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Comparative Analysis of CNN-Based Image Denoising Techniques

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Abstract: - For this project, it aims to implement and enhance an automatic text summarization system using the recently popular BART (Bidirectional and Auto-Regressive Transformers) model. The system is trained on the CNN/DailyMail dataset and is also examined with the help of the ROUGE score where the system performs quite well in ROUGE-1, ROUGE-2, and the ROUGE-L test set. It was observed that the summaries generated were both logically connected and summarized data points were pertinent and hence, the capability of the BART model to work well in the field of abstractive summarization was proved. Altogether, the results shed more light on how the deep learning techniques can be used in improving the Information Retrieval and documents Management System. There is still more work that can be done in the future; considering to refine and enrich the dataset to enhance the model. The BART model integrates bidirectional context comprehension with autoregressive text generation to produce coherent and contextually relevant summaries. Performance was evaluated using ROUGE metrics, demonstrating the model's effectiveness in generating precise and informative summaries. This work underscores the potential of deep learning techniques in advancing summarisation technologies.

Keywords: Machine learning, Generative pretraining, repository, evaluation metrics, summarizing tool, NLP techniques, document indexing, ROUGE score, Abstracting techniques, model training data sets.

INTRODUCTION

It is common knowledge that image denoising is considered as a baseline method in many fields including medical imaging, security surveillance, and digital photography. Since such image has essential details that must not be obscured, it is important to have proper quality of images to restore and counter noise in the image. However, the process of removing noise or speckle remains a problem, from their removal is difficult because of the fine details of a highly corrupted image. Noise removal is a non-trivial problem always with the possibility of losing some important features of the images in the process. These challenges have in recent years been tackled using Convolutional Neural Networks (CNNs). Previous methods like the Gaussian filtering and the wavelet transforms have been shown to be surpassed by the CNN-based methods owing their inherent capability to learn several filters on their own from the noisy scenes. CNNs must also remain flexible in their architecture to better preserve edges and reduce noise, which has led to many steps forwards in terms of denoising performance. A comparison of image denoising methods using CNN will be made. The aim is, accordingly, to assess their advantages and drawbacks as well as the applicability of each one to various types of noise in accordance with the findings presented in the literature. There will be no actual software implementation; instead, the theoretical assessment approach will be retained, coupled with the existing literature studies the area of study of state-of-art methods in image de-noising will be evaluated while avoiding any actual software implementation.

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LITERATURE REVIEW

Traditional Denoising Methods

To denoise the image a number of traditional techniques have been used such as Gaussian filtering, wavelet transforms, and non-local means filtering. The goal has been to suppress noise and keep all important details while using these methods. Because of its simplicity, Gaussian filtering is commonly used but its edge detail retention is often said to be weak. Whereas wavelet transforms have been developed to decompose images in different frequency components and selectively remove noise in the transform domain (Liu and Zhang, 2023). Retained fine structures were achieved through the use of the wavelet transforms combined with the non-local mean filtering in which the method was used.

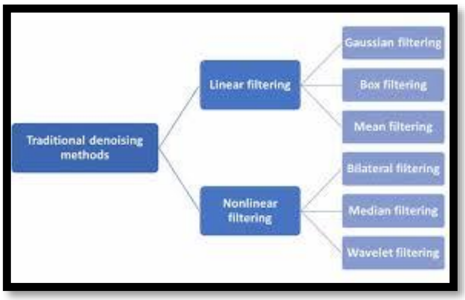

Figure 1: Traditional Denoising Methods

(Source: researchgate.net, 2024)

As an example, non-local means filtering has special interest in the fact that it uses self-similarity within an image to perform better smoothing, particularly in case of textured areas. Even though these techniques proved very effective, they are challenged by the fact that they are often limited by their dependence on handcrafted features, without which these techniques become very brittle with respect to the types of noise that they encounter.

Evolution of CNN-Based Denoising Techniques

CNN based methods, however, were brought about because of the advent of deep learning, which was able to address several limitations of traditional techniques. Significant milestones have characterized the evolution of CNN based denoising techniques, from DnCNN to FFDNet to MemNet that progresses the denoising performance.

