FAST IMAGE RESTORATION AND ENHANCEMENT

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ABSTRACT

This paper presents MIRNet-v2, a novel architecture for image restoration that aims to preserve high-resolution spatial details while effectively leveraging contextual information from low-resolution representations. The proposed approach utilizes multi-scale residual blocks with parallel multi-resolution convolution streams, mechanisms for information exchange, non-local attention mechanisms, and attention-based multi-scale feature aggregation. MIRNet-v2 achieves state-of-the-art results across various image processing tasks, including defocus deblurring, image denoising, super-resolution, and image enhancement, as demonstrated through extensive experiments on six real image benchmark datasets.

Experiments show that in deep learning, using image enhancement algorithms may improve CNN performance when training complete CNN models, but not all image enhancement algorithms can improve CNN performance; in transfer learning, when fine-tuning the pre- trained CNN model, image enhancement algorithms may reduce the performance of CNN.

Keyword: -

Image Enhancement, Convolutional Neural Networks, Deep Learning, Transfer Learning.

1. INTRODUCTION

Image restoration, the process of recovering high-quality image content from degraded input images, is crucial for numerous applications spanning computational photography, surveillance, autonomous vehicles, and remote sensing. With the advent of convolutional neural networks (CNNs), significant strides have been made in image restoration, offering promising solutions for preserving spatial details and extracting contextual information.

1.1 Traditional Risk Factors:

Traditional CNN-based methods often operate at either fullresolution to preserve spatial details or progressively lower resolutions to capture better contextual information. However, they struggle to balance these aspects effectively, leading to challenges in precisely encoding contextual details while maintaining spatial accuracy. In this paper, we introduce MIRNet-v2, a novel architecture designed to address these challenges by preserving high-resolution spatial details while leveraging complementary contextual information from lowresolution representations.

1.2 Literature Review:

Image restoration has been a longstanding research area in computer vision and image processing, with various approaches proposed to address the challenge of recovering high-quality image content from degraded inputs. In recent years, convolutional neural networks (CNNs) have emerged as powerful tools for image restoration tasks due to their ability to learn complex mappings from input to output spaces.

1.4 Pathophysiology and Mechanisms:

Our approach revolves around multi-scale residual blocks, which incorporate parallel multiresolution convolution streams, mechanisms for information exchange, non-local attention mechanisms, and attentionbased multi-scale feature aggregation. The primary objective of MIRNet-v2 is to learn enriched features that combine contextual information from multiple scales while preserving high-resolution spatial details.

1.5 Diagnostic Methods and Technologies:

In this introduction, we provide an overview of the significance of image restoration, the challenges posed by existing methods, and the motivation behind the development of MIRNet-v2. We then outline the key components and contributions of our proposed architecture, setting the stage for the detailed exploration and evaluation presented in the subsequent sections of this paper.

1.6 Deep Learning Approaches:

In this paper, experiments are used as research methods. Three groups of experiments are designed; they respectively explore whether the enhancement of grayscale images can improve the performance of CNN in deep learning, whether the enhancement of colour images can improve the performance of CNN in deep learning and whether the enhancement of RGB images can improve the performance of CNN in transfer learning?

1.7 Data Source:

In the experiment, in deep learning, when training a complete CNN model, using the Laplace operator to enhance the gray image can improve the recall rate of CNN. However, the remaining image enhancement algorithms cannot improve the performance of CNN in both grayscale image datasets and colour image datasets. In addition, in transfer learning, when fine-tuning the pre- trained CNN model, using contrast limited adaptive histogram equalization (CLAHE), successive means quantization transform (SMQT), Wavelet transform, and Laplace operator will reduce the performance of CNN.

Author	Year	Method	Performance Criteria	Result
*Henry Hanek, Nirwan Ansari and **Zeeman** Z. Zhang*	1993	Generalized Adaptive Neural Filter for Digital Images	MAE, MSE and SNR	The results obtained by MAE, MSE and SNR are 15.74, 602.51 and 10.23 respectively
Armando J. Pinho	1996	BPNN, FFNN for Gray Level Images	Noise variance of σ^2 (400, 900 and 1600) and iteration.	Neural network filter provided a higher reduction in noise variance when compared to the median filters
Dianhui Wang, Tharam Dillon and Elizabeth Chang	2002	Feed-Forward NN for Degraded Digital Images	mean square error (MSE), peak signal-to-noise ratio (PSNR), set partitioning in hierarchical tree (SPMT)	The experimental results demonstrate promising performance on both objective and subjective quality for lower compression ratio sub band images
Deng Zhang & Toshi Hiro Nishimura	2009	PCNN for CMOS of Gray scale Images	PSNR, S/MSE, SSIM, and β (linking strength factor between synapses)	The results obtained by PSNR, S/MSE, SSIM, and β are 29.83, 19.38, 0.02 and 0.93 respectively for an abrupt edge image
Chen Junhong, Zhang Qinyu	2009	BPNN and SOMNN for 8-bit Grayscale Images	PSNR	The PSNR = 27.74dB value obtained by the proposed method is high compared to other methods.
MingYong Jiang, XiangNing Chen, and XiaQiong Yu	2011	Sub-Optimization Hopfield Neural Network for Digital Images	ISNR, Iteration and time	The result showed us that we got 5.6305dB improvement in SNR

