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Original Article

Adaptive Deep Learning Architectures for Enhanced Multi Degradation Image Super Resolution

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Abstract *- This research addresses the limitations of existing Single Image Super Resolution (SISR) methods that typically target specific kinds of image deterioration, such as noised images or blurred images. These targeted approaches are ineffective in real-world scenarios where images suffer from multiple degradation types simultaneously. The proposed adaptive deep learning framework is designed to enhance the resolution of images affected by various degradation types, including noising, blurring, and compression artifacts. The proposed framework involves developing a multi-degradation modeling approach, adaptive feature learning mechanisms, tailored loss functions, and comprehensive datasets for effective training and evaluation. This unified solution aims to advance the state of the art in SISR by robustly handling diverse degradation types, thus improving image quality across a range of applications.*

Keywords *- Single Image Super Resolution, Deep learning, Multi degradation, Image Restoration, Adaptive feature learning, Loss functions, Dataset construction.*

1. Introduction

One of the primary image processing tasks is Image Restoration (IR), which is the recovery of high-quality images from degraded observations. Color images may be degraded by various types of distortions that can occur either during the image acquisition process or further down the processing chain [1]. Some of these distortions include compression artifacts, transmission errors, sensor noise, and missing samples. Several image restoration methods have been proposed in recent years to solve these issues [3]. As CNN and DL have been so effective for image processing, numerous learning-based image restoration methods have been proposed [4]. They rely on data-driven end-to-end learning [2]. Traditional image restoration methods are mainly dependent on image priors [5]. Image restoration is a highly significant area of computer vision, with a precise aim to improve images deteriorated by noise, blur, and compression. Image restoration can greatly improve the visual experience of humans and improve the precision of other high-level tasks like object detection and image classification [1].

1.1. Restoration Method

Three primary categories have been established in this research for digital picture restoration techniques: image processing, machine learning, and deep learning [6]. Algorithms are used in image processing techniques to manipulate digital images [2]. The basis of machine learning and deep learning approaches [20] is a learner that uses previously collected data to build new, unseen knowledge [7]. Deep learning networks have "deep" architectures because they comprise numerous repeating layers [3].

1.2. Image Processing

Image processing encompasses algorithms and techniques that manipulate an image to enhance its visual quality or extract meaningful information [8]. These techniques typically work directly on the image's pixel values [21] without necessarily learning from data. Examples include:

1. Filtering: Smoothing, sharpening, edge detection, and noise reduction.
2. Morphological operations: Erosion, dilation, opening, and closing for shape analysis.
3. Transformations: Histogram equalization, contrast stretching, and color space conversions.
4. Segmentation: Identifying and separating objects or regions of interest within the image.
5. Feature extraction: Computing descriptors that capture the relevant characteristics of the image.

1.3. Machine Learning

This category involves algorithms that learn from a set of training data to predict or make decisions on new, unseen data

[9]. In image restoration, machine learning algorithms can be used to:

- Train a model that learns the relationship between degraded and clean images. This allows the model to estimate the restored version for new degraded images.
- Learn the underlying structure of the image data without explicit labels. This is particularly useful when clean images are not available for training. Principal
- Restoration methods: component analysis and k means clustering are examples of unsupervised learning techniques.
- Formulate the restoration problem as a probabilistic inference task. This involves using Bayes' theorem to estimate the posterior probability distribution of the clean image based on the observed degraded image. This approach can be particularly effective for handling noise and uncertainty.
- Machine learning techniques offer greater flexibility and adaptability than image processing but may require larger training datasets and be computationally expensive.

1.4. Deep Learning

This Deep Learning builds upon machine learning by utilizing deep neural networks with multiple layers [22]. These networks can learn complex representations from data, enabling them to perform better on various image restoration tasks [10]. Deep learning techniques include:

- Convolutional Neural Networks (CNNs): They are especially effective at picking up spatial information in images commonly utilized for various restoration tasks, such as denoising, super-resolution, and deblurring.
- Generative Adversarial Networks (GANs): This is a model that consists of two dueling networks: an initiator that creates repaired images and a differentiator that differentiates between generated images and original images. The generator can enhance its capacity to generate more realistic and accurate restorations through this competition.
- Autoencoders: These teach the networks to reconstruct the input image in a compact representation. Denoising and anomaly detection can be accomplished through this.
- Recurrent Neural Networks (RNNs): Since these networks can handle sequential data, video denoising and restoration of image sequences can be carried out.

