Comparative Analysis of KNN, PCA, and Wavelet-Based Image Denoising Methods

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Abstract: Image denoising is an essential process in digital image processing that aims to remove noise while preserving important image details and structures. Various noise sources, such as Gaussian noise, salt-and-pepper noise, and speckle noise, can significantly degrade image quality during acquisition, transmission, or storage. This review paper presents a comparative study of robust image denoising strategies based on K-Nearest Neighbor (KNN), Principal Component Analysis (PCA), and Wavelet Transform techniques. The study analyzes the working principles, effectiveness, advantages, and limitations of these methods in reducing noise and improving image clarity. KNN-based methods utilize similarity between neighboring pixels for noise reduction, PCA techniques focus on dimensionality reduction and feature extraction, while Wavelet-based approaches perform multi-resolution analysis for efficient denoising. The paper also discusses performance evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM). Comparative analysis indicates that Wavelet methods generally provide better preservation of image details, PCA offers efficient data representation, and KNN methods are simple and effective for localized noise reduction. The review highlights recent advancements, challenges, and future research directions in image denoising, emphasizing the importance of hybrid and machine learning-based approaches for achieving higher accuracy and computational efficiency in real-time applications.

Keywords: Image Denoising, K-Nearest Neighbor (KNN), Principal Component Analysis (PCA), Wavelet Transform, Noise Reduction, Digital Image Processing, Gaussian Noise, Salt-and-Pepper Noise, Image Enhancement, PSNR, MSE, SSIM, Machine Learning, Feature Extraction, Signal Processing.

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I. INTRODUCTION

Digital images play a significant role in various fields such as medical imaging, satellite communication, computer vision, surveillance systems, multimedia applications, and artificial intelligence. During image acquisition, transmission, or storage, images are often corrupted by different types of noise, including Gaussian noise, salt-and-pepper noise, speckle noise, and Poisson noise. Noise degrades image quality, reduces visual clarity, and negatively affects the performance of image analysis and recognition systems. Therefore, image denoising has become an important research area in digital image processing.

Image denoising refers to the process of removing unwanted noise from an image while preserving important features such as edges, textures, and fine details. An effective denoising method should achieve a balance between noise reduction and detail preservation. Over the years, numerous denoising techniques have been developed, ranging from traditional filtering approaches to advanced machine learning and transform-based methods. Among these techniques, K-Nearest Neighbor (KNN), Principal Component Analysis (PCA), and Wavelet Transform methods have gained significant attention due to their robustness and effectiveness.

KNN-based denoising techniques utilize similarity measures between neighboring pixels or image patches to identify and reduce noisy components. These methods are simple, adaptive, and effective in preserving local image structures. PCA-based denoising methods focus on dimensionality reduction and feature extraction by transforming image data into principal components. PCA helps in separating noise from useful image information, leading to improved image reconstruction and compression efficiency. On the other hand, Wavelet Transform-based denoising methods perform multi-resolution analysis by decomposing images into different frequency components. These methods are highly effective in preserving edges and textures while removing noise from images.

The growing demand for high-quality digital images in real-time applications has increased the need for robust and computationally efficient denoising techniques. Researchers have also explored hybrid approaches that combine multiple denoising methods and machine learning algorithms to achieve better accuracy and performance. Evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM) are commonly used to measure the effectiveness of denoising algorithms.

