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Embedded Deep Learning to Improve the Performance of Approaches for Extinct Heritage Images Denoising

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ABSTRACT: Many advanced deep convolutional neural network (DCNN) methods have proven their efficacy in reconstructing the texture of super-resolution images (SR) from low-resolution images (LR). Nevertheless, the objective of achieving super-resolution (SR) reconstruction using Deep Convolutional Neural Networks (DCNN) becomes difficult when the input image is distorted by noise. Photographs captured at the inception of the camera are presently regarded as a cultural heritage that chronicles an important period in human history; however, they are marred by low resolution and noise as a result of obsolescence and the primitive nature of the technology that captured them, in contrast to the technological advances that cameras benefit from today. We proposed embedded deep learning to improve the performance of approaches for extinct heritage images denoising to denoise and reconstruct Baghdad heritage images. First, stage super-resolution (SR) noisy image generation from low-resolution (LR) heritage noisy image aims to enable to extraction of noise features for the target images. Second, remove visible noise features on images and restore their surface texture, giving them a more modern and clearer scene while preserving their original identity. PSNR, SNR, and SSIM quantitative metrics and the visual comparison analysis between the proposed method and state-of-art methods: Total variation denoising (TV), Bilateral filter denoising (BF), Median filter Denoising (MF) Gaussian filter image denoise (GF), and Non-Local Bayes (NLB) denoising demonstrated a better performance in reducing noise from the target images and a high-frequency flow with more information. Our approach restores heritage in a way that mimics modern photographic scenes using deep learning algorithms.

Keywords: Heritage image denoising, Deep convolutional neural network, Super-resolution, Features-extraction, Image reconstruction.

1. INTRODUCTION

There is an urgent need to restore the cultural heritage of people and enhance the preservation of their cultural heritage from loss with the advancement of generations [1]. The restoration of photographs has also become more important with deep learning algorithms for automating 2D images and restoring the digital features of such photos by repairing damaged data and giving them a color update that gives them an antique look that reflects our present digital effects on images [2].

The fields of computer vision and deep learning have recently recognised the importance of heritage as a topic for study. Repairing the surface texture of the photos and rehabilitating their essential features in a manner that is free of blur and noise caused by the effects of time, inadequate preservation, or accumulations caused by the use of outdated technology is how this is achieved [3]. Conventional methods either include the construction of geometric models that are based on the geometric consistency and similarity of the picture content or involve the development of textures in order to repair damaged regions or small parts of images. The objective of deep approaches is to identify incomplete solutions to the problem of inadequate integration between high-level semantic understanding and low-level image features [4].

Various methods have demonstrated significant improvements in the restoration of heritage images, wherein a contemporary digital appearance is given to them by removing noise and rectifying damaged components [5]. This is accomplished through the use of filters aimed at mitigating the optical distortions that were common in these images throughout earlier periods. The existence of visual distortions in these heritage photos resulted in a significant loss of crucial information pertaining to their image features, diminishing their prominence in contemporary times.

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Iraq is replete with historical and cultural occurrences; it has a rich, popular heritage stretching back centuries [6], as evidenced by the abundance of ancient archaeological images that have accompanied its events since the turn of the last century, which made them vulnerable to damage. However, these images are deteriorating due to antiquity and corrosion, rendering them susceptible to damage, loss, and erosion of the heritage identity of Baghdad, the capital, and its inhabitants. Those important periods represent a great legacy for current generations, who have the right to preserve their heritage and know the lifestyle of their ancestors.

The proposed method, cumulative denoising of heritage images by embedded deep learning algorithms [7], aims to improve the Baghdadi heritage scene by taking advantage of deep learning techniques. This approach involves the application of advanced algorithms to transform heritage images, resulting in a more contemporary appearance. Specifically, the method focuses on lowering cumulative noise and eliminating visual imperfections in these images.

Hierarchical improvement experiments carried out on old images [8] in terms of quality and clarity necessitate both quantitative assessment and visual comparison. These evaluations determine the effectiveness of our proposed method (HIDD) in comparison to other methods, specifically in terms of reducing noise and mitigating damage to 2D heritage images. To quantitatively compare the images, we employ metrics that include the Peak-Signal-to-Noise Ratio (PSNR) [9], Signal-to-Noise Ratio (SNR) [10], and Structural Similarity Index Measure (SSIM) [11]. Particularly, our approach has produced innovative results in the restoration of historic Baghdad heritage images, imbuing them with a vibrant, low-noise quality that conceals flaws and repairs damages.

2. RELATED WORK

2.1 Single Image Restoration

A considerable amount of research has been attempted with the intention of putting forward an approach that is both efficient and explicit for picture restoration. In order to analyse the two fundamental features of 2D images, namely the cross-scale similarity and the anisotropic image characteristics.

