Image denoising techniques and their applications for CNNs

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Abstract—**This study explores the efficacy of three distinct image denoising techniques, namely Singular Value Decomposition (SVD) [2], Total Variation (TV) inpainting [4], and Robust Principal Component Analysis (RPCA) [1], in the context of improving Convolutional Neural Network (CNN) accuracy on the MNIST dataset [?]. The research involves the application of these denoising methods to enhance the quality of input data for CNNs, with a focus on understanding their individual contributions to accuracy improvement.**

The experimental results reveal that among the considered techniques, RPCA consistently outperforms SVD and TV inpainting in reducing image noise and preserving essential features. This finding underscores the robustness of RPCA in effectively separating clean signal from noise components, thereby yielding superior denoising outcomes. Subsequently, the denoised images are employed as input data for CNNs, and the impact on accuracy is evaluated.

Furthermore, the study investigates the collaborative utilization of CNNs and RPCA (CCNS) to discern their combined influence on enhancing the accuracy of the MNIST dataset. The results demonstrate that the integration of RPCA significantly contributes to improving the performance of CNNs, validating its potential as a powerful preprocessing step for enhancing accuracy in the presence of noise. The synergy between RPCA and CNNs is particularly pronounced, highlighting the complementary nature of these techniques in mitigating the adverse effects of noise on image classification tasks.

Index Terms—**Optimization, SVD, TV inpainting, RPCA, image denoising, CCNs**

I. Introduction

In recent years, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in various computer vision tasks, ranging from image classification to object detection. Despite their effectiveness, CNNs are susceptible to noise present in input images, which can adversely affect their performance. To address this challenge, researchers have explored the integration of image denoising techniques as a preprocessing step to enhance the quality of input data for CNNs.

In this study, we investigate the impact of three distinct image denoising algorithms—Singular Value Decomposition (SVD) [], Total Variation (TV) inpainting [4], and Robust Principal Component Analysis (RPCA) [1]—on the accuracy of CNNs. Our primary objective is to evaluate whether the application of these denoising methods contributes to improved performance and generalization of CNNs on image classification tasks.

The motivation behind this research stems from the observation that noisy input data can introduce unwanted variability, hindering the ability of CNNs to learn meaningful patterns. By leveraging advanced denoising techniques, we aim to preprocess images effectively, providing cleaner inputs to the CNN model. Our experimental results indicate a positive correlation between the use of denoising algorithms and enhanced CNN accuracy, suggesting the potential of such preprocessing steps in optimizing neural network performance.

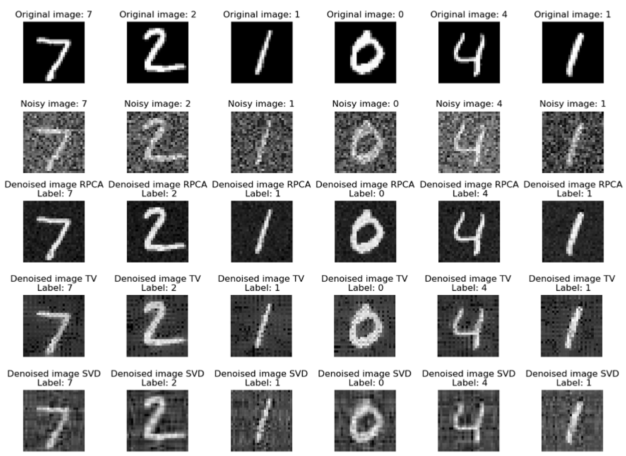

Fig. 1. ”Comparison of Denoising Techniques: SVD with a 0.65 data retention ratio introduces subtle blurring, while TV inpainting struggles to preserve smoothness under high noise levels. In contrast, RPCA emerges as the superior method, adeptly denoising images even in the presence of substantial noise. This suggests that RPCA holds significant potential for enhancing CNN accuracy by effectively mitigating noise without compromising image quality.”