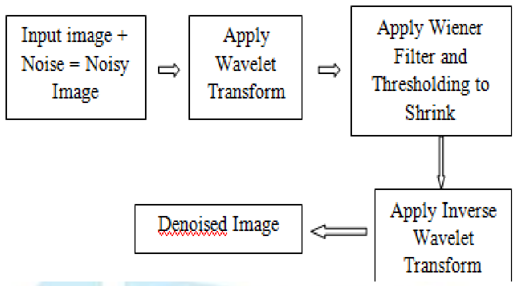

Figure 1: Basic model for denoising of image

II. LITERATURE REVIEW

Sigit Auliana et. al. [2024] - The project involved testing various image types and evaluating the performance of the proposed technique, which outperformed existing methods, as evident from the comparison table. Future endeavours will focus on detecting infected cells within tumors or cancer using innovative segmentation and classification techniques. This article primarily discussed the fundamental aspect of medical image processing: filtering of medical images. However, in future endeavors, we aim to advance beyond basic filtering processes and delve into more complex tasks such as segmentation and classification. By applying the enhanced foundational steps discussed in this article, we intend to assess the performance of classifiers in medical image processing, focusing on specific types of images [01].

C. Tamilselvi. et al [2024] Denoising is an integral part of the data pre-processing pipeline that often works in conjunction with model development for enhancing the quality of data, improving model accuracy, preventing overfitting, and contributing to the overall robustness of predictive models. Algorithms based on a combination of wavelet with deep learning, machine learning, and stochastic model have been proposed. The denoised series are fitted with various benchmark models, including long short-term memory (LSTM), support vector regression (SVR), artificial neural network (ANN), and autoregressive integrated moving average (ARIMA) models. The effectiveness of a waveletbased denoising approach was investigated on monthly wholesale price data for three major spices (turmeric, coriander, and cumin) for various markets in India. The predictive performance of these models is assessed using root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE). The wavelet LSTM model with Haar filter at level 6 emerged as a robust choice for accurate price predictions across all spices. It was found that the wavelet LSTM model had a significant gain in accuracy than the LSTM model by more than 30% across all accuracy metrics. The results clearly highlighted the efficacy of a wavelet-based denoising approach in enhancing the accuracy of price forecasting [02].

Mehrad Nikzadfar et. al (2024) - The potential of combining non-destructive inspection HSI techniques with ML to enhance quality and safety in food, each with a general demonstration of success. However, it would be even stronger in offering a more specific assessment of how such methods apply to real-world food safety scenarios. In this respect, the applicable models and techniques include the use of a convolutional neural network and Support Vector Machine for feature extraction and classification in systems, respectively, due to the high accuracy they present. Other examples of such tasks involve wavelength selection and dimensionality reduction, which are going to be essential in making the models more scalable and efficient for real-time use toward ensuring food safety across the food chain. The control authorities, external and internal, may be contacted in order to show that, through the combination of HSI and AI, this may offer quicker assessment times, more precise, and non-destructive ones, reducing the risk of contamination together with costs related to the recall of food products. In fact, this review will certainly stimulate further research, covering other ML techniques for the non-destructive assessment of food quality [03].

Nada Jasim Habeeb et. al. [2023] - The Wiener filter is widely used in image de-noising. It is used to reduce Gaussian noise. Although the Wiener filter removes noise from the image, it causes a loss of edge detail information, resulting in blurring of the image. The edge details are considered high-frequency components. The Wiener filter is unable to reconstruct these components. In this paper, the proposed filter based on the Wiener filter and the high-boost filter for medical images is presented. The proposed filter is applied to the degraded image. First, using Fourier Transformation, the degraded image and the high boost filter are converted in the frequency domain. Secondly, the wiener filter is applied to the image along with the high boost filter. Thirdly, the deconvolution process is achieved on the image with the high boost filter. Finally, to reconstruct the sharper image in the spatial domain, the inverse of the Fourier transformation is applied. The proposed filter works to suppress the additive noise at the same time. It can keep the image's edge details. Some focus operators are used, which are image contrast, gradient energy, histogram entropy, and spatial frequency, in order to test the proposed algorithm [04].