Yawei Li et al. [12] proposed that a network called GRL be constructed with the aim of automating hierarchical 2D image sequences through the attention-enhancing convolution of special features and the recovery of real and artificial image settings. The experimental outcomes revealed significant advancements in the decompression of JPEG images through the implementation of image data synthesis.

Y.-T. Zhou et al. [13], In an effort to repair the damaged grey-level photos, employed more noise in addition to a neural network to enable the constant blur function. The recovery mechanism is based on two stages: the first is estimating the factors and parameters of the neural network to reconstruct the images, which represents the model's computational efficacy and error tolerance. The grey representation level is the sum of the differences in the neuron's state. Applying this model to produce a high-quality image is the next stage. This method also presents an algorithm with a low computational cost. Keming Cao et al. [14], For the purpose of estimating the ambient light of an image scene, proposed a method for determining the disparity in intensity between ambient light and projected light by utilising depth-dependent color switching. In cooperation with the IFM image formation model, adaptive color correction was utilised to eliminate undesirable colors during contrast restoration. The efficacy of this approach in rectifying image degradation was found to be preferable to different approaches deploying the IFM model.

2.2 2D Image Denoising

Morteza et al. [15] proposed a new method named adversarial distortion learning (ADL) for clearing biomedical image data in 2D and 3D formats. The method combines two auto-encoders, a denoiser and a discriminator, to eliminate noise and compare the denoised output to the original data. The Efficient-Unet architecture allows for application to various biomedical data, and experiments on MRI, dermatoscopy, electron microscopy, and X-rays show that the method consistently outperforms other approaches. Kaixuan Wei et al. [16], The study suggests a novel method for using a 3D neural network to reduce noise in HSI hyperspectral images. It uses 3D convolution to extract the structural correlation of the simultaneous spectrum that follows the development of the image. It contains cognitive spatial correlation and is dependent on the duration of the GCS spectrum. In comparison to prior studies, practical experiments demonstrate minimising the impact of noise on images and restoring accuracy with a reduced calculation time.

Hongyu Chen et al. [17], the proposed method For HSI denoising, attempts to collect objects with the same spectral pattern and capture long-range spatial contextual information—development of a U-shaped three-dimensional transformer architecture for multiscale feature aggregation. Afterwards, an information-extracting multi-head global spectral attention module is incorporated into the spectral transformer block to process data from various spectral patterns. To validate the efficiency of Hider, an extensive array of simulated and actual experiments were conducted. In comparison to other state-of-the-art methods, Hider obtains acceptable evaluation metrics and visual assessments, as demonstrated by the denoising outcomes on both simulated and real-world datasets. [18] Kaiyan Li et al. This method simultaneously recognises the binary signal for statistically determined signal conditions (SKS) in the presence of background envelopes with a statistical character, indicated as BKS, by training noise reduction-specialised neural networks that, using a hybrid loss function, are identified as a supervisory follower on the SLNN-NO neural network.

By integrating a sigmoid-activated loss function and a bi-entropy loss function with a joint denoising network, this training method effectively preserves and analyses image information in the context of CT images. The evaluation of this method's performance demonstrates optimal outcomes for achieving a regulated distinction in accordance with conventional metrics that denote image excellence.

An algorithm for image denoising which is created by Shan Wang et al. [19] using adaptive bi-dimensional stochastic resonance (ABSR). As a bi-dimensional signal, the sampled image is used to build an adaptive bi-dimensional dynamic nonlinear system model. The ideal model parameters are automatically determined by modifying the dynamic nonlinear system parameters via reverse positioning. Dynamic adaptive bi-dimensional stochastic resonance restores images more accurately than mean filter, median filter, and one-dimensional stochastic resonance. Dynamic adaptive bi-dimensional stochastic resonance demonstrates better image processing denoising and noise intensity robustness.

3. METHOD

Our goal is to reduce the noise of low-resolution heritage images that suffer from disappearance or loss due to time ageing. This research sheds light on the old heritage of Baghdad images as a study sample, as shown in Fig. 1, by choosing three different models of low-quality images in which noise prevails in the general scene (Model A = 189 KB resolution) (Model B = 65.9 KB resolution), and Model C = 66.3 KB Resolution).

Model A Model B Model C

FIGURE 1. - Models (A, B, and C) of noisy Baghdadi heritage images

The architecture of our approach, as shown in Fig. 2, is divided into two stages. The first works to increase the quality of low-resolution noisy images I_{LR} to high-resolution images I_{SR}. The aim is to enable the noise reduction algorithm to easily extract noise features for the target images [20], which represents the second stage. Super-resolution (SR) image algorithms enlarge low-resolution (LR) images by increasing the information flow of the dynamic scene of the 2D image so that it mimics the original high-resolution (HR) images [21]. Low-resolution images suffer from restrictions on opacity and aliasing, damage to basic features, and accumulation of noise in their details, and this is a major reason for the loss of high frequencies of the image and damage to its surface textures [22].