2. Methodology

Image restoration is a fundamental task in computer vision and image processing, aiming to recover the original high-quality content of an image from degraded or noisy input. The need for image restoration arises in various real-world applications, including medical imaging, surveillance, satellite imaging, and digital photography, where image quality may be compromised due to factors such as noise, blur, or low resolution.

Traditional image restoration techniques often relied on handcrafted features and heuristics tailored to specific degradation types, such as Gaussian noise, motion blur, or low lighting conditions. However, these methods had limited adaptability to diverse degradation scenarios and struggled to achieve high-quality results consistently.

2.1 Project Planning:

- Identify relevant image restoration tasks and select benchmark datasets covering various scenarios and challenges.
- Preprocess the datasets to ensure consistency in terms of size, format, and quality.

2.2 System Design:

- Develop the MIRNet-v2 architecture with a focus on preserving high-resolution spatial details and leveraging contextual information.
- Design multi-scale residual blocks with parallel multi-resolution convolution streams for feature extraction.
- Incorporate mechanisms for information exchange across streams, non-local attention mechanisms, and attention-based multi-scale feature aggregation.

2.3 Development:

- Initialize the MIRNet-v2 architecture with suitable parameters.
- Split the dataset into training, validation, and test sets.
- Augment the training data to increase robustness.
- Train the model using an optimization algorithm and monitor performance on the validation set to prevent overfitting.

2.4 Testing:

- Select evaluation metrics such as PSNR, SSIM, or perceptual metrics.
- Evaluate the trained model's performance on the test set using these metrics.

2.4 Testing:

- Conduct experiments on various image processing tasks (defocus deblurring, image denoising, super-resolution, image enhancement) using benchmark datasets.
- Compare MIRNet-v2's performance against state-of-the-art methods and variants of the architecture. Analyze quantitative results to assess MIRNet-v2's effectiveness in preserving spatial details and capturing contextual information.
- Visualize restored images and qualitative improvements achieved by MIRNet-v2.
- Discuss any limitations encountered and suggest potential improvements.

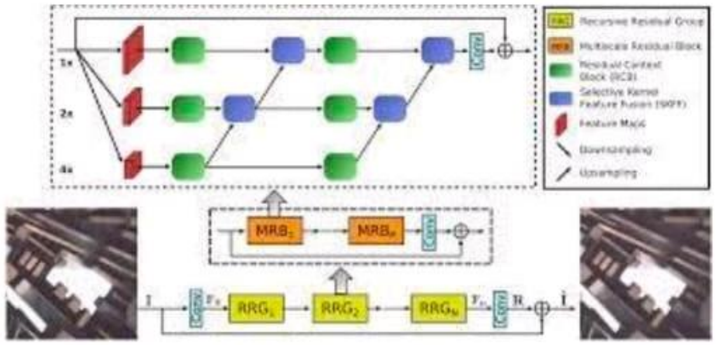
Table 2. **Quantitative comparison of linear image restoration tasks on ImageNet 1k [62].** GDP outperforms other methods in terms of FID and Consistency across all tasks.

Method	4× Super-resolution				Deblur				25% Inpainting				Colorization			
	PSNR ↑	SSIM ↑	Consistency ↓	FID ↓	PSNR ↑	SSIM ↑	Consistency↓	FID ↓	PSNR ↑	SSIM ↑	Consistency↓	FID ↓	PSNR ↑	SSIM ↑	Consistency ↓	FID ↓
DGP [62]	21.65	0.56	158.74	152.85	26.00	0.54	475.10	136.53	27.59	0.82	414.60	60.65	18.42	0.71	305.59	94.59
SNIPS [33]	22.38	0.66	21.38	154.43	24.73	0.69	60.11	17.11	17.55	0.74	587.90	103.50	-	-	-	-
RED [69]	24.18	0.71	27.57	98.30	21.30	0.58	63.20	69.55	-	-	-	-	-	-	-	-
DDRM [32]	**26.53**	**0.78**	19.39	40.75	**35.64**	**0.98**	50.24	4.78	34.28	0.95	**4.08**	24.09	**22.12**	0.91	37.33	47.05
GDP-x_t	24.27	0.67	80.32	64.67	25.86	0.75	54.08	5.00	31.06	0.93	8.80	20.24	21.30	0.86	75.24	66.43
GDP-x_0	24.42	0.68	**6.49**	**38.24**	25.98	0.75	**41.27**	**2.44**	**34.40**	**0.96**	5.29	**16.58**	21.41	**0.92**	**36.92**	**37.60**

