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Mohamed BADIY [1], Fatima AMOUNAS [1], Mourade AZROUR [1], Mohammad Ali A. HAMMOUDEH [2]

[1] ***IMIA Laboratory, MSIA Team, Moulay Ismail University of Meknes, Errachidia, Morocco***
[2] ***Department of Information Technology, College of computer, Qassim University, Buraydah, Saudi Arabia***

ADVANCED IMAGE SUPER-RESOLUTION USING DEEP LEARNING APPROACHES

The subject *of this article is Image Super-Resolution (ISR) using deep learning techniques. ISR is a rapidly evolving research area in computer science that focuses on producing high-resolution images from one or more low-resolution sources. It has garnered substantial interest due to its broad applications in areas such as medical imaging, remote sensing, and multimedia. The rise of deep learning techniques has brought a revolution in ISR, providing superior performance and computational efficiency compared to traditional methods and driving further advancements in overcoming the challenges associated with enhancing image resolution.* ***The goal*** *of this study is to enhance the quality of super-resolved images by developing a novel deep learning approach. Specifically, we explore the integration of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to address the inherent challenges of producing high-quality images from low-resolution data. This study aims to push the boundaries of ISR by combining these architectures for greater precision and visual fidelity.* ***The tasks*** *are as follows: 1) design and implement a hybrid model using CNNs and GANs for image super-resolution tasks; 2) train the model on benchmark datasets like Set5, Set14, DIV2K, and specialized datasets such as X-ray images; 3) assess the model's performance using numerical metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM); 4) to compare the proposed method against existing state-of-the-art ISR techniques and demonstrate its superiority. The following* ***results*** *were obtained in this study: Our deep learning model, which integrates the Super-Resolution Convolutional Neural Network (SRCNN) and the Super-Resolution Generative Adversarial Network (SRGAN), demonstrated significant performance improvements. The CNN successfully learned to map low-resolution image patches to their high-resolution counterparts, and the GAN further refined the images, enhancing both precision and visual quality. The evaluation metrics yielded highly promising results, with Peak Signal-to-Noise Ratio (PSNR) reaching up to 36.1368 dB and Structural Similarity Index Measure (SSIM) reaching 0.9670. These values exceed the benchmarks set by contemporary ISR methods, thus validating the superiority and effectiveness of our approach in the field of image super-resolution.* ***Conclusions****. This study demonstrated the potential of combining CNN and GAN in the domain of image super-resolution. The proposed model exhibits significant advancements over existing ISR methods, offering higher accuracy and improved image quality. The findings confirm the efficiency of deep learning methods in overcoming traditional imaging challenges, making the proposed model valuable for both academic research and practical applications in ISR.*

Keywords: *Deep learning; Image Super-resolution; Convolutional Neural Network; Generative Adversarial Network; SRCNN; SRGAN.*

1. Introduction

1.1. Motivation

Nowadays, the need for high-quality images has led to the development of Image Super-Resolution (SR), a key category of image processing techniques aimed at enhancing the resolution of images. This method focuses on reconstructing high-resolution (HR) images from low-resolution (LR) images in image processing. It has numerous practical applications, including medical imaging, surveillance, and security. Due to its extensive range of applications, SR has garnered significant interest, and it is currently one of the most active research topic in image processing [1]. In recent years, significant advancements in image super-resolution have been achieved using deep learning techniques. The SR method improves an image's resolution by analyzing its visual features and generating a higher-resolution version. These features range from simple elements such as outlines, shapes, and shades to more complex ones like textures and luminance. By analyzing these features and extending the details to a higher resolution, image super-resolution aims to produce images with improved clarity without requiring additional capturing hardware. This inherent ability to learn and extrapolate features encourages us to consider deep learning as an ideal solution to this computational challenge. Recent advances in image super-resolution have been achieved through deep learning approaches. However, there are many challenging open topics related to deep learning for image SR. Various deep learning techniques have been applied to tackle super-resolution (SR) tasks, starting with initial methods like SRCNN [2, 3] based on Convolutional Neural Networks (CNNs) and progressing to more advanced approaches such as SRGAN [4, 5], which utilize Generative Adversarial Networks (GANs). SRCNN utilizes a neural network to address the SR problem by learning detailed features from extensive datasets. CNN architectures like SRCNN have demonstrated effectiveness in super-resolution tasks, but they come with several limitations. These include challenges in handling extremely low-resolution images, the high computational cost due to its shallow design, and the potential for blurriness in high-frequency areas. In addition, its performance can be heavily affected by the quality of the training data and may be less resilient to noise. To overcome these issues, researchers frequently turn to more advanced techniques like SRGAN to enhance image quality.