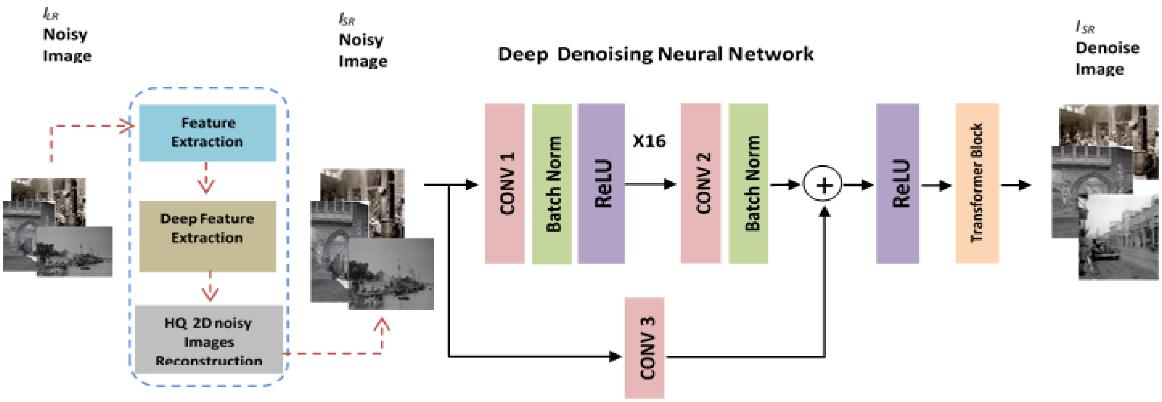

FIGURE 2. - Main architecture of our approach, divided into two stages: First, stage super-resolution (SR) noisy image generation from low-resolution (LR) heritage noisy images. Second, remove visible noise features on images and restore their surface texture

Low-resolution (LR) pixels are employed for the implementation of a super-resolution (SR) image. On the other hand, single-2D image SR extracts LR features and utilises them to generate an image of a similar scene with an LR image [23]. The sparse representation construction for single-image (SR) [24] addresses the issues above by setting their sparse representation to create the final SR image. Equation 1 represents the limitations of reconstruction in the following manner:

$$I_{SR} = D_{SR}\, G_f\, Y \qquad (1)$$

Where D_{SR} represents the Super-Resolution Denoising version, G_f Gaussian blurring function [25], and Y is the sampled and deblurred operator. Most state-of-the-art studies rely on "Deep Convolutional Networks for Image Super-Resolution" (SRCNN) [26], [27], [28] to create SR Images from LR images generated from high-resolution image HR [29]. As a result of this procedure, the SRCNN method approaches the fastest and best 2D image quality. Deep feature extraction is the first level, which is specified as a function, $Feature_1$, [30], as seen in equation 2. These functions are applied to extract image features by developing the image.

$$Feature1(YILR) = MAX\ (0, X1\ YILR + b1) \qquad (2)$$

Where YI_{LR} represents the input low-resolution 2D image, X_1 is filtered, and b1 is biased. The size of X_1 is: ch × f1 × f1 × nc1, where ch represents the number of image channels, f1 is the size of filter, and nc1 is the number of convolution filters. Furthermore, the filter output is subjected to the Rectified Linear Unit (ReLu). In this process, since the 2D image samples are old and low quality, we do not need to generate low-resolution images (LR) from original high-resolution images (HR). Therefore, we consider these images as input. Vector of deep, noisy features appears in the super-dimensional image. Each non-linearly mapped vector expresses a patch of an SR noisy image is described by equation 3 as:

$$Feature_{Deep}(YI_{SR}) = MAX\ (0, X_2\ YI_{SR} + b2) \qquad (3)$$

The goal is to recover a denoised and high-fidelity image from a super-resolution noisy image. In this technique, we create our Deep Denoising Neural Network using 16 recursive residual blocks, as depicted in the Figure. Utilise a single 3 × 3 convolutional layer with a padding of 1, stride of 1, and 128 channels. Apply Batch Normalisation (BN) [31] and then a ReLU layer to extract the shallow features with noise. We utilise 16 recursive residual blocks to extract the intermediate and advanced features. Transformer blocks, which are composed of three modules for preprocessing, local-global feature extraction, and reconstruction, have been suggested for image denoising. The information from the provided noisy images is concurrently captured by these transformer blocks, which are extensively skip-connected to fuse the features from multiple layers. To maximise the effectiveness of our denoising image position, we propose to optimise every channel using L1 loss. Pairs of noisy images and their matching clean images make up the training set N $\{I_{noisy}, I_{clean}\}$. The transformer's training objective is to reduce the L1 loss function, as shown in Equation 4.

