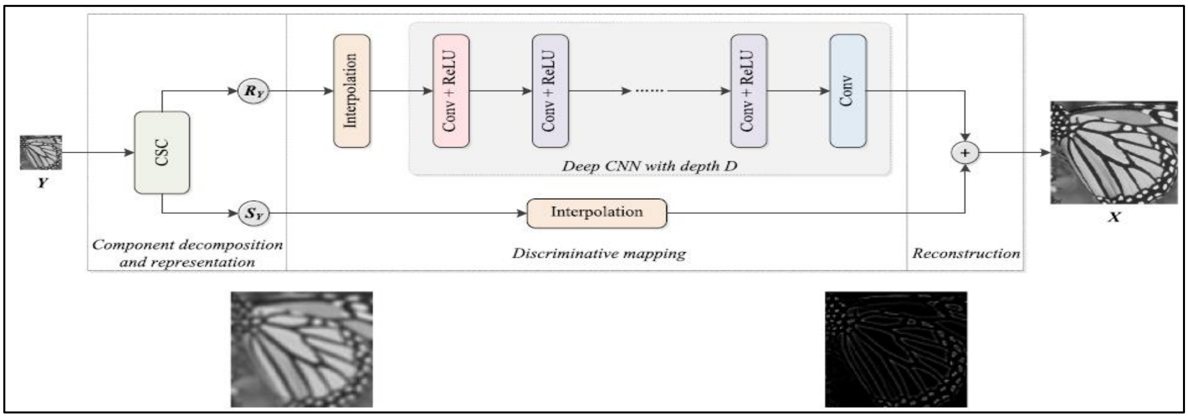

Figure 7 Network Structure design

2-1-1 Components Breakdown and Illustration:

The initial section's objective is to conduct a thorough deconstruction and representation. Essentially, the intention is to depict the whole image in the culmination from multiple unique pieces with predetermined physical meanings in order to perform a global breakdown of the low-resolution input (LR Input) Y. Based on the previous analysis, two different element types—the smooth element (S_y) and the residual element (R_y) have been selected to be taken into account throughout the decomposition technique in this work. Consequently, the global decomposition of the low-resolution input (LR Input) can be expressed as follows:

$$Y = S_y + R_y \quad (2)$$

First, a modified convolutional sparse coding model is used to extract the smooth component (S_y) from the low-resolution image which may be expressed as follows:

$$S_y = f * z, s.t. \arg\min_Z \{\|Y - f * Z\|_2^2 + \Phi\|h * Z\|_2^2 + \varphi\|v * Z\|_2^2\} \quad (3)$$

Here, f, h and v are the additional filters required to calculate the derived values along both directions, respectively, and Z is the sparse characteristic map convolved with the related low-pass filter. The weightings for the final two penalty components are ∅ and φ.

It is significant to note that, despite being able to be trained not all the different filters in the preceding equation require training because each one has a unique significance and purpose. Rather, the results of these filters may be experimentally provided subsequently, according to their distinct roles: h and v are (1-D filters) with values [1,−1] and [1;−1], respectively; *ff* is given as a (2-D filter) of dimension 3×3, with every component equal to 1/9.

It is clear that the observed outcomes are exactly in line with both the initial objective of the research and our subsequent assessment. Furthermore, even though the actual dimensions differ, we can see that the poor-quality residual element is similar to the high-resolution counterpart, with the exception that the patterns inside it is less distinct and more unclear compared to that in the excellent quality version.

2-1-2 Discriminative Mapping:

This unit's objective is to use distinct transformation relationships for every component in order to convert the low-resolution (LR) image elements into high-resolution (HR) space. Cubic interpolation and other upscaling algorithms are used to expand the smooth component. A deep CNN is used to upscale the residual component while it learns the proper transformation function. To maintain uniformity in feature map sizes and prevent problems at image borders, zero-padding is employed.

2-1-3 Reconstruction:

It is obvious that the last unit must provide the final result by synthesizing the high-resolution complete image from the two high-resolution components that were previously obtained. However, here we rely on a basic and easy mechanism: elementwise addition, to finish the synthesis, instead than employing common methods like weighted averaging, concatenating, or using another parametric layer like a ([1×1] convolution). This unit can be regarded as a type of non-parametric layer that applies pointwise operations to its inputs, since the final result is just the combined value of the two high-resolution components.