This paper is organized into four sections. In Section 2, dedicated to the methodology, we delve into the theoretical underpinnings of three denoising algorithms. This section provides a comprehensive exploration of the mathematical principles underlying each algorithm. Moving on to Section 3, we present the results and accuracy evaluation of our Convolutional Neural Network (CNN) model. We analyze the performance under various optimizers and denoising techniques, enabling a comparison of the model's convergence under different assumptions. Finally, the last section serves as a summary, consolidating insights from all denoising algorithms discussed in the paper. It concludes with a comprehensive interpretation of the results and their implications for image denoising applications.

II. Methodology

I employed three prominent image denoising techniques, namely Singular Value Decomposition (SVD), Total Variation (TV) inpainting, and Robust Principal Component Analysis (RPCA). Each denoising algorithm was applied to preprocess the input images independently, aiming to reduce noise and enhance image clarity.

TABLE I

Comparison of Train and Test Accuracy for Noisy and Denoised Images

	CNN/Original(Adam)	CNN/Original(SGD)	CNN/Noisy(Adam)	CNN/Noisy(SGD)	CNN/Denoised RPCA(Adam)
Train Accuracy	98.66	96.26	96.43	92.79	98.99
Test Accuracy	99.31	97.58	98.52	95.58	99.2
	CNN/Denoised TV(Adam)	CNN/CNN/Denoised TV(SGD)	CNN/Denoised SVD(Adam)	CNN/Denoised SVD(SGD)	CNN/Denoised RPCA(SGD)
Train Accuracy	98.11	94.67	97.6	94.52	95.95
Test Accuracy	98.92	96.73	98.55	96.57	97.51

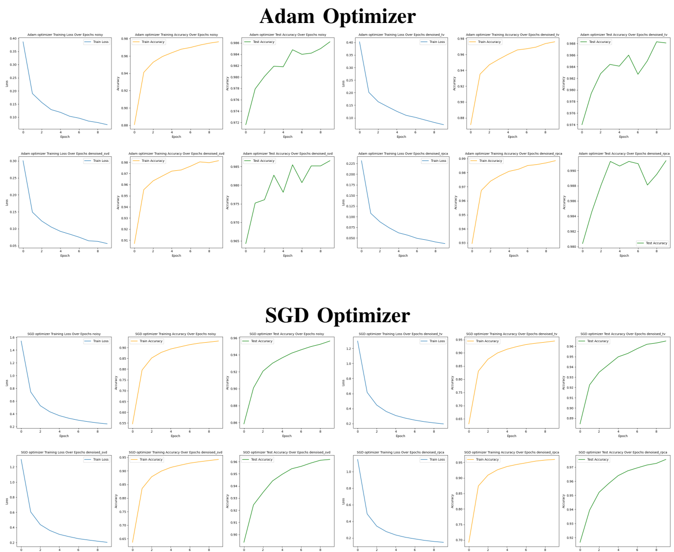

Fig. 2. The average of distance matrix $\mathcal{G}$ over different classes for Office-31, Office-Home, and DomainNet. Lighter color means smaller distance.

Subsequently, the denoised images were fed into our designed Convolutional Neural Network (CNN) architecture. The CNN was trained on the denoised dataset to evaluate the impact of each denoising method on the model's learning and classification performance.

To quantify the effectiveness of the denoising techniques, we conducted comprehensive experiments comparing the accuracy of the CNN using denoised inputs against a baseline model trained on the original, noisy dataset. The results were analyzed to assess the contribution of each denoising algorithm to the overall improvement in CNN performance.

A. Image Denoising Techniques

1) Singular Value Decomposition (SVD): SVD is a matrix factorization technique that decomposes an image matrix X into three matrices as follows:

$$X = U\Sigma V^T \tag{1}$$

where U is the left singular vector matrix, Σ is a diagonal matrix containing the singular values, and V is the right singular vector matrix. The denoised image is then reconstructed using a truncated version of the SVD components.

2) Total Variation (TV) Inpainting: TV inpainting is a variational method that minimizes the total variation of the image subject to fidelity constraints. The denoised image is obtained by solving the following optimization problem:

$$\arg\min_u \lambda\|\nabla u\|_1 + \frac{1}{2}\|u - f\|_2^2 \tag{2}$$

where u is the denoised image, f is the noisy input image, ∇u is the image gradient, and λ controls the strength of the total variation regularization.