Michael Elad et al [2023] - Image denoising – removal of additive white Gaussian noise from an image – is one of the oldest and most studied problems in image processing. An extensive work over several decades has led to thousands of papers on this subject, and to many well-performing algorithms for this task. Indeed, ten years ago, these achievements have led some researchers to suspect that “Denoising is Dead”, in the sense that all that can be achieved in this domain has already been obtained. However, this turned out to be far from the truth, with the penetration of deep learning (DL) into the realm of image processing. The era of DL brought a revolution to image denoising, both by taking the lead in today’s ability for noise suppression in images, and by broadening the scope of denoising problems being treated. Our paper starts by describing this evolution, highlighting in particular the tension and synergy that exist between classical approaches and modern Artificial Intelligence (AI) alternatives in design of image denoisers [05].

Caixia Liu et. al [2023] - Denoising is the basis and premise of image processing and an important part of image preprocessing. Denoising can effectively improve image quality, which contributes to subsequent image processing such as image segmentation, feature extraction, and so on. In this paper, we propose a novel image denoising method based on wavelet transform and nonlocal moment mean filtering approach (NMM). The noisy image is firstly denoised by a wavelet-based soft-thresholding denoising technique and NMM is then utilized to further eliminate the rest noises. Meanwhile, the fusion of moment invariants increases the robustness of our denoising algorithm due to the invariance of image scaling, translation, and rotation of color moments. Experiments show that our algorithm achieves a better denoising effect compared with some other denoising approaches [06].

Eelandula Kumaraswamy et.al (2023) - The second most prominent cause of death worldwide, arises from the transformation of normal cells into tumor cells due to an interaction between a person’s genetic factors and external agents. An early detection of cancer can help in determining the best treatment. In this context, we outline a variety of machine learning based cancer detection algorithms and models developed in past. The limitations of the existing models and research gaps in the past studies are also elaborated. Additionally, one case study is provided on the working of conventional classifiers trained on the features extracted from breast cancer histopathological images using handcrafted feature descriptors to demonstrate the potential of conventional machine learning algorithm in cancer detection [07].

Nitin et. al [2022] - This study proposed an effective and novel image denoising method to reconstruct the high noisy images. It is the hybridization of the Gaussian filter and DWT method to minimize the noise on digital images. Furthermore, the proposed method has good details as well as the edge-preserving capability and reflects a good similarity ratio between the denoised and the original image. The result shows that the proposed algorithm gave superior quantitative results as compared with the existing methods in case of high noise. But the PSNR value reduces at the low noise level ($\sigma < 0.05$). For the future scope, the proposed method will be used with genetic algorithms for parameter optimization [08].

Amarjeet Kumar Ghosh et.al [2022] - There are numerous image regularization denoising methods are presents. Selection of a specific image denoising method is depends upon the requirement and noise presents in image. Image regularization denoising technique is utilized to find the best estimation of the original image given by its corresponding noisy image. Among various regularization schemes, wavelet and adaptive filtering methods have drawn much attention in the image processing application. Moreover, most of the image regularization denoising schemes deals with Gaussian noise model. Various existing spatial-domain and transform-domain image denoising filters are studied and their filtering performances are compared to choose appropriate method and develop an efficient algorithm for novel image regularization denoising. In this work a novel image denoising approach has been proposed with wavelet decomposition with SYM3 filter and adaptive median filtering scheme [09].

III. METHOD

Image Preprocessing

The initial step in the methodology involves the acquisition of a grayscale image, which is loaded for further processing. Once the image is obtained, it is converted into a floating-point format to facilitate precise computations. This conversion is essential, as it ensures that pixel values can be manipulated with greater accuracy during the denoising process. Following this, normalization is performed on the pixel intensity values, scaling them to a range between 0 and 1. Normalization is crucial because it standardizes the input data, minimizing the variability that can arise from different image brightness levels and providing a consistent baseline for subsequent analysis. To simulate realistic scenarios, Gaussian noise is then added to the original image. The Gaussian noise, characterized by its mean (μ) and standard deviation (σ), defines the statistical properties of the noise distribution. This step is vital as it creates a noisy version of the image, which acts as a test case for evaluating the effectiveness of the denoising algorithms. By introducing noise into the original image, a challenging environment is created that allows for an effective assessment of the performance of the denoising algorithms under realistic conditions, thereby providing a comprehensive understanding of their capabilities and limitations.