$$L(YI_{SR}) = 1/N \sum_{i=1} \|\, H_{DenS}\,(I_{noisy}) - (I_{clean})\, \|1, \qquad (4)$$

We are using the features extracted by the decoder during deep network training to reconstruct less-noise, higher-quality images that are more improved than noisy, lower-resolution (LR) images. Thus, we obtain super-resolution (SR) images whose texture surface is close to the original images (HR).

4. EXPERIMENTS

This section provides a quantitative evaluation of our method in comparison to the other methods currently available: Total variation denoising (TV) [32], Bilateral filter denoising (BF) [33], Median filter Denoising (MF) [34], Gaussian filter image denoise (GF) [35], Non-Local Bayes (NLB) denoising [36], on three models (A, B, and C) of heritage of Baghdad denoise-images that are characterised by high-noise and low-resolution. The results in Table 1 show progress in the performance of our method by achieving better rates of noise reduction.

Quantitative metrics PSNR, SNR, and SSIM results prove our method obtains (28.44 dB, 33.26, 0.7220) of model A denoise image, while the quantitative result of model B is (27.93 dB, 35.11, and 0.5978). Model C obtains (28.98dB, 36.11, and 0.8491) improvements over state-of-art methods.

In Fig 3, the results of the metrics curves, we can notice the improvement in the quantitative results on the Models (A, B, and C) denoise-SR images of our approach compared to (TV, BF, MF, GF, and NLB) methods. Our method demonstrated an improvement in reducing noise and increasing the surface texture resolution of the image.

The visual subjective comparison results of each approach show that our method performs better at removing the actual noise from the noisy images of the three models (A, B, and C). We also show how different methods improve visual denoising. Especially, Fig. 4 shows the surface textures that are difficult to identify from the deep noise. Other denoising methods often eliminate both noise and edge features at the same time, which results in too smooth results. The Total Variation (TV) denoising method partially preserves the structure of the image but does not effectively remove noise.

Table 1. - Quantitative comparison denoising results of our proposed method and state-of-art

Method	Model A			Model B			Model C		
	PSNR↑	**SNR↑**	**SSIM↑**	**PSNR↑**	**SNR↑**	**SSIM↑**	**PSNR↑**	**SNR↑**	**SSIM↑**
TV Denoising [32]	13.00	28.79	0.1836	15.45	30.39	0.2520	13.39	28.82	0.1599
BF Denoising [33]	23.09	30.29	0.3588	24.27	31.57	0.3575	21.25	29.66	0.4360
MF Denoising [34]	25.75	32.95	0.6030	26.35	34.28	0.5255	22.75	32.61	0.5712
GF Denoising [35]	27.01	32.16	0.7200	26.50	32.53	0.5736	24.05	31.01	0.7061
NLB Denoising [36]	26.77	32.03	0.6194	27.13	34.23	0.5428	26.68	33.58	0.7660
Ours	**28.44**	**33.26**	**0.7220**	**27.93**	**35.11**	**0.5978**	**28.98**	**36.11**	**0.8491**

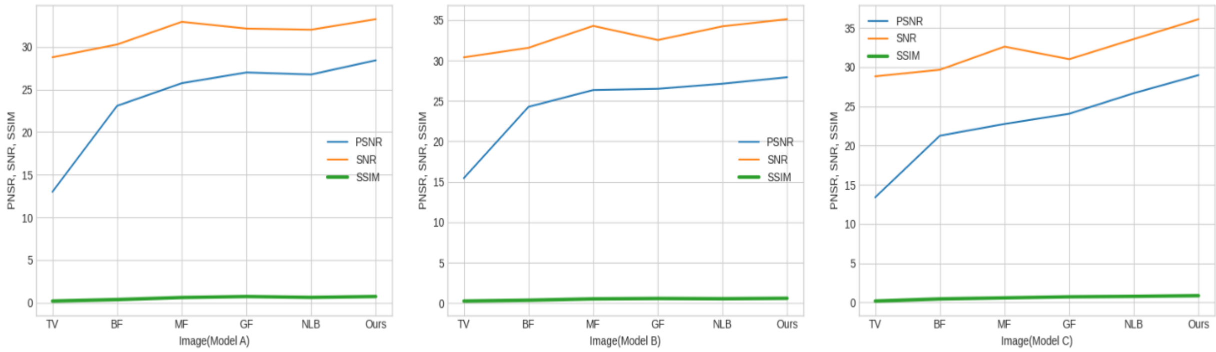

FIGURE 3. - PSNR, SNR, SSIM values of our proposed method and other methods on models (A, B, and C), Baghdad heritage denoise image