Despite its simplicity, the final unit has the following advantages:[11]

- Elementwise addition is among the most computationally effective processes in forward as well as backward passes.
- It requires no additional parameters for further training.
- By using this unit, it is clear that the proposed DNCSC model's general structure is very similar to Residual Networks (ResNets). [11, 13]

2-2 Training:

The proposed network can predict the high-resolution image X from the low-resolution input Y through acquiring the appropriate mapping formula $F(Y) \approx X$. To learn this potential mapping function, the network's training parameters "I" must all be optimized during the training phase.

The training approach then consists of employing Mini-Batch Random Gradient Descent according to Standard Backpropagation to minimize the Mean Squared Error (MSE). In contrast to SRCNN, this papers proposes to use a greater learning rate to improve the deep network training process. Yet, adopting a high learning rate may simply result into an acknowledged phenomenon called gradient explosion. A gradient clipping approach is used to solve this issue.

Discussion

A program was developed in the MATLAB environment to train a Very Deep Super-Resolution (VDSR) neural network. This network was then utilized to estimate a high-resolution image from a single low-resolution image.

Figure (8) Flowchart for high resolution image estimation in MATLAB.

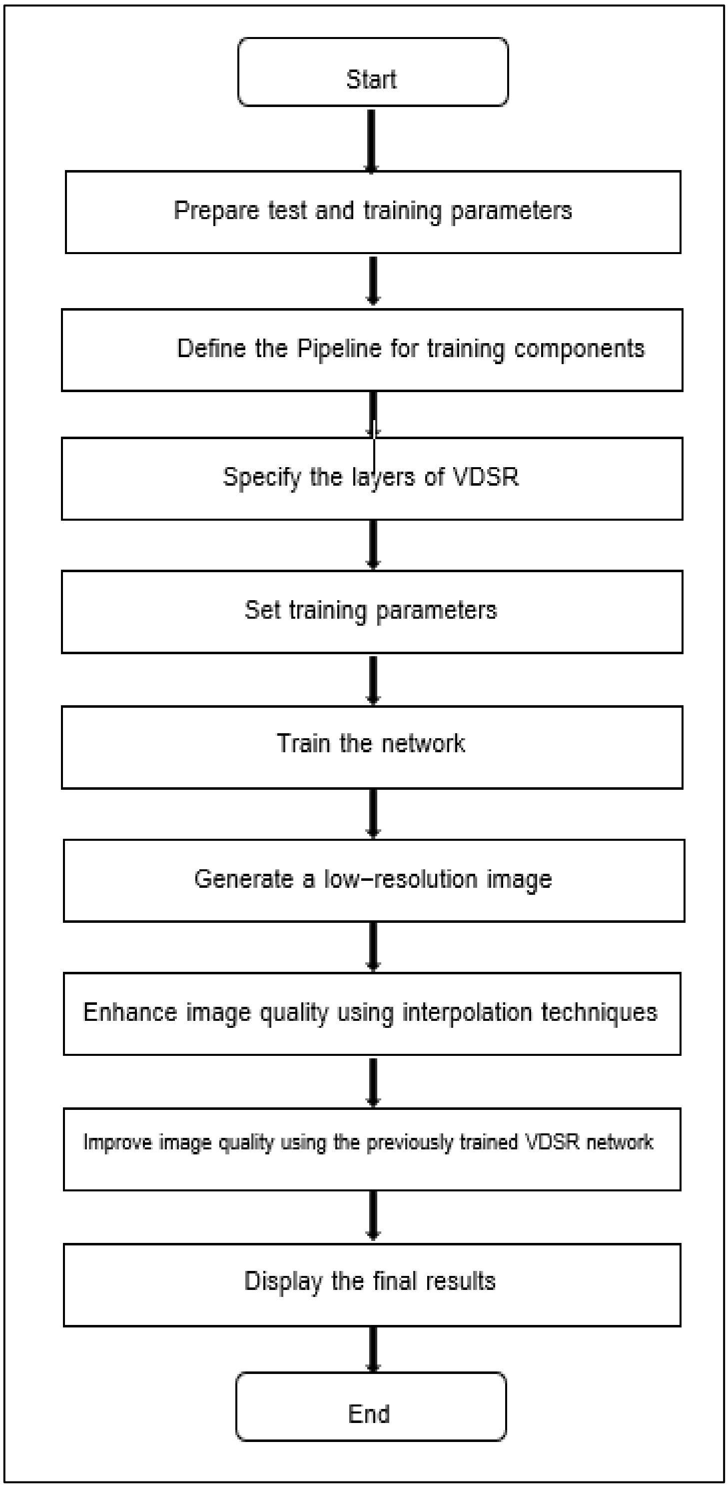

Figure (8): Flowchart for high resolution image estimation in MATLAB

Figure (9) illustrates the flowchart for the data preparation process.