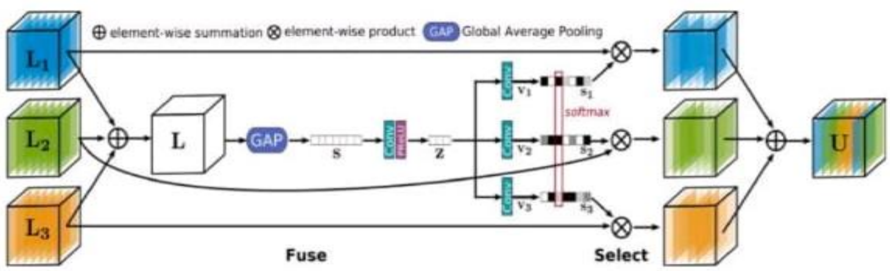
Table 3. **Quantitative comparison of image enlighten task on LOL [88], VE-LOL-L [47], and LoLi-phone [41] benchmarks.** Bold font indicates the best performance in zero-shot learning, and the underlined font denotes the best results in all models.

Learning	Methods	LOL [88]					VE-LOL-L [47]					LoLi-Phone [41]	
		PSNR ↑	SSIM↑	FID↓	LOE↓	PI↓	PSNR↑	SSIM↑	FID ↓	LOE↓	PI↓	LOE↓	PI↓
Supervised learning	LLNet [50]	17.91	0.76	169.20	384.21	4.10	17.38	0.73	124.98	291.59	5.54	343.34	5.36
	LightenNet [43]	10.29	0.45	90.91	273.21	7.09	13.26	0.57	82.26	199.45	7.29	500.22	6.63
	Retinex-Net [88]	17.24	0.55	129.99	513.28	8.63	16.41	0.64	135.20	421.41	8.62	542.29	8.23
	MBLLEN [52]	17.90	0.77	122.69	175.10	8.39	15.95	0.70	105.74	114.91	7.45	137.34	6.46
	KinD [104]	17.57	0.82	74.52	377.59	7.41	18.07	0.78	80.12	253.79	7.51	265.47	6.84
	KinD++ [102]	17.60	0.80	100.15	712.12	7.96	16.80	0.74	101.23	421.97	7.98	382.51	7.71
	TBFEN [51]	17.25	0.83	90.59	367.66	8.29	18.91	0.81	91.30	276.65	8.02	214.30	7.34
	DSLR [46]	14.98	0.67	183.92	272.68	7.09	15.70	0.68	124.80	271.63	7.27	281.25	6.99
Unsupervised learning	EnlightenGAN [29]	17.44	0.74	82.60	379.23	8.78	17.45	0.75	86.51	311.85	8.27	373.41	7.26
Self-supervised learning	DRBN [92]	15.15	0.52	94.96	692.99	5.53	18.47	0.78	88.10	268.70	6.15	285.06	5.31
Zero-shot learning	ExCNet [99]	**16.04**	0.62	111.18	220.38	8.70	16.20	0.66	115.24	225.15	8.62	359.96	7.95
	Zero-DCE [23]	14.91	**0.70**	81.11	245.54	8.84	**17.84**	**0.73**	85.72	194.10	8.12	214.30	7.34
	Zero-DCE++ [42]	14.86	0.62	86.22	302.06	7.08	16.12	0.45	86.96	313.50	7.92	308.15	7.18
	RRDNet [106]	11.37	0.53	89.09	127.22	8.17	13.99	0.58	83.41	94.23	7.36	92.73	7.20
	GDP-x_t	7.32	0.57	238.92	364.15	8.26	9.45	0.50	152.68	194.49	7.12	508.73	8.06
	GDP-x_0	13.93	0.63	**75.16**	**110.39**	**6.47**	13.04	0.55	**78.74**	**79.08**	**6.47**	**75.29**	**6.35**