FIGURE 4. - Denoising visual results of different existing methods compared with our proposed method

On the other hand, the Bilateral Filter (BF) and Median Filter (MF) denoising methods tend to smooth the edges of the images excessively. The Gaussian Filter (GF) method, however, is slightly more accurate than the previous two methods. Non-Local Bayes (NLB) denoising restores cleaner images. The best details of the surface textures that make up the image are not well restored during the noise reduction process. The reason for this is a delay in extracting high-frequency features. In contrast, our method, shown in Fig. 5, was able, through the quantitative and visual results it provided, to reconstruct the local details of the images, which are characterised by their high frequency, as it was able to restore the basic details of the image during the reconstruction process. The improved transformer in our approach during the model training process contributed to improving deep details, preserving the original edges of the image, and restoring its original data.

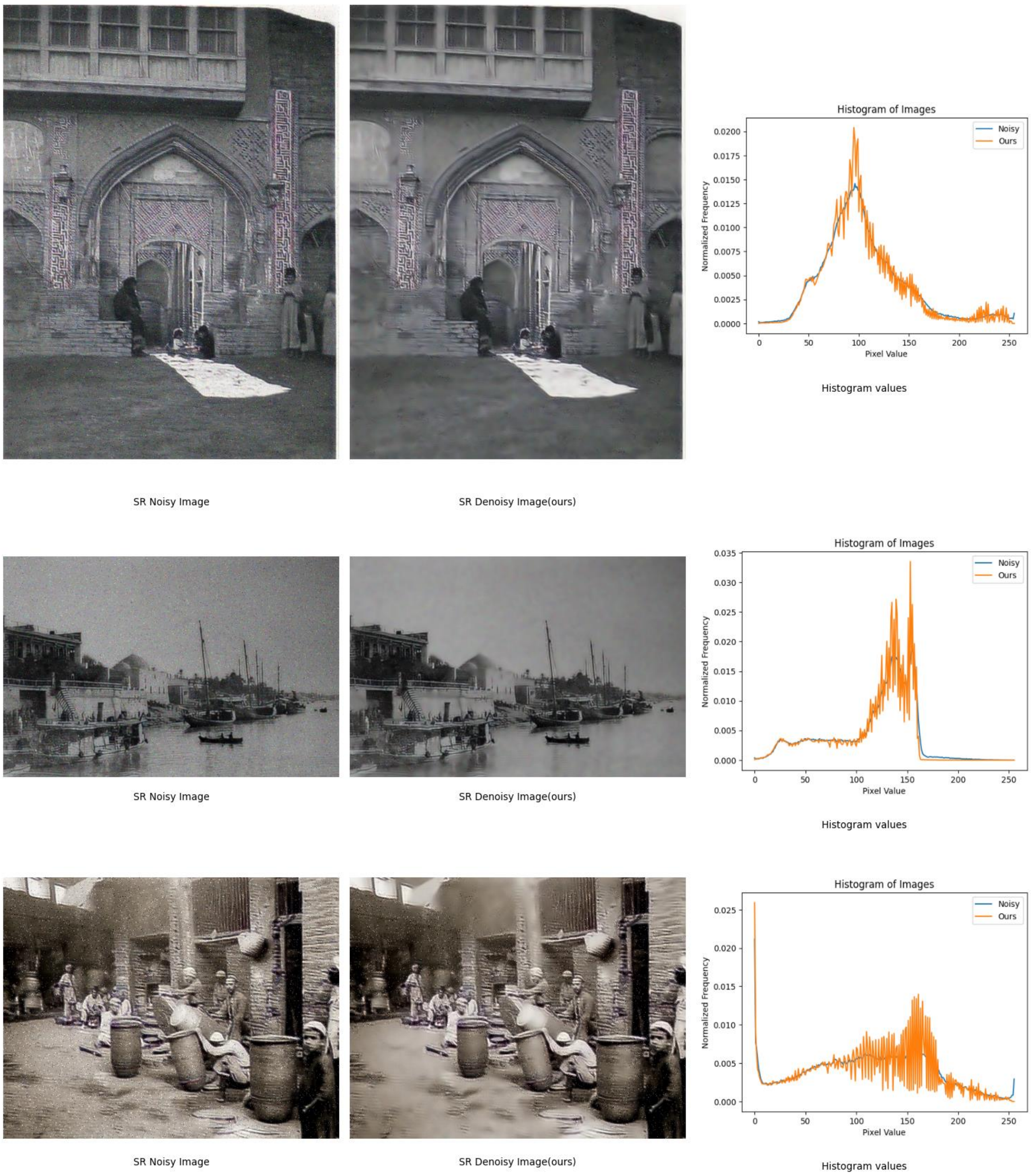

FIGURE 5. - Histogram scale of super-resolution denoise images (A, B, and C) results compared to SR, noisy images