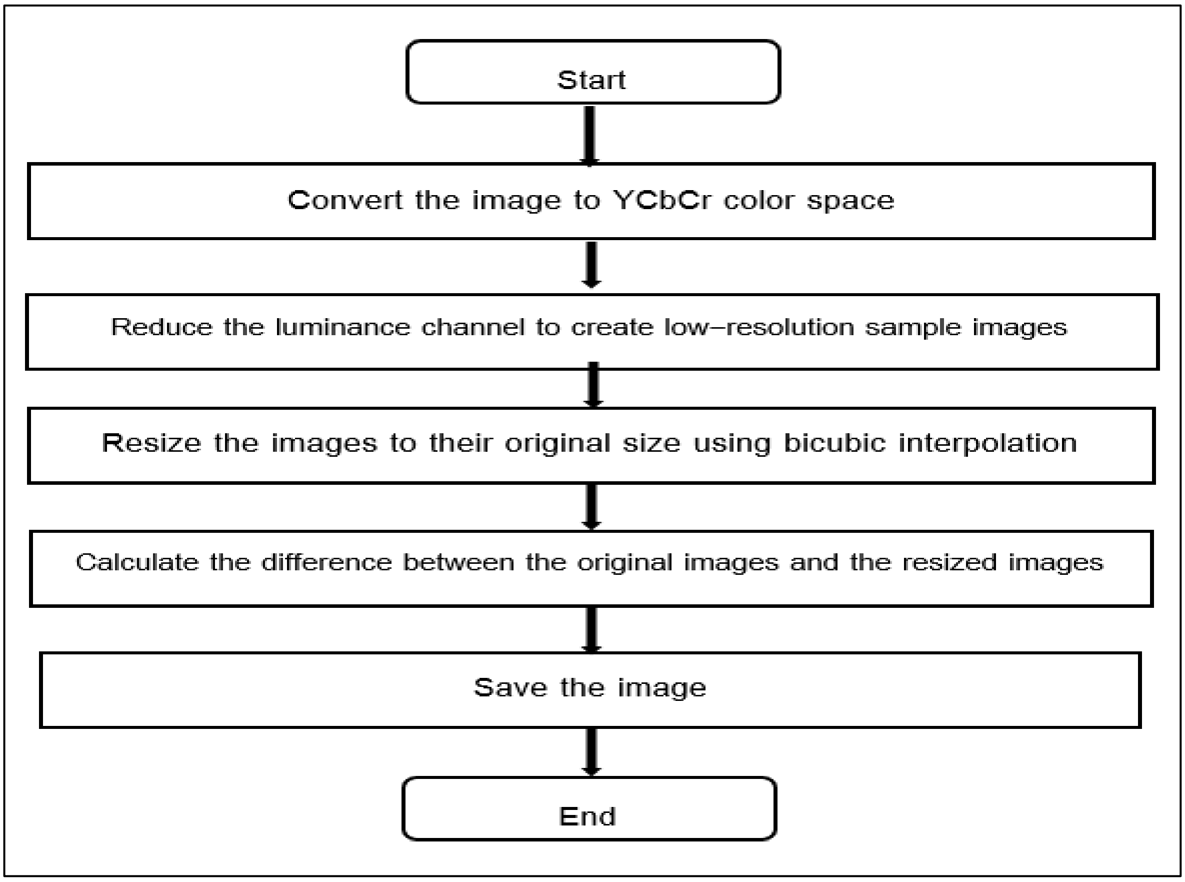

Figure (9) Data preparation flow chart in MATLAB

Figure (10) shows a portion of the samples used in the algorithm.