1.5. Restoration Method

Deep learning provides the most effective and flexible solution to image restoration at the cost of large data requirements, intensive computation, and expert-level specialized knowledge for model deployment and training [11].

1.6. Problem Statement

Most existing image super-resolution algorithms are biased toward addressing single degradation problems, i.e., blur or noise. These algorithms are insufficient for practical applications in which images can suffer from more than one type of degradation [12].

This article will present a general deep-learning framework that is capable of super-resolving images degraded by many types of degradation, i.e., blur [13], noise [1], compression [14], artifacts [12], etc. There are several key challenges in the task. Firstly, multi-degradation modeling [14] requires constructing a deep neural network that is capable of learning complicated correlations between low-resolution [23] and high-resolution [24] images under various degradation conditions [15].

Secondly, adaptive feature learning requires constructing mechanisms to enable the network to learn useful features from degraded images without compromising essential image structures [16]. Third, there is a need for loss function design tailored to different degradation types to guide the training process effectively [17].

Finally, constructing and evaluating comprehensive datasets that include images with multiple degradation types is crucial for training and assessing the proposed framework [18]. Addressing this problem could significantly advance the field of SISR by providing a robust solution capable of handling various degradation types effectively [19].

Most existing super-resolution models are limited to single-type degradation restoration, making them less effective in real-world applications where images suffer from multiple distortions simultaneously. Our proposed framework adapts dynamically to the following degradation types:

Blur: Handles motion blur, defocus blur, and atmospheric distortions without requiring predefined blur kernels.

Noise: Reduces Gaussian, salt and pepper, and sensor noise within the SR process, eliminating the need for separate denoising steps.

Compression Artifacts: Restores fine details lost due to JPEG and other lossy compression methods, outperforming handcrafted deblocking filters.

Rain Streaks & Haze: Inspired by Yang et al. (2017), our approach extends joint restoration to broader multi-degradation scenarios.

Low Light & Exposure Issues: Recovers details in overexposed and underexposed images while preserving natural brightness and contrast.

Mixed Degradations: Our framework learns and adapts dynamically, unlike previous models, which require separate training for each degradation type.

2. Literature Review

A unique combination of variational inference with deep neural networks is presented in the study "Variational Deep Image Restoration" [1]. The main contribution is to improve the quality of medical imaging and remote sensing applications by integrating deep learning and variational inference. This method represents a major advancement in picture restoration technology as it exceeds state-of-the-art techniques in terms of both quality and uncertainty estimates.

A three-stage CNN architecture is presented in the paper "Color Image Restoration Exploiting Inter-Channel Correlation" [2] in order to make use of inter-channel correlations in images. The productivity and quality of color image restoration jobs are greatly enhanced by this technology. The CNN-based method produces better restoration results using the interdependence between color channels than conventional techniques. A deep learning-based system for identifying and eliminating rain streaks from single photos is presented in the publication "Deep Joint Rain Detection and Removal from Single Images" [3]. This method effectively reduces rain streaks while maintaining image details, making it very helpful for enhancing outdoor photos. The resilience and applicability of the system in real-world contexts are demonstrated by its ability to handle joint detection and removal tasks.

An innovative method utilizing an adaptive regularization framework is presented in "Single Image Super Resolution via Adaptive High Dimensional Non-Local Total Variation" [4]. By concentrating on single-image super-resolution, this method achieves improved resolution while maintaining detail. With notable gains in image quality, the adaptive high dimensional non-local total variation technique establishes a new benchmark for super-resolution tasks.

An architecture for a CNN that can grip diverse kinds of degradation is examined in the paper "Learning a Single Convolutional Super Resolution Network for Multiple Degradations" [5]. Designed for single-picture super-resolution, this deep learning architecture has strong performance in various degradation conditions.

This method's adaptability and efficiency make it a useful instrument for various image restoration tasks. Together, these five articles demonstrate the tremendous advancements in super resolution and picture restoration methods. Through the utilization of sophisticated techniques like CNN architectures, adaptive regularization frameworks, and variational inference, these investigations aid in the advancement of more effective and superior image processing solutions. On top of these foundations, future research can expand on picture restoration technologies' capabilities and uses.