The histogram scale of super-resolution denoise images [37] results in Fig. 5 shows the information flow of super-resolution (SR) denoising images reconstructed using our method compared to super-resolution noisy images. It gives the overall appearance of the images higher clarity and less noise with a high frequency that achieves smoothness in restoring the surface information of old heritage images. The denoising image pixel Histogram indicates the amount of distortion-corrected data compared to the frequency intensity values, where we obtain a clear improvement in most parts of the image restored using our method, significantly enhancing the texture of the image. Figures (6,7, and 8), demonstrate the high-performance effectiveness provided by our method in reconstructing super-resolution (SR) images with low noise, even though they suffer from distortion and ageing because they were taken in the past, which gave them a heritage character. Accordingly, our method provides a clear decrease in the noise levels and an increase in the frequency spectra that make up those images with more information.

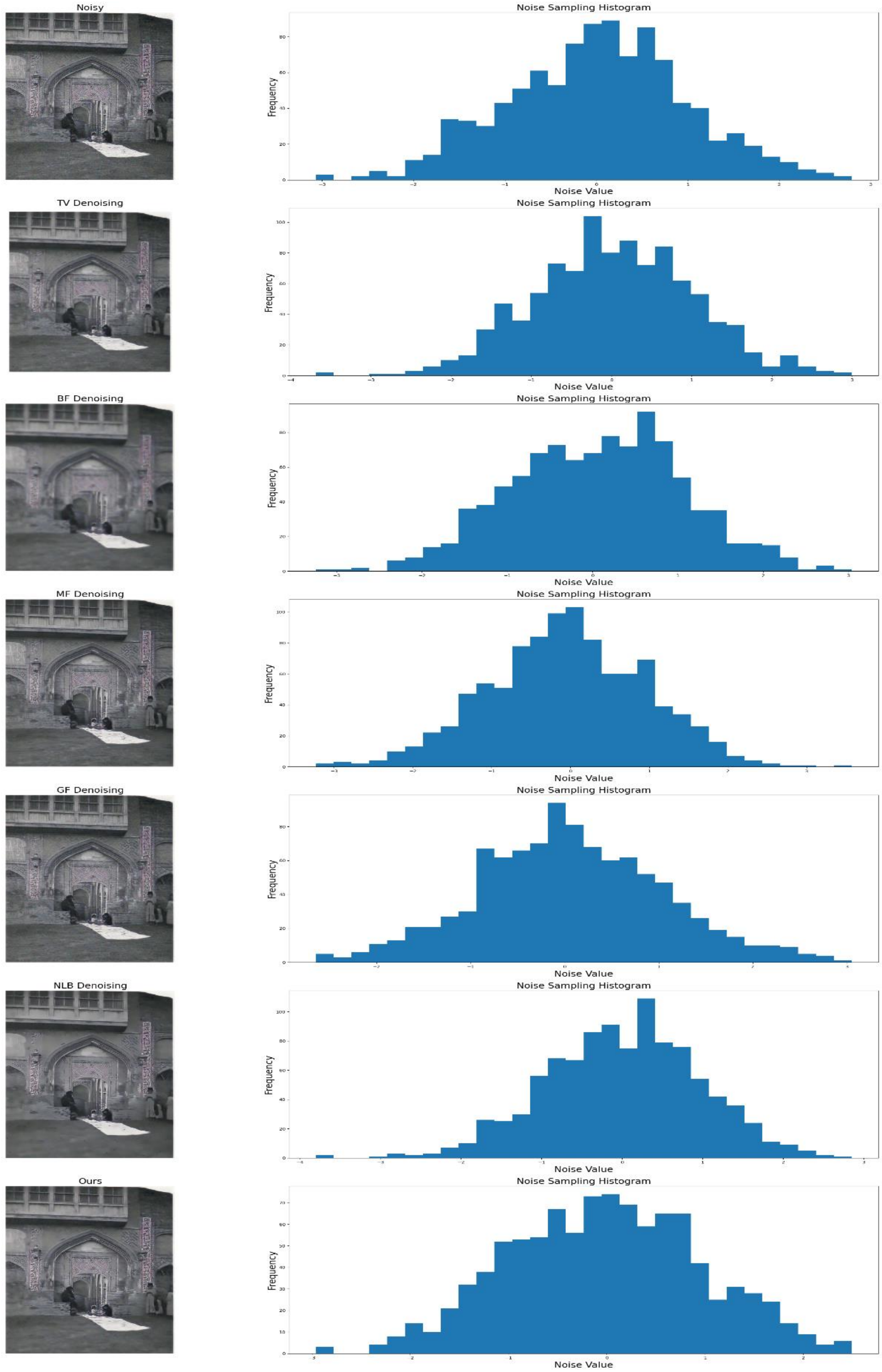

FIGURE 6. - Histogram of super-resolution denoise images model (A), display noise value to frequency of image pixels between or method and state-of-art methods