1.2. State of the art

Numerous DL methods for image super-resolution (SR) have been reported in recent studies. For instance, Chen et al. in [6] introduced a method for enhancing the resolution of single-depth images using Convolutional Neural Networks (CNNs). The authors proposed a CNN-based approach tailored specifically for depth images, which are commonly used in applications such as 3D reconstruction and robotics. The proposed method improves the quality of depth images by increasing resolution while preserving depth information. The effectiveness of the proposed approach was demonstrated through experimental results and performance comparisons. Jian Lu, Weidong Hu, and Yi Sun [7] presented a novel approach to image super-resolution (SR) that leverages geometric similarity. The authors proposed a deep learning method that improves the resolution of low-resolution images by focusing on the geometric relationships within the image. This method enhances the SR process by identifying and using similar geometric structures, leading to more accurate and visually appealing high-resolution images. The effectiveness of this approach was demonstrated through experiments and comparisons with existing SR methods. The paper proposed by K. Chauhan et al. [8] reviewed recent advances in single-image super-resolution (SISR) techniques based on deep learning. The authors surveyed various methods to improve the resolution of low-quality images, focusing on deep learning models such as CNNs and GANs. This review discusses the challenges in SISR, evaluates different architectures, and compares their performance. The paper also highlighted future research directions, emphasizing the potential of deep learning in improving image quality across various applications. Chung, M. et al. [9] introduced a novel two-stage approach called the bicubic-downsampled low-resolution image-guided generative adversarial network (BLG-GAN) for enhancing the super-resolution (SR) of remote sensing images. In the first stage, real-world low-resolution (LR) images are transformed into cleaner, bicubic-like LR images using synthetic LR images generated by bicubic downsampling as a reference. These refined images are then input into a super-resolution network, which learns to map them to high-resolution (HR) images. By splitting the SR task into two distinct steps, BLG-GAN achieves higher image quality with reduced network complexity than existing state-of-the-art models. The effectiveness of the proposed approach was validated through experiments on high-resolution satellite image datasets, which demonstrated significant improvements in image quality. More recently, a study [10] investigated the application of the Super-Resolution Convolutional Neural Network (SRCNN) to improve image resolution. The authors outlined the structure of SRCNN, emphasizing its three key components: patch extraction and representation, non-linear mapping, and reconstruction. They highlighted how SRCNN, a recognized deep learning model, can be successfully applied to improve image resolution and visual quality, particularly in scenarios where high-resolution images are crucial. The results revealed that SRCNN outperforms traditional image enhancement techniques, particularly in preserving sharpness and reducing noise in the reconstructed images, making it a highly effective tool for applications requiring superior image restoration. In the same year, the authors of the study [11] presented an innovative super-resolution technique that integrates Generative Adversarial Networks (GANs) with quantum feature enhancement. Their method was specifically designed to enhance aerial agricultural images with the aim of improving image quality and detail for better analysis and monitoring. By integrating quantum features into the GAN framework, the proposed approach addressed challenges related to image resolution and fidelity, thereby demonstrating improved performance in aerial image applications.

Hassan et al. [12] proposed an innovative deep learning approach for Single Image Super-Resolution (SISR) using an Autoencoder architecture with residual connections. Unlike conventional interpolation-based and reconstruction-based techniques, the proposed model uses convolutional and transposes convolutional layers without subsampling, ensuring high-quality image reconstruction while maintaining computational efficiency. By incorporating skip connections between the down-sampling and up-sampling stages, the network effectively preserves fine details, which improves the generation of high-resolution images. The evaluation covers both quantitative and qualitative aspects of image restoration, highlighting the proposed method's superiority over existing SISR techniques. Another study, which integrated deep learning for both super-resolution reconstruction and segmentation to improve photoacoustic imaging (PAI), was developed by Johnson et al. [13]. Their method proposes an enhanced deep super-resolution minimalistic network (EDSR-M) that addresses computational complexity and parameter count while improving image quality. The results revealed significant enhancements in both image quality and segmentation performance. This method highlights the potential of deep learning techniques to overcome challenges such as low resolution, noise, and image artifacts, ultimately advancing the clinical applications of PAI. The introduction of deep learning by Hwang et al. [14] facilitated greater developments in Super Resolution, particularly in improving the quality of magnetic resonance imaging (MRI) for the diagnosis and treatment of trigeminal neuralgia (TN). By applying SR to various MRI techniques, including T1-weighted, T2-weighted, VISTA, contrast-enhanced T1, and proton density imaging, the study demonstrated that SR significantly improved image quality. The findings of this study highlighted its potential as a powerful tool for both diagnosing and treating TN.

The main contribution of the recent study by Lee et al. [15] is the development of an advanced super-resolution technique for enhancing the quality of medical images, particularly for melanoma diagnosis. The authors proposed a CNN-based architecture that features a convolutional self-attention block that combines channel and spatial attention mechanisms. Their model employs subpixel convolution to improve image resolution and produces high-quality results with enhanced preservation of textures and contours. Evaluation on the ISIC 2020 dataset showed that the proposed model outperformed existing methods, demonstrating its effectiveness in improving medical image quality for more precise diagnostic applications.

State-of-the-art methods in super-resolution imaging, such as CNNs, GANs, and attention mechanisms, have shown progress; however, they face challenges like artifacts, detail loss, and high computational demands. This research introduces a novel deep learning framework that combines CNNs for feature extraction and GANs for texture synthesis to improve resolution, detail preservation, and training stability.

1.3. Objectives and the approach

SRCNN and SRGAN models have demonstrated impressive results in a range of image processing applications, including image super-resolution. There has been a distinct gap in the exploration of new models, particularly GANs, for super-resolution.

The primary contributions of this research are as follows:

- We propose a lightweight strategy that merges SRCNN and SRGAN to produce high-resolution images from low-resolution sources;
- The proposed method uses an advanced CNN and GAN to generate high-quality images, thereby enabling accurate identification and analysis;
- We examine the metrics used to achieve optimal performance.
- We compare the proposed method with conventional SR techniques to demonstrate its superiority in terms of preserving details, minimizing artifacts, and enhancing overall image quality.

This paper has the following structure: Section 2 presents foundational information relevant to the field of image resolution. Section 3 describes the methods used to develop our image resolution architecture. This includes information about two key processes: the SRCNN and the SRGAN processes. Section 4 provides an in-depth discussion of the experimental results and conclusions. The last Section summarizes the conclusions of the study.

2. Background Information

2.1. Image Super-Resolution

Image Super-Resolution is a technique used to enhance the resolution of images by converting low- and high-resolution images. This area has experienced substantial progress has been made with the use of deep learning methods, especially CNNs and GANs. Image SR techniques span a wide range of approaches including Interpolation-Based Methods, Reconstruction-Based Methods and Learning-Based Methods. Several techniques developed over the years have yielded significant results, Specifically Learning-Based Methods. These techniques include CNNs and GANs. Different methods can achieve super-resolution images.

2.2. CNN for Super-resolution

CNN models are extensively employed for image super-resolution (SR) owing to their ability to learn intricate features and patterns from images [16]. The CNN architecture for SR typically involves layers of convolution operations, where each layer is responsible for capturing different levels of features from the input image.