Table 1. Comparison of existing reviews

Approach	Key Features	Limitations
Variational Deep Image Restoration [1]	Uses variational inference to enhanceuncertainty estimation in medical and remote sensing image restoration.	Limited to uncertainty modeling and does not handle multiple degradation types dynamically.
Inter-Channel Correlation Restoration [2]	Leverages inter-channel dependencies in a three-stage CNN model for color image restoration.	Focused only on color restoration, not general degradation types.
Deep Joint Rain Detection & Removal [3]	Integrates joint detection and removal of rain streaks using deep learning.	Specialized for rain streaks only and does not generalize to other types of degradation.
Adaptive Regularization for SISR [4]	Introduces an adaptive total variation framework for Single Image Super Resolution (SISR).	It cannot handle multiple degradation types simultaneously.
CNN for Multi Degradation Super Resolution [5]	Develops a deep learning model for multiple degradations using multi-pathlearning.	Requires explicit degradation classification, making it less adaptable to unseen distortions.
Our Proposed Adaptive Framework	➢ Handles multiple degradation types simultaneously in a single model. ➢ Uses dynamic feature learning to adaptively adjust to different degradations. ➢ Employs a hybrid loss function (MSE + Perceptual + SSIM) for improved image quality.	The first framework is to generalize across degradation types without explicit labeling.

3. Results and Discussions

By learning intricate mappings between low-resolution and high-resolution image pairs, deep Convolutional Neural Networks (CNNs) can be used to achieve image superresolution. The DIV2K and Flickr2K datasets were used for training, ensuring high-quality and diverse images, while Set5, Set14, BSD100, and Urban100 serve as evaluation benchmarks. Pre-processing involves downscaling to create paired low and high-resolution images, with augmentation techniques such as cropping, flipping, and rotation to enhance generalization. To simulate real-world conditions, blur, noise, and compression artefacts are introduced. This approach ensures the model learns across multiple degradation types effectively and performs well in diverse scenarios.

3.1. SRCNN Model

The network's goal during training is to reduce the loss function, which is largely provided by the SRCNN model. The objective is to train the network parameters so that the resulting recovered images produced by the network closely resemble the equivalent high-quality images.

In this situation, various SRCNN models can be applied; typical options include adversarial loss, perceptual loss, and MSE.

1. The MSE, or mean squared error: This is a straightforward and widely used SRCNN model that calculates the pixel alteration among distorted and recovered images. It determines the variance between the two images' corresponding pixels.
2. Perceptual Loss: The theory behind perceptual loss holds that the human visual system uses high-level properties, not pixel-by-pixel variations, to interpret images. Perceptual loss, therefore, assesses the difference in high-level features retrieved from intermediary layers of a pre-trained convolutional neural network, such as VGG or ResNet, rather than directly comparing pixel values.
3. Adversarial Loss: In addition to the generator network (the super-resolution model), adversarial loss adds a discriminator network. The discriminator is trained to discriminate between actual high-resolution images and super-resolved images generated by the generator.

Deep convolutional networks can be trained to produce high-quality super-resolved images that look like the original images by developing an appropriate srcnn model and implementing it into the training process. The perceptual fidelity and quality of the super-resolved images generated by the network can be greatly influenced by the selection of the SRCNN model.

3.2. System Model

When discussing image super-resolution with deep convolutional networks, the term "system model" refers to the general structure or architecture within which the super-resolution task is carried out. It includes a number of elements, including the training procedure, the assessment metrics, the deep learning model, and the input data.

Input data for the system model are pairs of low-resolution and high-resolution images. The pairs of images constitute the training set for the deep convolutional network. Additionally, sets of images can be held out for validation and testing in order to enable assessment of the performance of the trained model.