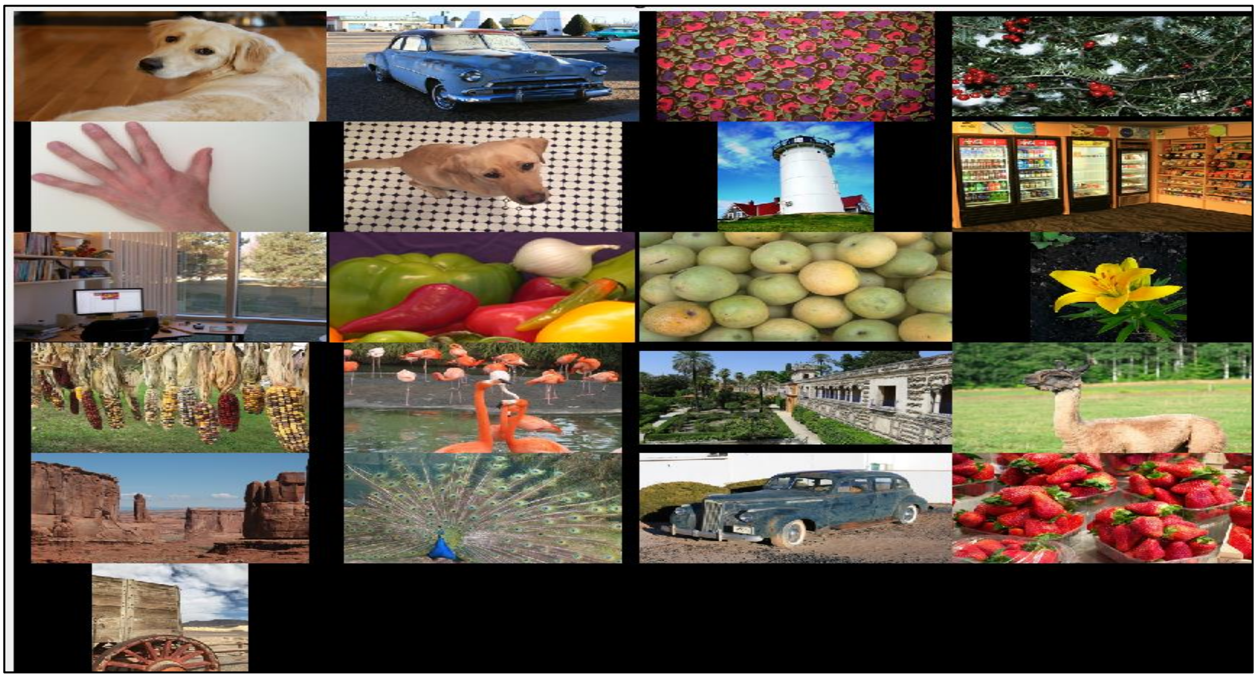

Figure (10) Some samples used in the estimation process

An image is selected from the dataset to serve as a reference image as shown in Figure (11).

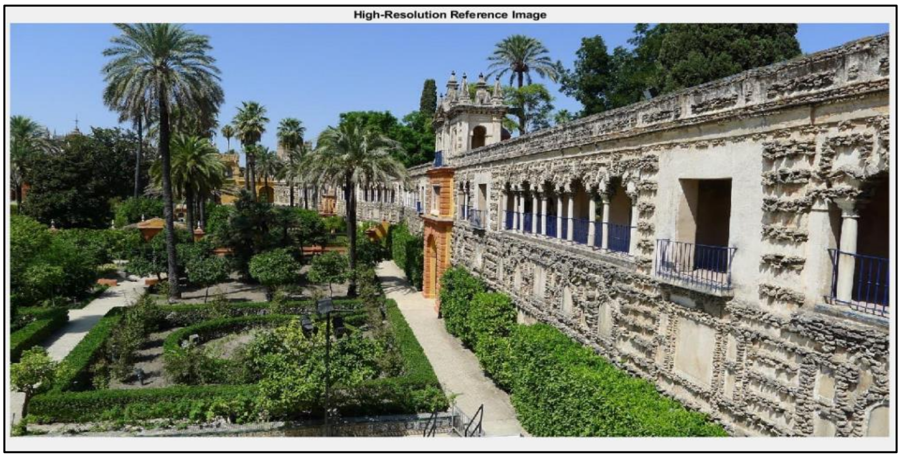

Figure (11) High resolution reference image

High-frequency components are eliminated during the down sampling process with a scale factor of 0.30, producing an image with poor resolution as shown in Figure (12).

Figure (12): Low resolution image

Image quality is enhanced using both bicubic interpolation (without deep learning) and deep learning (VDSR algorithm). As shown in Figure (13) demonstrates a comparison between the two methods.