The network gradually refines the image resolution by learning to predict missing details. The Super-

Resolution Convolutional Neural Network (SRCNN) is one of the earliest and most influential deep learning models for image SR. The SRCNN works by establishing a transformation from low-resolution images to high-resolution images. The network was trained on an extensive dataset of corresponding low- and high-resolution images. Once trained, the network can upscale a low-resolution image by predicting the high-resolution details [17].

2.3. GAN for Super-Resolution

The Super-Resolution Generative Adversarial Network (SRGAN) is a more advanced model that leverages the adversarial learning paradigm of GANs to produce high-resolution photo-realistic images from low-resolution inputs [18, 19].

Figure 1 shows the SRGAN architecture [20], which consists of two components: a generator and a discriminator:

- Generator: this model is typically a deep CNN designed to transform a low-resolution image into a high-resolution counterpart. The goal of the generator is to produce images that are indistinguishable from real high-resolution images;
- *Discriminator*: the discriminator model is trained to distinguish real-life high-resolution images from images generated by the generator. The generator and discriminator are trained together in a process in which the generator enhances its ability to deceive the discriminator, while the discriminator becomes more adept at distinguishing between real and generated images.

3. Methodology

The application of deep learning techniques in image super-resolution has led to significant advancements, offering new opportunities and capabilities. This study introduces a robust method that combines SRCNN and SRGAN to produce super-resolution images from low-resolution inputs. Figure 2 presents the architecture of the proposed approach, highlighting the complex layers and processes involved in achieving enhanced super-resolution.

Our architecture includes two key processes: the SRCNN process and the SRGAN process:

- *SRCNN Process*: The SRCNN model takes a low-resolution (LR) image, which is resized to the target dimensions using bicubic interpolation [21], and processes it through three layers. The first layer, known as Feature Extraction, uses 64 filters of size 9x9 to capture crucial features from the LR image. The second layer, Non-linear Mapping, applies 32 filters of size 1×1 to refine and integrate these features, thereby creating a more detailed representation. The final layer, Reconstruction, uses a single 5x5 filter to generate high-resolution (HR) images from the processed features. This layer combines and enhances the features to produce a super-resolution image with improved detail and sharpness compared to the original LR input;