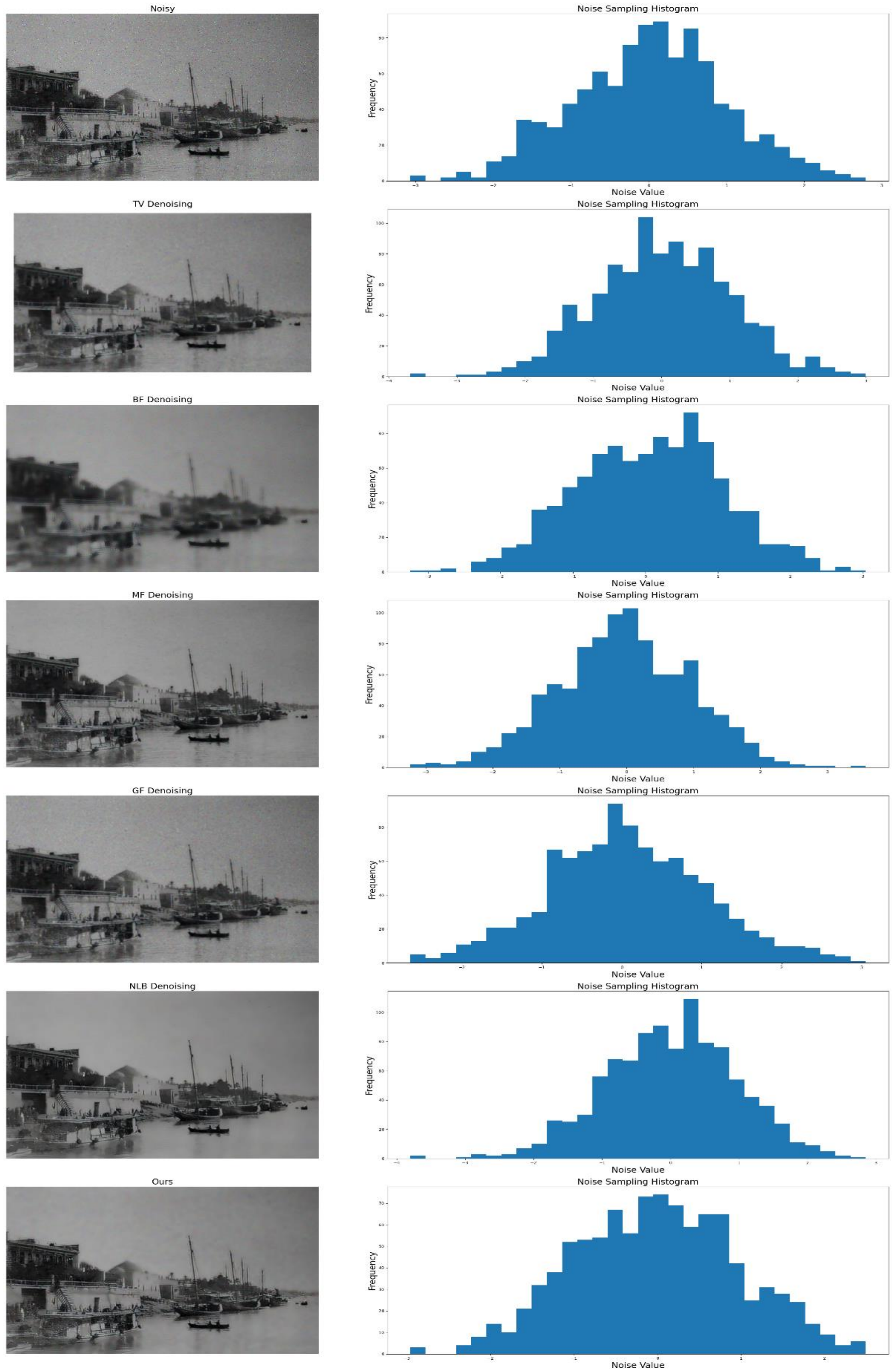

FIGURE 7. - Histogram of super-resolution denoise images model (B), display noise value to frequency of image pixels between or method and state-of-art methods