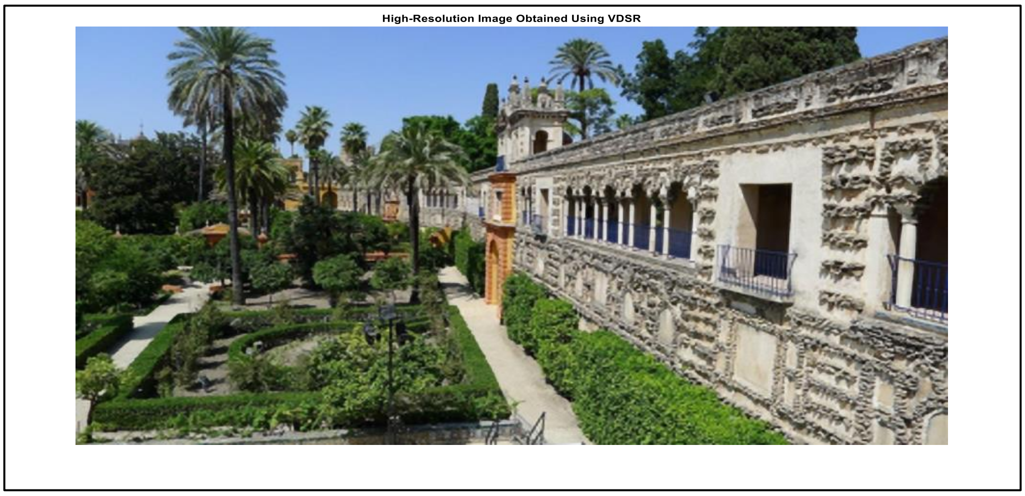

Figure (13) High resolution image using deep learning

Figure 14 Comparison of a high-resolution image generated with deep learning and one generated without deep learning.

Figure (14) High resolution image using deep learning (right) and without deep learning (left)

Conclusion

In this work, a Very Deep Super-Resolution (VDSR) network design is suggested for predicting high-resolution images from low-resolution ones. Through flowcharts of the MATLAB code, the basic idea of the technique is demonstrated. The outcomes are shown and contrasted with estimating techniques like bicubic interpolation that don't rely on deep learning. The outcomes showed that deep learning could enhance image quality. By depending on deep learning to develop the network that uses all image features, the algorithms employed in the estimate procedure can be further refined to produce results that are more accurate and images that disclose all features.

Reference

[1].Triwijoyo BK, Adil AJJIK. Analysis of medical image resizing using bicubic interpolation algorithm. 2021;14(2):20-9.

[2].Triwijoyo BK, and Ahmat Adil. Analysis of medical image resizing using bicubic interpolation algorithm. Jurnal Ilmu Komputer 142. 2021:20-9.

[3].Zhu Y, et al. An efficient bicubic interpolation implementation for real-time image processing using hybrid computing. Real-Time Image Processing. 2022:1211-23.

[4].Z. Wang DL, J. Yang, W. Han, and T. Huang. Deep networks for image super-resolution with sparse prior. IEEE international conference on computer vision. 2015:370–8.

[5].C. Dong CCL, K. He, and X. Tang. Image super-resolution using deep convolutional networks. IEEE transactions on pattern analysis and machine intelligence. 2015:295–307.

[6].V. Dumoulin IB, B. Poole, O. Mastropietro, A. Lamb, M. Arjovsky, and A. Courville. Adversarially learned inference. arXiv preprint arXiv. 2016.

[7].W. Shi JC, F. Huszar, J. Totz, A. P. Aitken, R. Bishop, D. Rueckert, and Z. Wang. Real-time single image and video superresolution using an efficient sub-pixel convolutional neural network. IEEE conference on computer vision and pattern recognition. 2016:1874–83.

[8].C. Dong CCL, K. He, and X. Tang,. Image super-resolution using deep convolutional networks. 2015.

[9].Meng N, et al. High-order residual network for light field super-resolution. Proceedings of the AAAI Conference on Artificial Intelligence. 2020.

[10].Tan C, Liejun Wang, and Shuli Cheng. Image super-resolution via dual-level recurrent residual networks. 2022.

[11].Esmaeilzehi A, Ahmad MO, Swamy MJIA. Compnet: A new scheme for single image super resolution based on deep convolutional neural network. 2018;6:59963-74.

[12].Peleg T, Elad, M. A statistical prediction model based on sparse representations for single image super-resolution. IEEE Trans Image Process. 2014:2569-82.