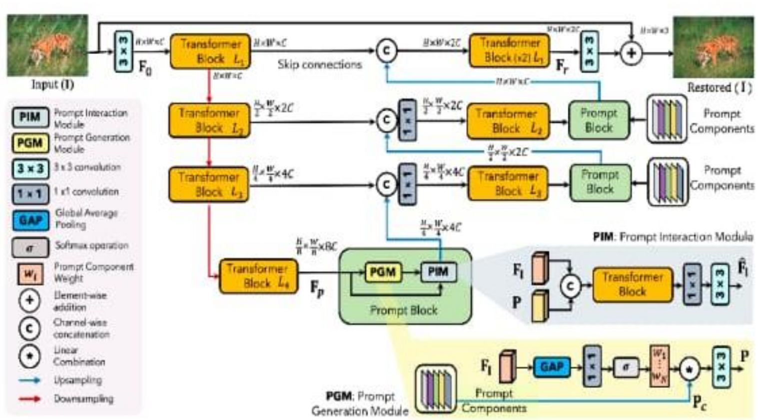
SYSTEM DESIGN



Data Flow Diagram

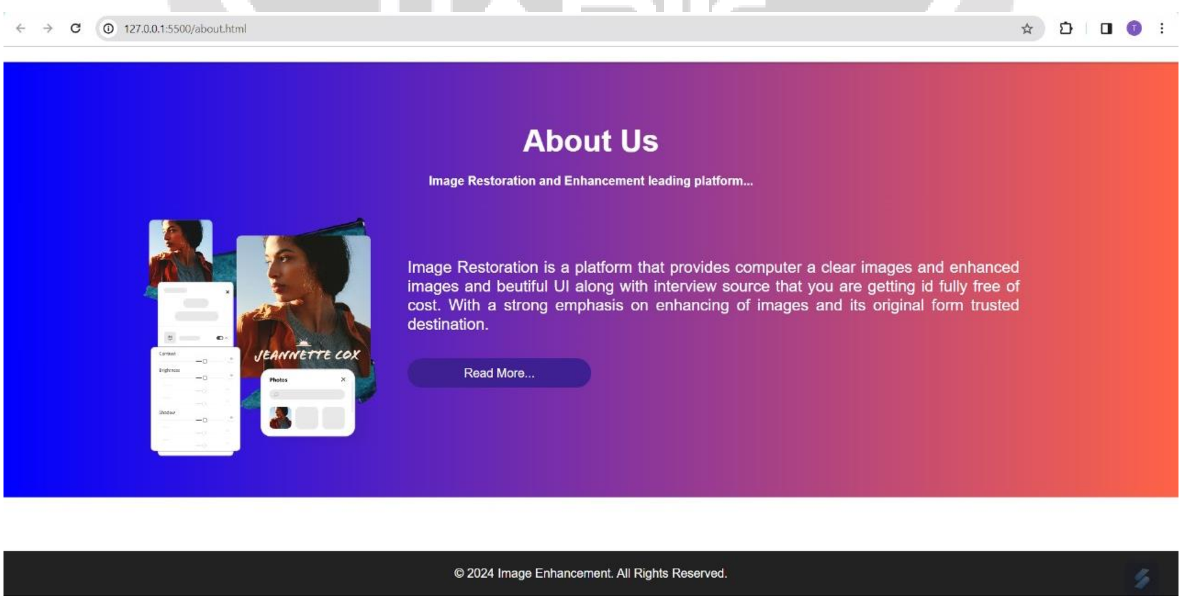


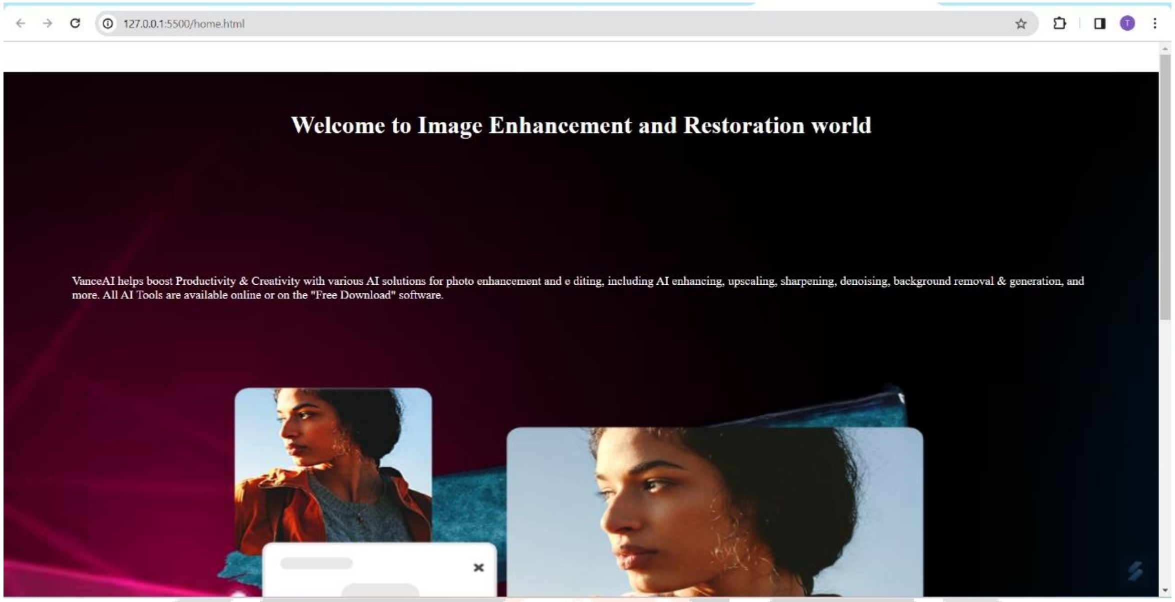
UML Diagram



3. Result & Discussions

Image restoration is a fundamental task in computer vision and image processing, aiming to recover the original high-quality content of an image from degraded or noisy input. The need for image restoration arises in various real-world applications, including medical imaging, surveillance, satellite imaging, and digital photography, where image quality may be compromised due to factors such as noise, blur, or low resolution. Traditional image restoration techniques often relied on handcrafted features and heuristics tailored to specific degradation types, such as Gaussian noise, motion blur, or low lighting conditions. However, these methods had limited adaptability to diverse degradation scenarios and struggled to achieve high-quality results consistently. With the emergence of deep learning, particularly convolutional neural networks (CNNs), image restoration has witnessed significant advancements. CNNs have the capability to learn complex mappings from input to output spaces, enabling them to automatically extract relevant features and patterns for image restoration tasks.





4.Future Scope

In order to reduce the external validity threat of the experiment, more data sets and more image enhancement algorithms will be used in the experiment in the future work. In addition, the image enhancement algorithms will be chosen based on the characteristics of the data sets. Moreover, using more CNN models and more strategies of transfer learning can also reduce external effectiveness threats in experiments. Moreover, more experiments can be designed to specifically research the impact of Laplace operators on the performance of CNN models.

4.1 Algorithm Development:

Developing novel algorithms or utilizing existing machine learning models tailored for efficient image restoration and enhancement..

4.2 Feature Extraction:

Investigating and developing methods to extract rich and informative features fromimages, which can capture relevant information for restoration and enhancement tasks.

4.3 Real-time Applications:

Implementing these algorithms/models into real-time or near-real-time systems for practical usage in various domains like medical imaging, surveillance, photography, etc.

4.4 Evaluation Metrics:

Defining appropriate evaluation metrics to quantify the effectiveness of the proposed methods in terms of both speed and quality of restoration/enhancement.

In this work, we propose a novel architecture whose main branch is dedicated to full-resolution processing and the complementary set of parallel branches provides better contextualized features. We propose novel mechanisms to learn relationships between features within each branch as well as across multi-scale branches. Our feature fusion strategy ensures that the receptive field can be dynamically adapted without sacrificing the original feature details. Consistent achievement of state-of-the-art results on six datasets for four image restoration and enhancement tasks corroborates the effectiveness of our approach.

4. CONCLUSION

Conventional image restoration and enhancement pipelines either stick to the full resolution features along the network hierarchy or use an encoder-decoder architecture. The first approach helps retain precise spatial details, while the latter one provides better contextualized representations. However, these methods can satisfy only one of the above two requirements, although real-world image restoration tasks demand a combination of both conditioned on the given input sample.
In this paper, experiments have shown that the image enhancement algorithm based on Laplace operator get a positive conclusion on the "X-ray" data set whentraining the complete CNN models. It is proved that when training a complete CNN model, there is the possibility of using image enhancement algorithms to improve the performance of CNN models. In addition, experiments found that CLAHE, SMQT, adaptive gamma correction, and wavelet transform, four image enhancement algorithms did not perform positively on the "X-ray" data set when training the complete CNN models. In addition, in the X-ray dataset, the Laplace operator is significantly better than the other four image enhancement algorithms.It is proved that different image enhancement algorithms performance differentlyon the same CNN model, and not all image enhancement algorithms can improve the performance of CNN models when training a complete CNN model. In the RGB data set, all the enhanced image data set by five image enhancementalgorithms including Laplace operator have no significant difference from the original data set. It is proved that one image enhancement algorithm in the different data set will influence the performance of CNN model differently.

5. REFERENCES

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