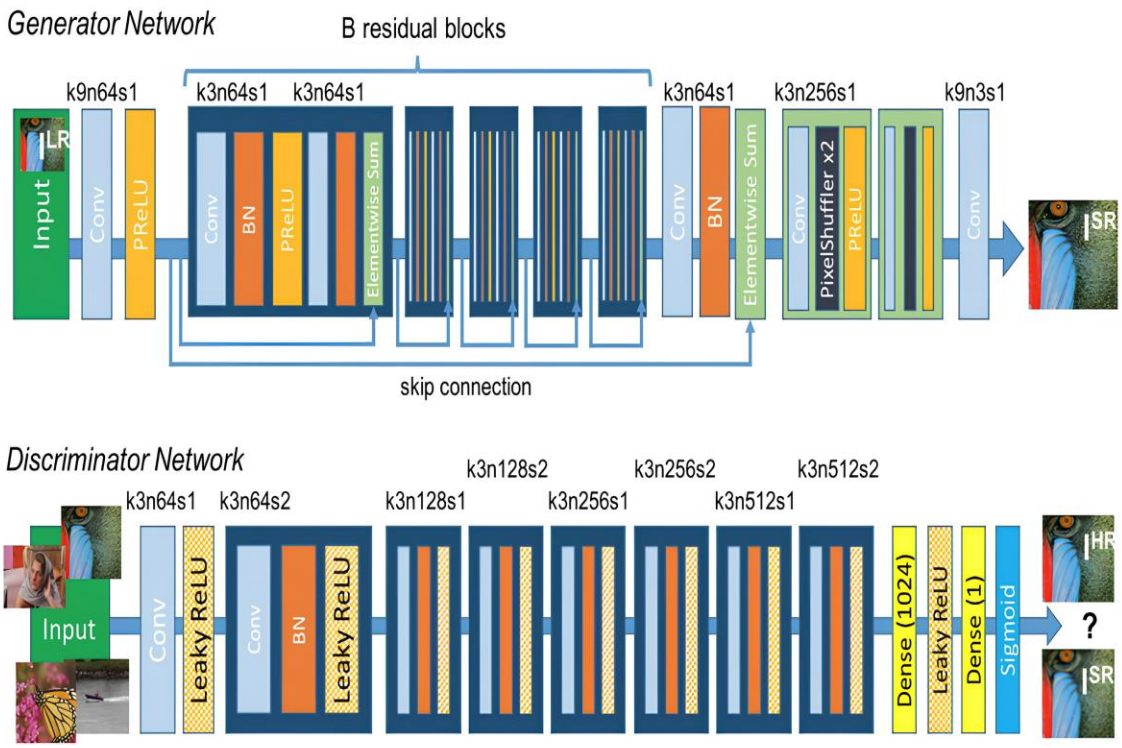

Fig. 1. The detailed architecture of SRGAN

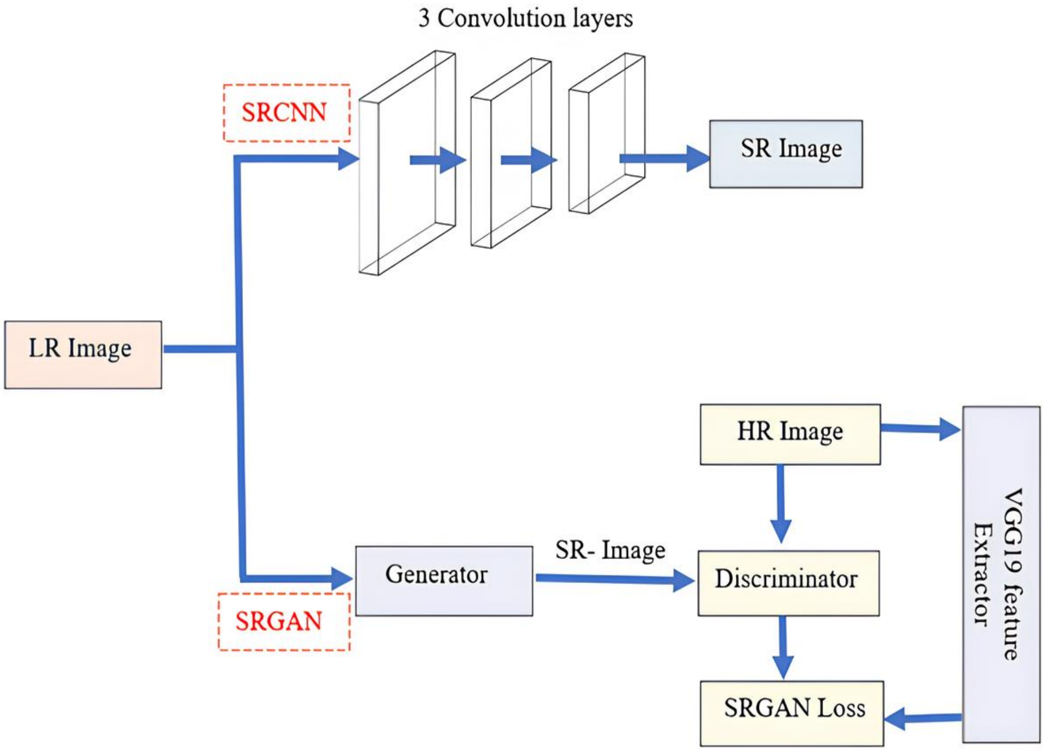

Fig. 2. The structure of our Methodology

- *SRGAN Process:* The SRGAN process uses two distinct neural networks: the generator, which creates new data, and the discriminator, which evaluates the quality of the data. This involves five key steps. First, the process begins with a low-resolution (LR) image, a downscaled version of the high-resolution (HR) image that lacks finer details. Next, the generator enhances the LR image's resolution through multiple layers, including residual and scaling blocks, to produce a high-resolution image by restoring missing details. The discriminator then assesses the quality of the generated high-resolution image, differentiating between real HR images and those created by the generator, thus refining its output. For feature extraction, a pretrained VGG19 model is employed to capture high-level features from HR images, and this model helps evaluate the perceptual quality of the generated images. Finally, the SRGAN loss is calculated by comparing the feature maps of the generated and real HR images, and we update both the generator and discriminator to improve the quality of the generated images until they are nearly indistinguishable from the real images.

4. Experiment details

After thoroughly examining the principles and architecture of the proposed approach, its implementation was performed using Python scripts designed to enhance image quality. The execution occurred on a machine with 16 GB RAM and an Intel Core i5 CPU running Windows 11. To address the computational demands, the Google Colab environment was used, leveraging its cloud-based resources. This section presents a detailed analysis of the experimental results, beginning with a comprehensive description of the dataset and highlighting its characteristics and relevance to the study. Subsequently, the outcomes of the training process are explored, including a discussion of performance metrics and an analysis of the results to demonstrate the effectiveness of the proposed approach. In addition, the proposed method was evaluated in comparison with existing super-resolution techniques.

4.1. Datasets

In the field of super-resolution (SR), several image datasets are widely recognized and frequently used as benchmarks to assess and compare the effectiveness of different SR techniques. For this study, three well-known datasets were strategically selected: DIV2K (https://data.vision.ee.ethz.ch/cvl/DIV2K/), Set5, and Set14 (https://www.kaggle.com/datasets/ll01dm/set-5-14-super-resolution-dataset?select=Set5), along with a dataset of Generated X-ray Images (https://www.kaggle.com/datasets/anaselmasry/generated-images-xray). Figures 3, 4, and 5 show examples of images from these datasets. The use of these datasets enabled a rigorous evaluation and validation of the proposed SR method's performance.

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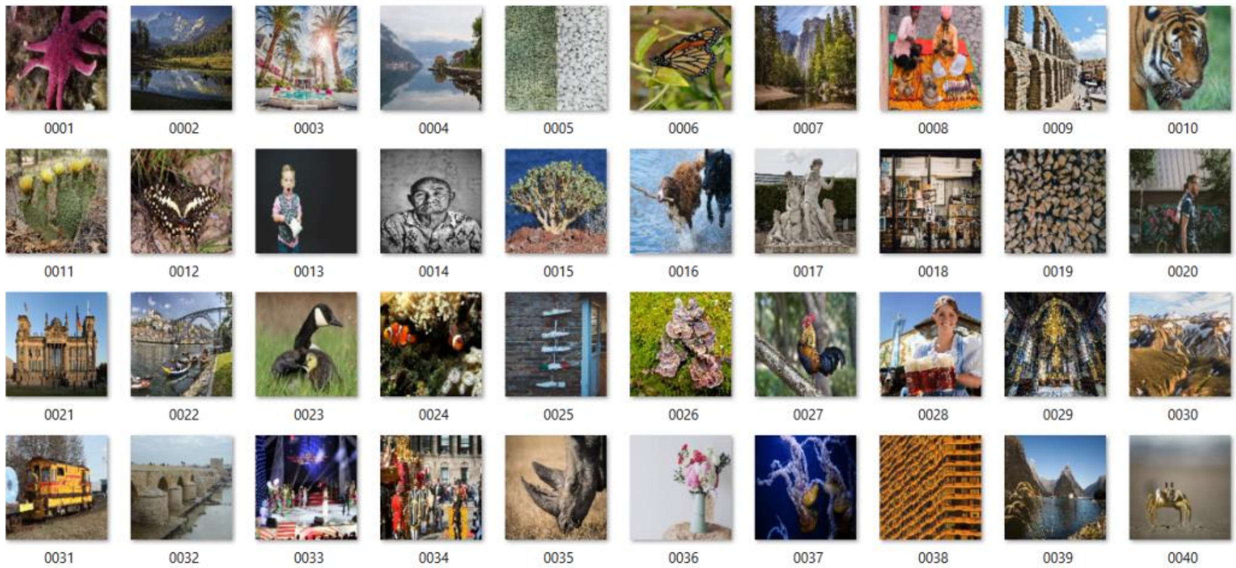