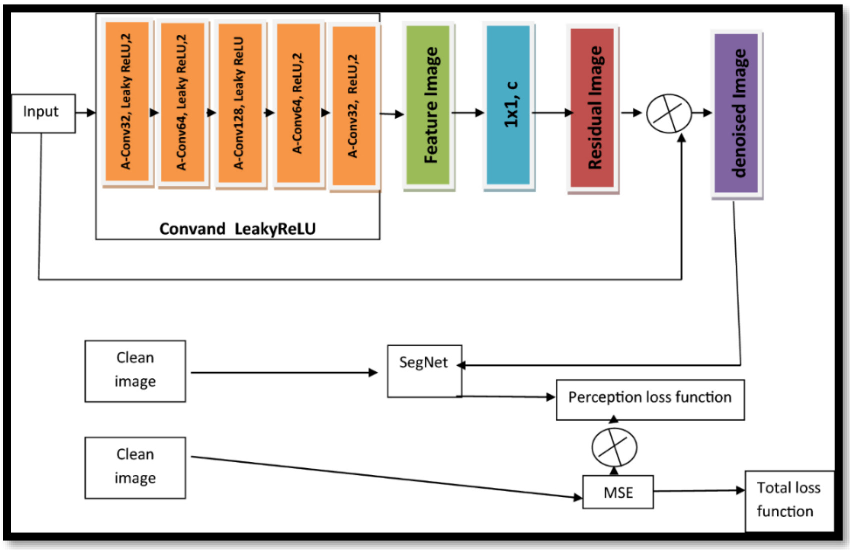

Figure 2: Methods for image denoising using convolutional neural network

(Source: link.springer.com, 2024)

By predicting noise directly, rather than denoised images, residual learning was first introduced to denoise images and simplified the learning task and produced better results with DnCNN (Zheng, Yong, & Zhang, 2021). This was further improved by FFDNet that incorporates variable noises level, such that the model can adapt to different noise intensities. By focusing on deep feature extraction, MemNet has further enriched the ability to hold the main image details beyond long term dependencies, with a developed model (Zheng, Yong and Zhang, 2021). CNN based models have largely been able to surpass traditional methodology in the setting of fine control over denoising through learning complex noise patterns within data to achieve superior image quality retention.

RECENT ADVANCEMENTS

In recent years research has been dedicated to the refinement of CNN architectures in order to improve denoising capabilities. Features at different resolutions are explored by designing multi scale networks to learn features at different resolutions in order to increase the robustness of the denoising process. One such network, which utilizes adaptive scaling, has been shown to outperform in the case when noise patterns differ substantially across images. Attention mechanisms have also been incorporated to CNNs in order to selectively focus on, or 'denoise', areas of the image where more intense denoising is needed, while mitigating existing critical details (Gou *et al.* 2022). However, with these advancements' networks can learn to adaptively prioritize important features for enhanced edge preservation. On a multi-scale adaptive network, it was investigated how multi field inceptions in a same model could both increase performance and possibly make up the cost of denoising.

COMPARATIVE STUDIES

A number of comparative studies have been done to investigate the performance of the traditional and CNN based techniques for denoising. Meta-analyses of past research have consistently demonstrated the superiority of CNN based methods to traditional approaches when these two types of problems arise in modern science: high noise or complex patterns (Ilesanmi and Ilesanmi, 2021). A study has been reported whose methods are faster, but are prone to over-smoothing or loss of fine details. In contrast, though their higher computational demands, CNN based models have superior peak signal to noise ratio (PSNR) and structural similarity index (SSIM). Indeed, recent studies have also shown that hybrid models which perform fusion of the two strengths of traditional filters with deep learning can strike a balance between computational efficiency and the denoising performance.

THEORETICAL ANALYSIS OF CNN-BASED DENOISING TECHNIQUES

Architectural Overview

Models of CNN-based image denoising employ different architectural designs in depth, kernel size, and are using skip connections. For this reason, deeper networks generally perform better to learn complex patterns, but introduce much higher computational costs (Gonwirat and Surinta, 2022). Then, kernel size determines how much context information, or spatial information is captured during the convolution process, increasing the computational complexity, but at the price of capturing more.