3) Robust Principal Component Analysis (RPCA): RPCA separates an image matrix X into low-rank and sparse components by solving the following optimization problem:

$$\arg\min_{L,S} \|L\|_* + \lambda\|S\|_1 \quad \text{s.t.} \quad X = L + S \tag{3}$$

where L represents the low-rank component (clean signal), S represents the sparse component (noise), $\|L\|_*$ is the nuclear norm of L, $\|S\|_1$ is the ℓ_1 norm of S, and λ is a regularization parameter.

B. Collaborative CNN and RPCA (CCNS)

To evaluate the collaborative impact of CNN and RPCA, denoised images obtained from each technique are fed into a CNN for image classification. The CNN model is trained and validated on the denoised datasets to assess the accuracy improvement achieved through the integration of RPCA and CNN.

III. Results and Experiments

Figure 2 demonstrates the training and test accuracy of our Convolutional Neural Network (CNN) under various denoising techniques. We assumed the presence of Gaussian noise, with a mean of 128 (center point of [0, 256]) and a standard deviation of 32, affecting 90% of pixels randomly. A comparative assessment of the model's performance is presented, employing three prominent denoising methods: Singular Value Decomposition (SVD), Total Variation (TV) inpainting, and Robust Principal Component Analysis (RPCA). The CNN was configured with a learning rate of 0.01, a weight decay of 1×10^{-5}, and utilized the cross-entropy loss function. Furthermore, our CNN architecture comprises two convolutional layers with 32 and 64 kernels, respectively.

A. Optimization Algorithm

For all experiments, we utilized the Adam Optimizer as the optimization algorithm due to its faster and more robust convergence compared to Stochastic Gradient Descent (SGD) [3].