Fig. 3. DIV2K dataset

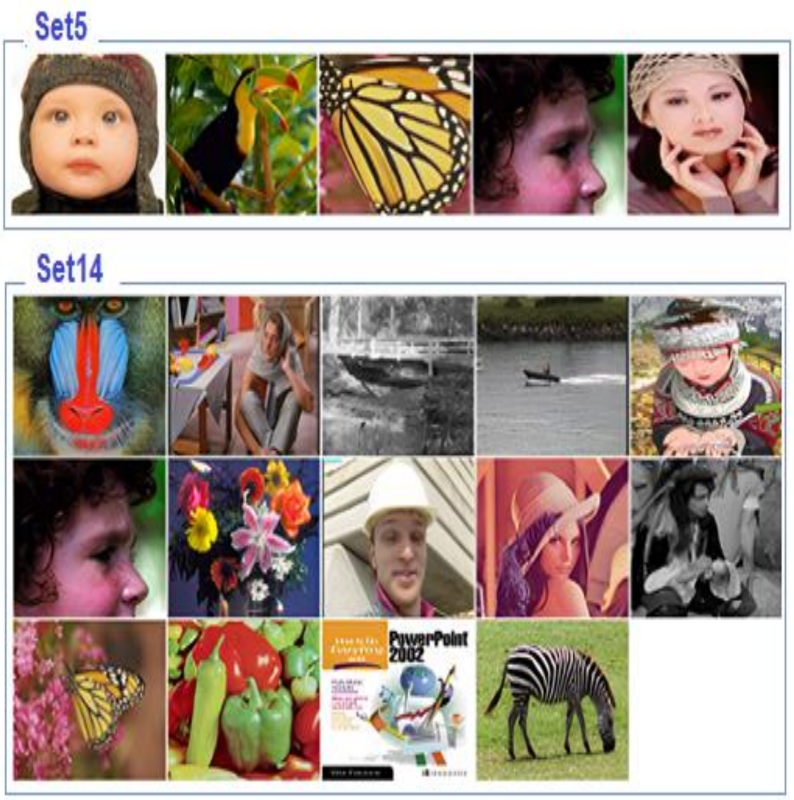

Fig. 4. Set5 and Set14 dataset

This selection allows us to benchmark the proposed method against established datasets while also evaluating its applicability to various types of images, including medical images:

- *DIV2K*: This dataset is extensively used for single-image super-resolution tasks and includes 1,000 diverse images. It was split into 800 images for training, 100 images for validation, and 100 images for testing. It was designed for super-resolution NTIRE2017 and NTIRE2018 super-resolution challenges and focuses on advancing research in image super-resolution by addressing more realistic degradations [22];

- *Set5:* This dataset includes five high-quality images commonly used for testing and benchmarking super-resolution methods. The images in Set5 include a variety of content, such as natural scenes and objects,

Fig. 5. Generated Images X-ray dataset

providing a good balance between textures and details [23]. Set5 was selected for its simplicity and effectiveness in highlighting the strengths and weaknesses of different SR techniques;

- *Set14*: Building upon the concept of Set5, Set14 comprises 14 images that encompass a wider variety of visual contents. This dataset includes both natural and man-made scenes, along with varying levels of texture and detail. Set14 presents a more challenging benchmark for super-resolution methods, as it assesses the algorithms' ability to generalize across diverse image types [24];

- *Generated Images X-ray:* This dataset consists of 1,160 medical images [25] classified into three categories: Covid-19, Normal, and Pneumonia. It is specifically designed to support research and development in medical imaging, with a focus on deep learning and machine learning applications.

4.2. Evaluation Metrics

In this study, we used the peak signal-to-noise ratio (PSNR) and structural similarity index measurement (SSIM) as evaluation indices to evaluate the spatial reconstruction quality of super-resolved images [26]. PSNR is one of the most frequently used metrics for evaluating image quality. However, it primarily measures the pixel-wise error between corresponding points and does not consider human visual perception. Consequently, its evaluation may not always accurately reflect human subjective judgment. The formula for this metric is as follows:

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right), \quad (1)$$

Where the MSE is calculated as follows:

$$\mathrm{MSE} = \frac{\sum_{n=1}^{N}(I^n - P^n)}{N}. \quad (2)$$

In this context, I^n represents the gray value of the n^{th} pixel of the original image, and P^n denotes the gray value of the n^{th} pixel after processing. The PSNR is measured in (dB), with higher values indicating better image quality.

The SSIM is an additional metric for evaluating the perceived quality of digital images. The SSIM is used to evaluate the structural similarity between images by analyzing various aspects, such as luminance, contrast, and structural details. The SSIM formula is given by Eq. (3):

$$\mathrm{SSIM}\left(I^{SR}, I^{HR}\right) = \frac{(2\mu_{I^{SR}}\mu_{I^{HR}}+C_1)(2\sigma_{I^{SR},I^{HR}}+C_2)}{(\mu_{I^{SR}}^2+\mu_{I^{HR}}^2+C_1)(\sigma_{I^{SR}}^2+\sigma_{I^{HR}}^2+C_2)}, \quad (3)$$

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where $\mu_{I^{SR}}$ and $\mu_{I^{HR}}$ represents the mean value of the image I^{SR} and I^{HR}, $\sigma_{I^{SR}}$, I^{HR} denotes the covariance of I^{SR} and I^{HR}, and $\sigma_{I^{SR}}$, and $\sigma_{I^{HR}}$, represent the variance of the image I^{SR} and I^{HR}. Constants C_1 and C_2 are used to prevent the divide-by-zero error, where $C_1 = (k_1 L)^2$, $C_2 = (k_2 L)^2$, with default values k_1 = 0.01, k_2= 0.03, and L representing the dynamic range of pixel values, which is 1 in our study.