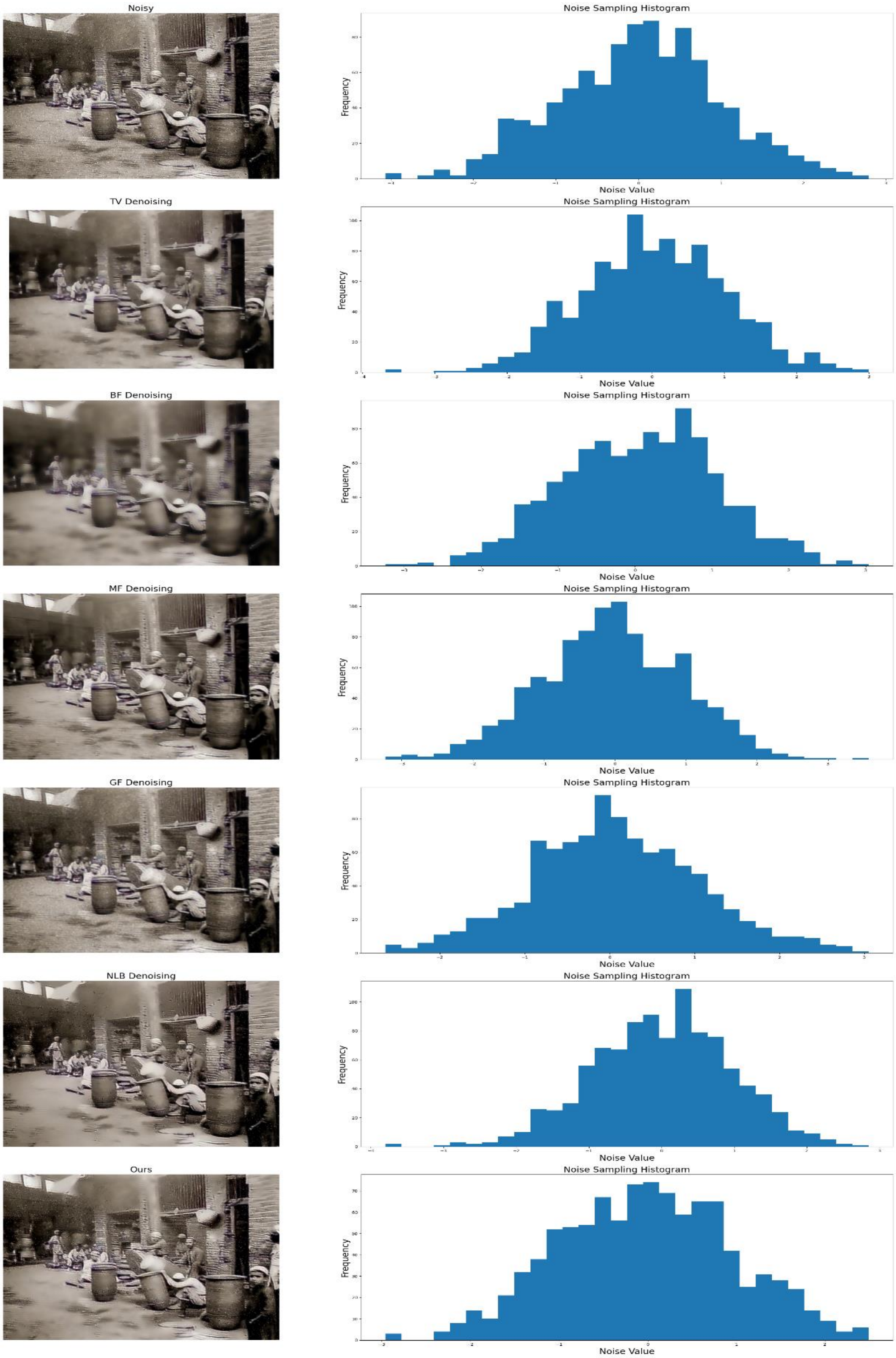

FIGURE 8. - Histogram of super-resolution denoise images model (C), display noise value to frequency of image pixels between or method and state-of-art methods

5. CONCLUSION

In the present study, we proposed a high-performance approach that helps restore people's cultural heritage by reconstructing the old, low-resolution (LR), and noisy Baghdad heritage images. Our approach worked in two stages: In order to identify noisy features and hidden faults in the pixels, we first created super-resolution (SR) images from those older images using deep neural networks. The second method is to reduce these features and replace them with noise-free, realistic features that are purer and have a realistic texture. When our method was compared to state-of-the-art methods, it clearly made progress in both quantitative and visual evaluations. Our approach calls on researchers to enable and preserve world heritage from obsolescence and loss using deep learning algorithms.

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