K-Nearest Neighbors (KNN) Denoising

The first technique implemented in this methodology is K-Nearest Neighbours (KNN) denoising, which operates on the principle that pixels in an image are often correlated with their neighbours. KNN is a non-parametric, instance-based learning algorithm that leverages the similarity of pixel intensities within a local neighbourhood to reconstruct denoised pixel values. The process begins with patch extraction, where the noisy image is divided into overlapping patches of size $k \times k$. Each patch is centred around a pixel, ensuring that every pixel in the image has a corresponding patch that captures its local context. This patch-based approach is vital, as it enables the algorithm to utilize spatial information effectively, leading to improved denoising results. For each pixel in the noisy image, a $k \times k$ neighbourhood is extracted from the padded version of the noisy image. Padding is essential to avoid boundary effects, ensuring that all pixels, including those near the edges, have a complete set of neighbouring pixels to consider. The denoised pixel value for each pixel is computed as the mean of the pixel intensities within its neighbourhood.

Algorithm for Image Denoising

Step 1: Image Pre-processing

Convert the Image to Float Format: Convert the input grayscale image to a floating-point format.

Normalize Intensity Values: Normalize the pixel intensity values to the range [0, 1].

Introduce Gaussian Noise: Add Gaussian noise to the normalized image.

Step 2: K-Nearest Neighbours (KNN) Denoising

Extract Overlapping Patches: Divide the noisy image into overlapping patches centered around each pixel.

Compute Denoised Pixel Values:

For each pixel in the noisy image: Compute the average intensity values of pixels within the local patches.

Reconstruct the Denoised Image: Update the image to reflect the computed denoised values for all pixels.

Step 3: Principal Component Analysis (PCA) Denoising

Create Overlapping Patches: Extract overlapping patches from the noisy image.

Flatten Each Patch: Flatten each patch into a 1D array.

Apply PCA: Perform PCA on the flattened patches to retain significant components.

Reconstruct Patches: Apply the inverse transformation of PCA to reconstruct the denoised patches.

Merge Denoised Patches: Combine the reconstructed patches back into a complete image.

Step 4: Wavelet Transform Denoising

Perform Wavelet Decomposition: Decompose the noisy image into wavelet coefficients using a wavelet transform.

Apply Soft Thresholding: Apply soft thresholding to the detail coefficients to reduce noise.

Reconstruct the Denoised Image: Use the processed coefficients to reconstruct the denoised image.

Step 5: Performance Evaluation

Calculate PSNR: Compute the Peak Signal-to-Noise Ratio (PSNR) for each denoised image.

Calculate MSE: Calculate the Mean Squared Error (MSE) between the original and denoised images.

Calculate RMSE: Determine the Root Mean Squared Error (RMSE) for further comparison

IV. SIMULATION AND RESULT

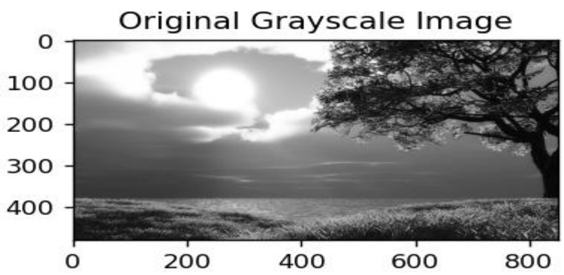

Figure 2: Original Grayscale Image:

This is the base image without any noise added. It’s a high-quality image of a natural scene with a tree and clouds in the sky. The contrast and details are clearly visible.