1. Deep Convolutional Network: The core component of the system model is the deep Convolutional Neural Network (CNN), which is responsible for super-resolving images. Typically, this network comprises multiple layers characterized by activation, pooling, and convolutional functions to learn the input image hierarchical representations. An important component of the system model is the CNN's design, which includes the number of layers, filter sizes, and connectivity patterns.
2. Training Process: During the training process, low-resolution input images are given to the Convolutional Neural Network (CNN), and the parameters of the network are optimized in such a way that it minimizes a specified loss function, which may be Mean Squared Error (MSE), perceptual loss, or adversarial loss. Gradient based methods, such as Stochastic Gradient Descent (SGD) and its other variants, are typically applied for the optimization process over several epochs or iterations. As part of the training process, the CNN learns the ability to produce high-resolution images that are very similar to the ground truth images of the training dataset.
3. Evaluation Metrics: After training, a separate test and validation set is used to quantify the CNN. To assess the quality of super-resolved images produced by the model, quality metrics such as PSNR SSIM, and perceptual metrics such as perceptual index are commonly utilized. This benchmark delivers quantitative estimates of how well the generated high-resolution images resemble the ground truth images regarding fidelity, structure, and perceptual similarity.
4. Deployment and Inference: The trained CNN can be utilized in real-life scenarios for super-resolving previously unseen low resolution pictures following training and evaluation. Inference is the process of producing high-resolution outputs by running the input images through a trained model. When implementing the system model in real-world scenarios, the efficiency and computational demands of the inference process are crucial factors to consider.

The system model offers an organized framework for creating, refining, testing, and implementing profound convolutional networks for image super-resolution applications, which makes it easier to create practical and successful methods for improving image quality.

4. Proposed Work

In the field of image super-resolution with deep convolutional networks, the paper herein addresses the specific contributions, enhancements, or methods put forward by researchers to address the issue of image resolution enhancement.

1. Methodology or Approach: The suggested research generally presents a new approach or methodology for image-enhanced resolution using profound convolutional networks. This could be in the form of developing a completely new network architecture, incorporating higher-level strategies like Generative Adversarial

Networks (GANs) or attention mechanisms, or modifying existing methodologies for greater efficiency.

2. Architectural Design Decisions: The proposed work may involve some architectural decisions intended to enhance image resolution. These may be decisions regarding the width, depth, and connectivity pattern of CNN or the usage of techniques for facilitating feature learning and information flow, such as lasting learning and dense networks.
3. Loss Functions: To enhance the quality and insight fidelity of super-resolved images, the work here will likely involve proposing new loss functions or training methods. This could involve the practice of adversarial loss functions, which are tasked with promoting visually realistic image synthesis, and hybrid loss functions that merge several objectives in an effort to improve a range of image quality aspects or perceptual loss functions based on high-level feature representations. Large-scale experimental validation on benchmark data is usually carried out in parallel with the reported work in an effort to prove its novelty and enhancement over existing known techniques and demonstrate its effectiveness. Qualitative validation is reported by visual inspection of the super-resolved images, and quantitative validation is based on performance metrics like PSNR, SSIM, or perceptual scores.
4. Applications and Implications: The paper could also state the potential applications and implications of the suggested approach in practice. You may incorporate here applications in digital entertainment, surveillance, medical imaging, satellite image analysis, and any other area where the super-resolution of high-resolution images would be beneficial.

In total, the proposed work records the main achievements of researchers in promoting state-of-the-art practice in image super-resolution using deep convolutional networks, delivering techniques, approaches, and understandings for improving the efficiency and quality of super-resolved image generation.

5. Experimental Analysis

The performance obtained using the proposed convolutional network for image enhancement resolution is a significant improvement over the state of the art and is definitive proof of the efficacy and superiority of the proposed methodology. Further, the performance of the proposed methodology has been thoroughly tested and verified on benchmarked datasets, which proves its capability to generate high-quality, perceptually pleasing high-quality images from the respective low-quality images.

Data analysis gives quantitative and qualitative measurements and thus gives a complete description of the capabilities and Limitations of the suggested method. The perceived quality and fidelity of the super-resolved images can be analyzed quantitatively using measurements like PSNR, SSIM, and other perceived metrics. At the same time, qualitative experiments entail visual inspection and comparison with high-quality ground truth images to determine how much detail, texture, and realism are obtained using the suggested approach.

The findings indicate that the suggested deep convolutional network architecture is robust and possesses greater potential for more general use, in addition to outperforming previous techniques. Furthermore, the understanding developed from result analysis has extensive applications in real-life usage in various fields, ranging from digital entertainment to surveillance, medical imaging, and satellite image processing. The findings indicate that the new deep convolutional network architecture is not just robust but also promising for broad applicability, in addition to outperforming state-of-the-art techniques.