4.3. Results

To reveal the testing outcomes and performance of our approach, the SRCNN technique was first applied to three widely used image super-resolution datasets: Set5, Set14, and DIV2K. The SRCNN method learns a mapping between low-resolution and high-resolution image pairs, making the presence of both types of images essential for successful training. In this study, we selected 91 images from the DIV2K dataset for training, ensuring that the network was exposed to a broad and high-quality range of images. To evaluate the trained SRCNN model's effectiveness, we employed 19 test images sourced from the Set5 and Set14 datasets, which are established benchmarks in the field of image super-resolution, offering a reliable basis for performance evaluation.

Figure 6 shows the loss curves of the proposed SRCNN model. We notice a pattern where the accuracy rate increased and the error rate decreased as the number of epochs increased. However, this improvement is not linear. Once a certain number of epochs is reached, the curves begin to stabilize, and the rate of improvement is reduced significantly compared to the earlier stages. In addition, the accuracy rate starts to decline beyond this point.

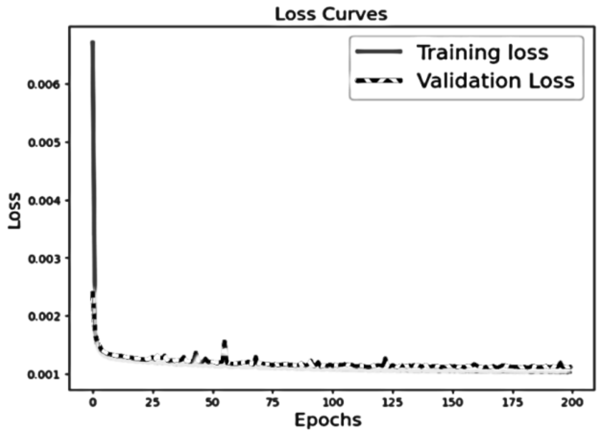

Fig. 6. Loss Graph of SRCNN

Based on this finding, we calculate the PSNR, MSE, and SSIM to comprehensively assess our model's performance in reconstructing degraded images. These metrics provide important insights into the quality of the reconstructed images by comparing them with the original high-resolution images. Figure 7 compares the PSNR, SSIM, and MSE values for the degraded and reconstructed images. This analysis demonstrates the effectiveness of our model in enhancing image quality, as indicated by the higher PSNR and SSIM values and lower MSE, demonstrating its ability to restore details lost during degradation.

Similarly, we trained the SRCNN model on 150 training images, 60 test images, and 60 degraded images. The quality metrics obtained from this evaluation demonstrate that the proposed model is highly effective in restoring image details and enhancing the overall quality of degraded images. Figure 8 shows a notable enhancement in both PSNR and SSIM scores, indicating the model's success in recovering fine details and reducing distortions from the degradation process. These results highlight the model's strong performance in image reconstruction, validating its effectiveness for image-super-resolution tasks.

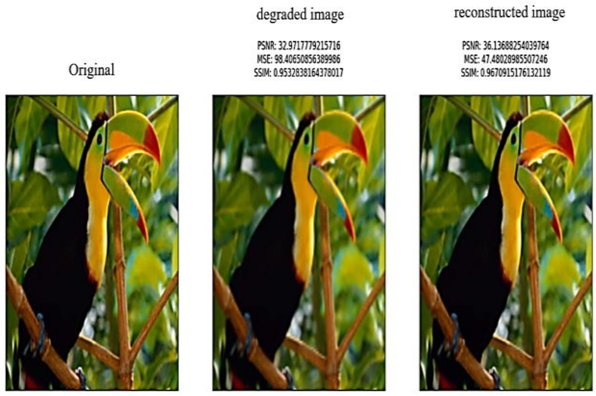

Fig. 7. The results of PSNR and SSIM on the Set5 dataset

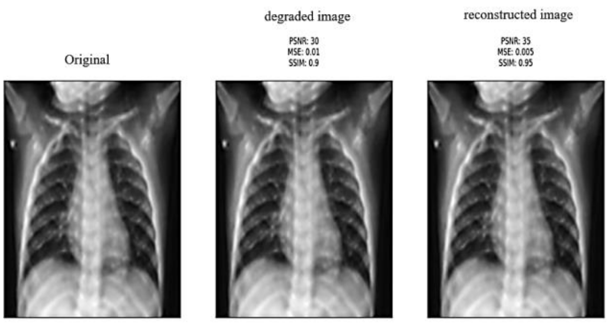

Fig. 8. The results of PSNR and SSIM on the X-ray dataset

For training our SRGAN model, a dataset of 110 LR images and 110 HR images was utilized, drawn from the DIV2K, Set14, and Set5 datasets, which are well-regarded in the image super-resolution field. The dataset was randomly split into training and testing sets for a thorough evaluation of model performance. Specifically, 74 images were used for training the model to learn the relationship between low-resolution and high-resolution images, while the remaining 36 images were reserved for testing to evaluate the model's ability to generalize to new, unseen data. This random split ensures that the performance metrics are reliable and are not skewed by any specific subset of images. Figure 9 shows the results of the SRGAN model, which was trained for 200 epochs, with a single image demonstrating significant improvements.