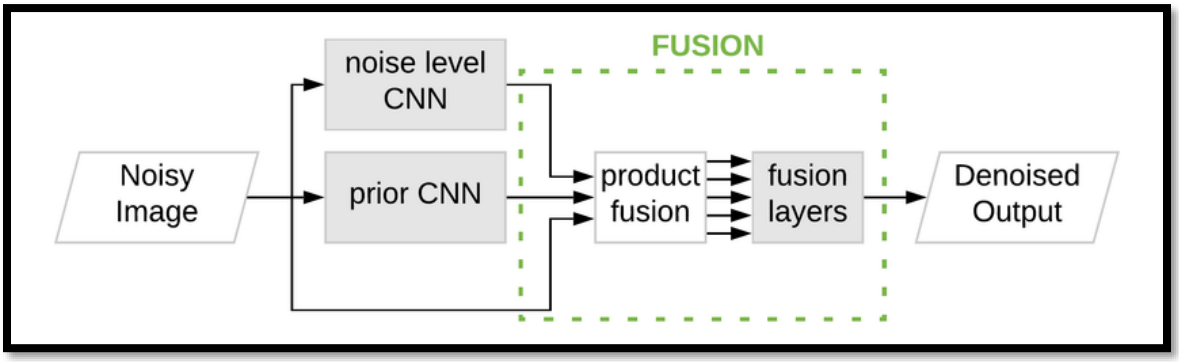

Figure 3: Schematic of the DnCNN residual learning approach for denoising

(Source: researchgate.net, 2024)

Many of models also feature skip connections, to help the flow of gradients through the network during training (e.g., to avoid gradient loss by avoiding deeper layers). We show how these differences in architecture affect the models' performance in terms of noise suppression, edge preservation and computational efficiency.

KEY TECHNIQUES

DnCNN

For the task of directly predicting the noise component in an image, one develops a new denoising CNN, DnCNN. Use a deep network with residual learning to improve the accuracies of denoising and learning the residual (the difference between noisy and clean images instead of the clean image) (Tian *et al.* 2020). Using batch normalization, DnCNN has multiple convolutional layers and are stabilized during training. This architecture can handle different levels of Gaussian noise, because this mapping from noisy to clean images is learned. However, DnCNN's performance is sensitive to non-Gaussian noise, and is susceptible to more complicated noise types.

FFDNet

FFDNet (Fast and Flexible Denoising Network) provides a lightweight and efficient design and can flexibly accommodate noise levels. In addition to the image, it presents a noise level map as an extra input, by which the model can dynamically change the denoising process according to the noise intensity (Tian *et al.* 2021). To make the network fast and efficient, we use fewer parameters and allow the network to handle real time denoising. We find FFDNet to be performing well over a wide range of noise levels, so it can handle images containing different types of noise characteristics. However, such flexibility comes at the cost of a model that underperforms when noise characteristics are more complex or involve a more specialized feature extraction.

MemNet

In this spirit, MemNet (Memory Network) proposes to use memory blocks to store and retrieve information from deeper layers of the network so that they can extract long-range dependencies in an image. Built upon this architecture, feature extraction is further improved by contextual information on multiple layers and specifically on denoising quality in complex images with complex noise patterns (Zangana and Mustafa, 2024). We show that MemNet improves on preserving fine image details while reducing noise. While it has the same memory-based structure as the above, it only works for reasonably small datasets at each point, because computational costs and model complexity are higher.

Strengths and Limitations

Unlike previous denoising techniques, CNN-based ones feature advantages of higher accuracy, better noise type adaptability and improved edge preservation. Gaussian noise is well handled by DnCNN but may not do as well with non-Gaussian noise. Though performance may degrade under complex noise conditions (Quan *et al,* 2021), FFDNet is flexible and lightweight and thus suitable for real time applications. Advanced feature extraction of MemNet through memory blocks allows superior denoising quality but at the expense of computational complexity. Usually, limitations of each model are related to the overfitting, particularly in deep networks and trade-offs between the denoising quality and computational boundedness.

COMPARATIVE ANALYSIS

Comparison Criteria

Currently, the performance of CNN based image denoising technique is usually compared based on the theoretical metrics of noise robustness, edge preservation, computational efficiency, and model complexity. In particular, the model should be noise robust, meaning efficient in removing noise and retaining image quality in the presence of none, Gaussian or speckle noise.