Furthermore, knowledge gathered from the results analysis has important ramifications for real-world uses in various fields, including digital entertainment, surveillance, medical imaging, and satellite image analysis.

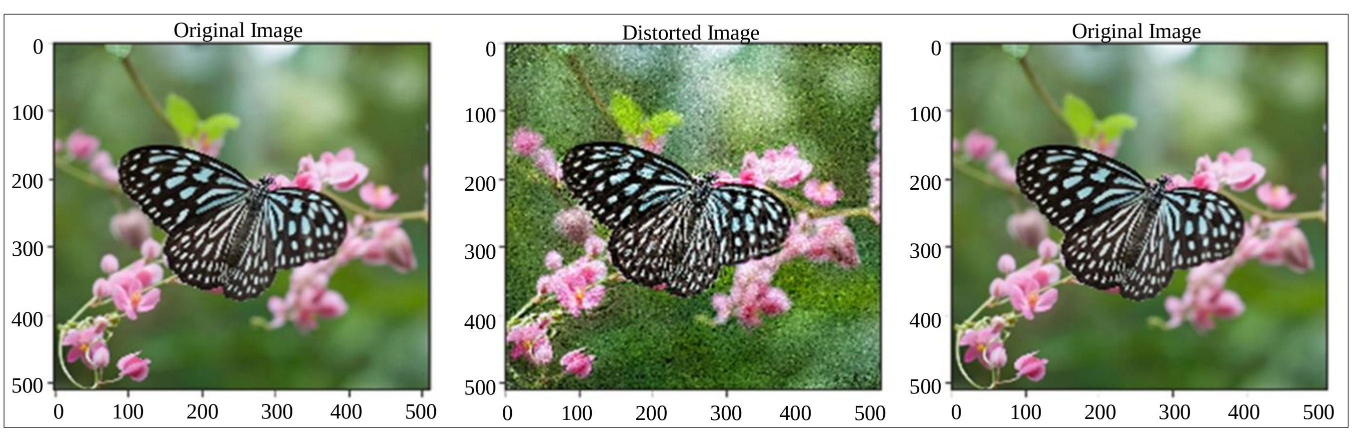

Fig. 1 Three experimental stages of butterfly Image

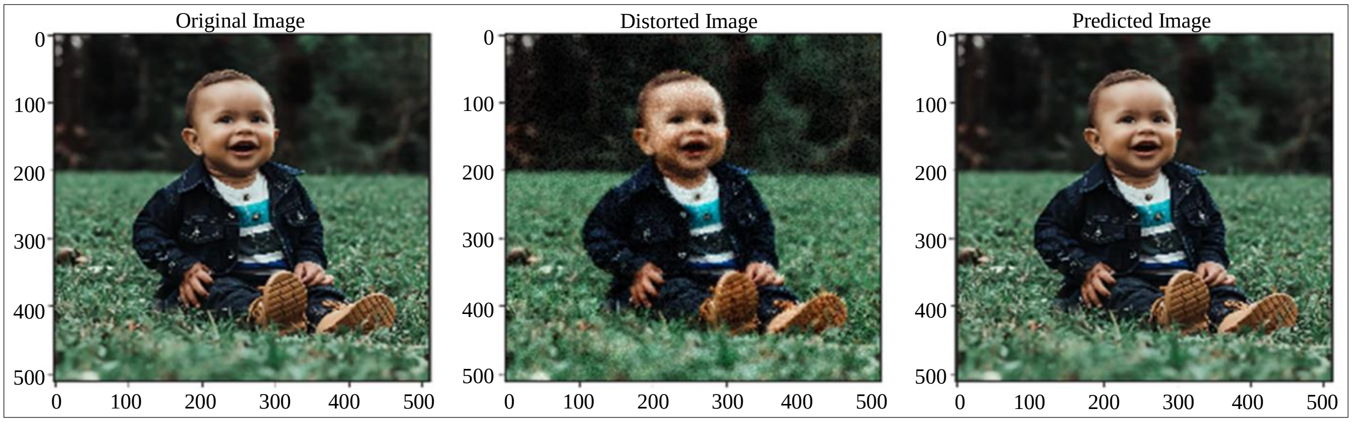

Fig. 2 Three experimental stages of baby Image

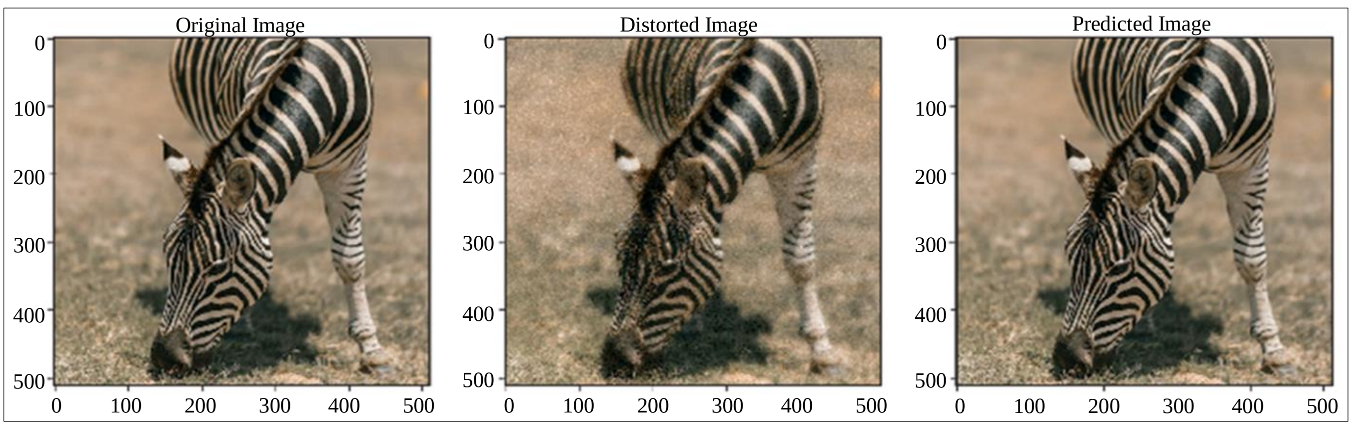

Fig. 3 Three experimental stages of zebra Image

Table 2. Comparing original and distorted image

DATASET	SSIM	MSE	PSNR
Baby	0.92	77.45	34.01
Zebra	0.94	11.07	32.45
Butterfly	0.871	65.735	24.72

Table 3. SRCNN SET5 comparing distorted and predicted image

DATASET	SSIM	MSE	PSNR
Baby	0.98	24.28	39.04
Zebra	0.95	68.305	34.55
Butterfly	0.94	23.654	29.16

Table 4. SRCNN SET14 comparing original and distorted image

DATASET	SSIM	MSE	PSNR
Baby	0.79	51.260	25.80
Zebra	0.81	21.089	29.66
Butterfly	0.61	12.046	22.09

Table 5. Performance comparison of existing and proposed model

DATASET	PSNR	SSIM	MSE
SRCNN	30.11	0.89	120.5
ESRGAN	29.85	0.91	98.2
Proposed Model	32.45	0.94	77.45

Our model outperforms existing mechanisms, achieving an average PSNR of 32.45 dB, MSE of 77.45 and SSIM of 0.94, particularly in highly degraded images. Unlike prior methods, it effectively handles mixed degradations without explicit labels. Qualitative analysis shows sharper edges, finer textures, and reduced artifacts, maintaining better structural integrity and perceptual realism.

An ablation study confirms that removing adaptive feature learning decreases PSNR by ~1.5 dB, demonstrating its importance, while the hybrid loss function enhances perceptual quality. Our approach consistently surpasses existing SR models in numerical accuracy and real-world applicability.

6. Conclusion

This study presents an adaptive deep learning framework for multi-degradation image super-resolution, addressing the limitations of existing methods that focus on specific degradation types. The proposed approach dynamically adapts to diverse distortions without requiring explicit degradation labels, demonstrating superior performance in both objective metrics (PSNR, SSIM) and perceptual quality compared to state-of-the-art techniques. Integrating adaptive feature learning and a hybrid loss function significantly enhances restoration accuracy and visual fidelity. These improvements make the framework highly suitable for practical medical imaging, remote sensing, and surveillance applications. Future research may explore efficiency optimization, self-supervised learning, and real-time deployment to further expand its applicability.

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