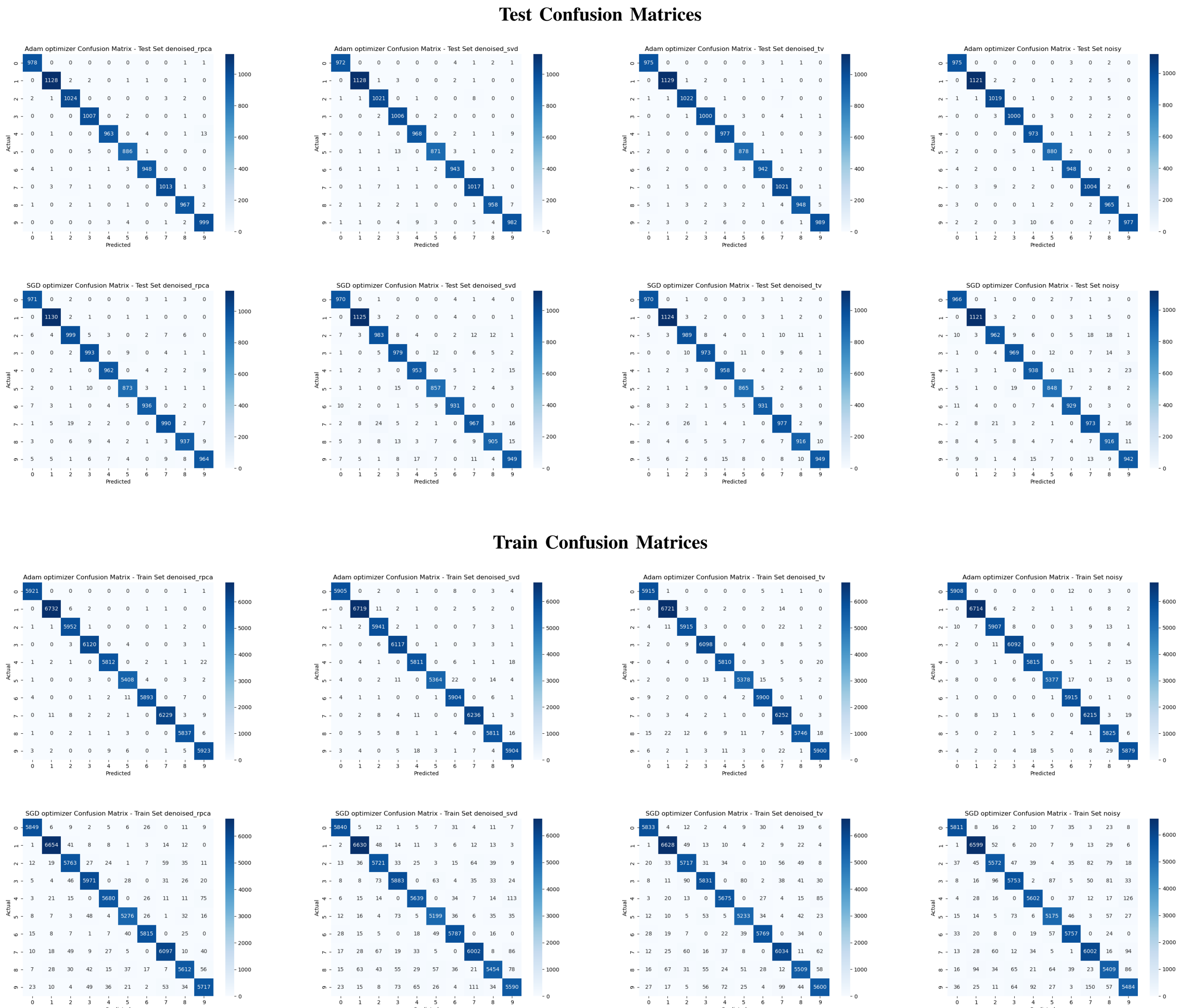

Fig. 3. Comparison of Denoising Techniques and Optimizers: Confusion matrices illustrating the performance of image denoising methods under various optimizers

B. SVD Denoising

SVD denoising emerged as a fast and efficient method for preprocessing images. However, it exhibited a drawback in terms of image blurring, which could impact the clarity of learned features.

C. TV Inpainting

TV inpainting demonstrated effective image inpainting but at the cost of increased computational time. Notably, the denoising process using TV inpainting took approximately 30 hours when applied to the MNIST dataset, highlighting its time-consuming nature.

D. RPCA (Robust Principal Component Analysis)

RPCA proved to be the most promising choice for image denoising in our study. It struck a balance between speed and denoising quality, making it an optimal solution for enhancing the performance of our CNN. The results indicate that RPCA outperformed both SVD and TV inpainting in terms of preserving image details and improving classification accuracy.

In summary, our experiments suggest that the choice of denoising technique significantly influences the performance of the CNN. While SVD and TV inpainting have their merits and drawbacks, RPCA stands out as the preferred method, offering a balanced solution that enhances denoising quality without sacrificing computational efficiency.

IV. Conclusion

In this study, we explored the integration of three distinct image denoising techniques—Singular Value Decomposition (SVD), Total Variation (TV) inpainting, and Robust Principal Component Analysis (RPCA)—as preprocessing steps for Convolutional Neural Networks (CNNs). Our objective was to evaluate the impact of these denoising methods on CNN performance in terms of accuracy and convergence.

The results presented in Figure 3 clearly indicate the significance of image denoising in enhancing the effectiveness of CNNs. Our findings show that the choice of denoising algorithm plays a crucial role in shaping the model's learning capabilities and classification accuracy.

Despite the image blurring associated with SVD denoising and the time-consuming nature of TV inpainting, each method demonstrated its unique strengths and limitations. However, the standout performer in our experiments was RPCA, showcasing its effectiveness in providing a balanced solution—improving denoising quality while maintaining computational efficiency [5].

Moreover, our decision to employ the Adam Optimizer for optimization proved beneficial, contributing to faster and more robust convergence during training.

In conclusion, this study underscores the importance of thoughtful preprocessing in the form of image denoising for CNNs. As we move forward, understanding the trade-offs and selecting appropriate denoising techniques tailored to specific datasets and applications will be crucial for unlocking the full potential of deep learning models in computer vision tasks [].

References

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