4.4. Performance Comparison

In this section, an in-depth evaluation is presented to compare the proposed architecture with existing SR methods. The overall comparison is presented in Table 1. As illustrated in Table 1, the proposed approach outperformed the other methods, achieving the highest PSNR of 36.1368 dB and SSIM of 0.9670. These results demonstrate the superior ability of the proposed method to reconstruct high-quality images with finer details and reduced distortions. Furthermore, IGAN-SRCP achieved the second-best performance with a PSNR of 31.1210 dB and SSIM of 0.9055, which represents a considerable margin compared to our approach. Compared to SRCNN, EDSR, ESRGAN, and RFB-ESRGAN, the proposed architecture shows significant improvements in terms of both PSNR and SSIM. For example, SRCNN, a preceding model in super-resolution research, achieves a PSNR of 29.8132dB and SSIM of 0.8796, which is significantly lower than the results of our approach. Similarly, advanced models like EDSR and ESRGAN exhibit moderate performance, with EDSR achieving a PSNR of 30.4251 dB and SSIM of 0.8901, and ESRGAN achieving a PSNR of 30.2009 dB and SSIM of 0.8986. The RFB-ESRGAN model, which integrates receptive field blocks into ESRGAN, improved slightly with a PSNR of 30.4116 dB and SSIM of 0.8910, yet still falls short of the performance demonstrated by our approach.

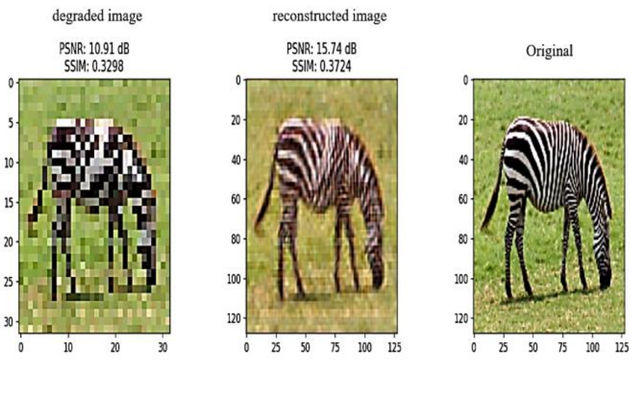

Fig. 9. The results of PSNR and SSIM on the Set14 dataset

Table 1

Performance comparison in terms of PSNR and SSIM values

Methods	PSNR(dB)	SSIM
SRCNN [27]	29.8132	0.8796
EDSR [28]	30.4251	0.8901
ESRGAN [29]	30.2009	0.8986
RFB-ESRGAN [30]	30.4116	0.8910
IGAN-SRCP [31]	31.1210	0.9055
Proposed approach	36.1368	0.9670

In summary, these comparisons underscore the effectiveness of the innovations introduced in the proposed architecture, which enable it to surpass existing SR methods in terms of generating high-quality, visually appealing images. The substantial gains in both PSNR and SSIM highlight the robustness and efficacy of the proposed method, making it a significant advancement in the field of image Super-Resolution.

4.5. Discussion

The proposed method enhances the quality of super-resolved images by integrating CNNs and GANs, leveraging their strengths in feature extraction and realistic texture generation. The proposed deep learning model, which combines SRCNN with SRGAN, demonstrated significant improvements in terms of performance. The CNN effectively learns to map low-resolution image patches to their high-resolution counterparts, and the GAN further refines the images, enhancing both precision and visual quality. The scientific novelty lies in the optimized combination of SRCNN for structural accuracy and SRGAN for perceptual enhancement, achieving a balanced trade-off between sharpness and realism. However, some limitations remain. The model's high computational complexity makes real-time processing challenging, especially in large-scale applications. In addition, performance is highly dependent on the quality and diversity of the training dataset, which may lead to suboptimal generalization for unseen images. In addition, although perceptual quality is improved, fine-grained texture reconstruction in highly degraded images remains a challenge.

5. Conclusions

Recently, there has been a significant shift from traditional algorithms to deep learning-based methods for super-resolution tasks. Deep learning has significantly influenced image-super-resolution applications, delivering exceptional reconstruction results because of its strong nonlinear mapping abilities. This paper introduces a lightweight approach for image super-resolution using deep learning techniques, including Convolutional Neural Network (CNN) and generative adversarial network (GAN) models. In addition, the performance of these models was evaluated by measuring PSNR and SSIM values and evaluating them across various datasets. The findings indicate outstanding average PSNR and SSIM values, demonstrating that the proposed approach outperforms other super-resolution methods. This makes it particularly suitable for applications requiring high-resolution imaging with improved detail and accuracy, such as medical imaging, remote sensing, and advanced surveillance systems. Future work will focus on enhancing super-resolution techniques for medical images in real-world applications by developing hybrid models that integrate attention mechanisms, transformer-based architectures, and novel loss functions to improve feature extraction and texture reconstruction. These advances could enhance performance in challenging conditions, such as low-light environments or images with significant noise. Additionally, adapting super-resolution techniques for domain-specific applications, particularly in medical imaging, will be a key area of research, with the goal of improving diagnostic imaging modalities like MRI, CT scans, and ultrasound, to aid in early disease detection. Another important direction is the exploration of federated learning to enable the distributed training of super-resolution models while ensuring data privacy, which is crucial in healthcare settings. Furthermore, the robustness of super-resolution models under real-world conditions, including varying levels of degradation, will be prioritized. By incorporating adaptive learning strategies, these models can dynamically adjust to different image types and resolutions, thereby enhancing their applicability in diverse fields, such as remote sensing, surveillance, and video enhancement.

Contributions of authors

All authors have contributed equally in preparing this paper

Conflict of Interest

The authors declare that they have no conflict of interest.

Financing

This study was conducted without financial support.

Data Availability

The data can be accessed through this link https://www.kaggle.com/mlg- ulb/creditcardfraud

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

All the authors have read and agreed to the published version of this manuscript.