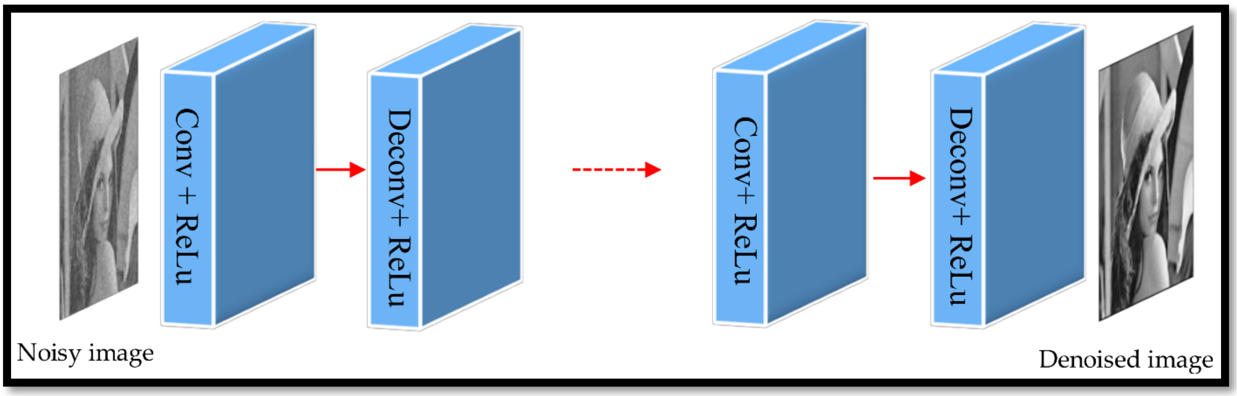

Figure 4: Fully Symmetric Convolutional Network for Effective Image Denoising

(Source: mdpi.com, 2024)

The edge preservation is the measure of how well the model maintains fine information and physical information in the image. Model Complexity however, is the total number of parameters and the network architecture's depth. Finally, Computational efficiency determines the model's ability to process the image quickly without a wastage of resources.

Findings from Literature

Previous studies have revealed that CNN based denoising models are good at different areas. While DnCNN generally does best with Gaussian noise, its performance on more complex noise is less strong. FFDNet was found to be flexible to varying noise level and computationally efficient such that it is feasible for real time applications (Komatsu and Gonsalves, 2020). Although MemNet has better edge preservation and robustness in challenging noise conditions, it has the computational cost due to the memory block structure.

Critical Insights

Trends common in the literature indicate model complexity vs denoising performance trade-off. MemNet has better denoising results than its shallow counterparts such as NIPS 88, however they are more computationally demanding (El-Shafai *et al.* 2022). Simpler model for FFDNet, balancing performance and efficiency, thus suitable for apps that can have resource constraints.

DISCUSSION

Interpretation of Findings

The identified conclusions imply that some CNN-based methods are more efficient for particular applications because of their peculiarities. For instance, DnCNN performs well when it is trained in Gaussian noise environments; hence, can be well-applied in medical imaging and other scenarios that mostly experience Gaussian noise. Based on the presence of FFDNet which is well equipped to handle various levels of noise in real time streaming such as video streaming, security, surveillance and more (Darıcı etal 2023). MemNet, on the other hand, in general provides better results in maintaining fine details which is very important when working with high resolution photographs of objects, or satellite images of big areas, though at the cost of being computationally heavier.

CONCLUSION

In this paper, the comparative analysis of the presented methods has shown the applicability and vulnerabilities of CNN-based image denoising techniques with reference to PSNR and different characteristics of noises. It was found that DnCNN was particularly efficient in removing Gaussian noise, while FFDNet would perform well regardless of the level of noise present. It is shown that MemNet achieves better edge preservation than GAN-CLS while it consumes more computational resources. It is also seen that the CNN-based denoising techniques have vast applicability in high impact real world applications like medical imaging, video surveillance, and photography due to their efficiency in terms of image quality and computational time. Further work should be reused to improve models' ability to operate under various noise conditions, decrease computationally complexity of model and investigate other architectures like combining CNN with transformers.

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