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РОЗШИРЕНА НАДВИСОКА РОЗДІЛЬНА ЗДАТНІСТЬ ЗОБРАЖЕНЬ З ВИКОРИСТАННЯМ ПІДХОДІВ ГЛИБОКОГО НАВЧАННЯ

Мохамед Баді, Фатіма Амунас, Мурад Азрур, Мохаммад Алі А. Хамудех

Предметом цієї статті є надвисока роздільна здатність зображень (Image Super-Resolution, ISR) з використанням методів глибокого навчання. Надвисока роздільна здатність зображень (ISR) - це галузь комп'ютерних наук, яка швидко розвивається і зосереджена на створенні зображень високої роздільної здатності на основі одного або декількох вхідних даних низької роздільної здатності. Він привернув значну увагу завдяки широкому застосуванню в таких галузях, як медична візуалізація, дистанційне зондування та мультимедіа. Розвиток методів глибокого навчання приніс революцію в ISR, забезпечивши вищу продуктивність і обчислювальну ефективність порівняно з традиційними методами, і стимулюючи подальший прогрес у подоланні проблем, пов'язаних з підвищенням роздільної здатності зображень. Метою цього дослідження є покращення якості зображень з надвисокою роздільною здатністю шляхом розробки нового підходу до глибокого навчання. Зокрема, ми досліджуємо інтеграцію згорткових нейронних мереж (CNN) та генеративних змагальних мереж (GAN) для вирішення проблем, пов'язаних з отриманням високоякісних зображень з даних низької роздільної здатності. Ця робота має на меті розширити межі ISR шляхом поєднання цих архітектур для більшої точності та візуальної достовірності. Завдання роботи полягають у наступному: 1) розробити та реалізувати гібридну модель з використанням CNN та GAN для задач надвисокої роздільної здатності зображень; 2) навчити модель на еталонних наборах даних, таких як Set5, Set14, DIV2K та спеціалізованих наборах даних, таких як рентгенівські знімки; 3) оцінити продуктивність моделі за допомогою кількісних метрик, таких як пікове відношення сигнал/шум (PSNR) та індекс структурної подібності (SSIM); 4) порівняти запропонований метод з існуючими сучасними методами ISR та продемонструвати його перевагу. У цьому дослідженні були отримані наступні результати: Наша модель глибокого навчання, яка інтегрує згорткову нейронну мережу з високою роздільною здатністю (SRCNN) та генеративну змагальну мережу з високою роздільною здатністю (SRGAN), продемонструвала значне покращення продуктивності. CNN успішно навчився зіставляти ділянки зображення з низькою роздільною здатністю з їхніми аналогами з високою роздільною здатністю, тоді як GAN ще більше покращив зображення, підвищивши точність і візуальну якість. Метрики оцінки дали дуже багатообіцяючі результати: пікове відношення сигнал/шум (PSNR) досягло 36,1368 дБ, а показник індексу структурної подібності (SSIM) - 0,9670. Ці значення перевищують показники, встановлені сучасними методами ISR, що підтверджує перевагу та ефективність нашого підходу в галузі надвисокої роздільної здатності зображень. Висновки. Це дослідження демонструє потенціал поєднання CNN та GAN в області надвисокої роздільної здатності зображень. Наша модель демонструє значні переваги над існуючими методами ISR, пропонуючи вищу точність та покращену якість зображень. Результати підтверджують ефективність підходів глибокого навчання у подоланні традиційних проблем обробки зображень, що робить цю модель цінним внеском як для академічних досліджень, так і для практичного застосування в галузі ДЗЗ.

Ключові слова: Глибоке навчання; надвисока роздільна здатність зображень; згорткова нейронна мережа; SRCNN; генеративна змагальна мережа; SRGAN.

Баді Мохамед – доктор філософії, R.O.AL&I Group, кафедра комп'ютерних наук, факультет наук і техніки, Університет Мулая Ісмаїла в Мекнесі, Еррахідія, Марокко.

Амунас Фатіма – доктор комп'ютерних наук, професор, професор кафедри комп'ютерних наук, R.O.AL&I Group, факультет наук і техніки, Університет Мулая Ісмаїла в Мекнесі, Еррахідія, Марокко.

Азрур Мурад – доктор комп'ютерних наук, професор, професор кафедри комп'ютерних наук, команда IDMS, факультет наук і технологій Мулая Ісмаїла Університету в Мекнесі, Еррахідія, Марокко.

Хаммудех Мохаммад Алі А. – доктор комп'ютерних наук, доцент, професор кафедри інформаційних технологій, Комп'ютерний коледж, Університет Кассіма, Бурайда, Саудівська Аравія.

Mohamed Badiy – PhD, IMIA Laboratory, MSIA Team, Computer Sciences Department, Faculty of Sciences and Technics, Moulay Ismail University of Meknes, Errachidia, Morocco,
e-mail: m.badiy@edu.umi.ac.ma, ORCID: 0000-0002-8848-3689, Scopus Author ID: 57721701200.

Fatima Amounas – Doctor of Computer Science, Professor, Professor at the Computer Sciences Department, IMIA Laboratory, MSIA Team, Moulay Ismail University of Meknes, Errachidia, Morocco,
e-mail: f.amounas@umi.ac.ma, ORCID: 0000-0001-5670-2210, Scopus Author ID: 55367059700.

Mourade Azrour – Doctor of Computer Science, Professor, Professor at the Computer Sciences Department, IMIA Laboratory, MSIA Team, Moulay Ismail University of Meknes, Errachidia, Morocco,
e-mail: mo.azrour@umi.ac.ma, ORCID: 0000-0003-1575-8140, Scopus Author ID:57193500437.

Mohammad Ali A. Hammoudeh – Doctor of Computer Science, Assistant Professor, Professor at the Department of Information Technology, College of computer, Qassim University, Buraydah, Saudi Arabia,
e-mail: maah37@qu.edu.sa, ORCID: 0000-0002-9735-2365, Scopus Author ID: 57219152564.