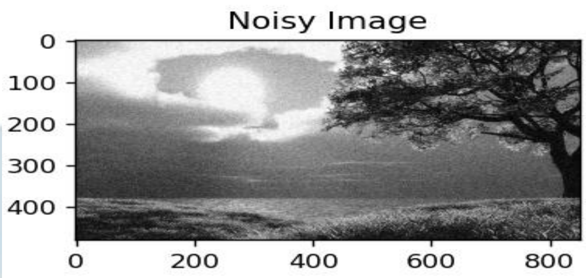

Figure 3: Noisy Image

Noise has been artificially added to the original image. The noise is likely Gaussian noise (common in image processing) and creates grainy distortion over the entire image. Details in the sky, tree, and landscape are harder to make out because the noise affects visibility.

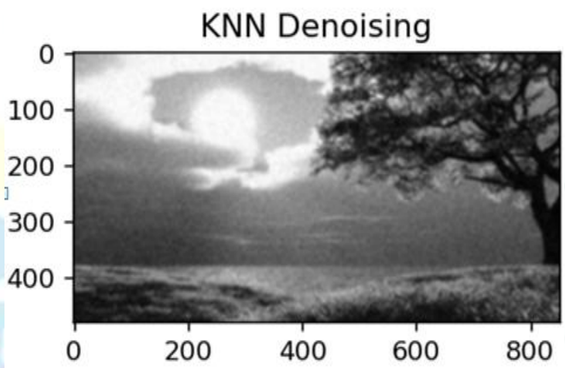

Figure 4: K-Nearest Neighbours (KNN) Denoising

Python

Python is a high-level, interpreted programming language known for its simplicity and readability. It was created by Guido van Rossum and released in 1991. Python emphasizes code readability and allows developers to express concepts in fewer lines of code compared to other programming languages. It supports multiple programming paradigms, including procedural, object-oriented, and functional programming. Python has a vast ecosystem of libraries and frameworks, which makes it suitable for a wide range of applications such as web development, data analysis, artificial intelligence, machine learning, automation, and more. Python's extensive community support and user-friendly syntax have contributed to its widespread adoption in both academia and industry.

Python’s design philosophy focuses on clarity and simplicity, which is reflected in its use of indentation to define code blocks instead of relying on curly braces or keywords. This makes Python code easier to read and maintain. It is also dynamically typed, meaning that variables do not need to be explicitly declared with a type, which further enhances flexibility during development.

Python is cross-platform, meaning that code written in Python can be run on different operating systems like Windows, macOS, and Linux without modification. This makes it an ideal choice for building portable applications. The language is also extensible, allowing developers to integrate Python with other languages such as C, C++, and Java, thus optimizing performance-critical parts of applications

V. CONCLUSION

The proposed methodology integrates KNN, PCA, and Wavelet Transform techniques to effectively denoise images affected by Gaussian noise. Each approach utilizes unique mathematical foundations and algorithmic strategies to enhance image quality while addressing the inherent challenges posed by noise. By employing well-defined preprocessing steps, thorough implementation processes, and rigorous performance evaluation metrics, this comprehensive approach not only contributes to theoretical knowledge but also has practical implications in various fields where image quality is paramount. The insights gained from this methodology will pave the way for future research endeavors aimed at further improving image denoising techniques and their applications in diverse areas such as medical imaging, remote sensing, and digital media.

Through the evaluation of three widely-used image denoising methods—K-Nearest Neighbors (KNN), Principal Component Analysis (PCA), and Wavelet Transform—it was found that each method offers distinct advantages depending on the type of noise and the image characteristics. KNN performs well in scenarios where local pixel similarity is essential, providing high-quality results for noise with similar local patterns. PCA, on the other hand, is effective in reducing noise by exploiting the image's principal components, excelling in situations where the noise is more complex or involves distortions. Wavelet-based denoising is highly versatile, providing excellent results in multi-scale decomposition, and is particularly beneficial for handling noise that varies across different image regions.

The choice of denoising method depends heavily on the nature of the noise and the specific characteristics of the image. Hybrid methods that combine these strategies may offer improved results, making them an appealing direction for future research. These findings emphasize the need for a tailored approach to image denoising, taking into consideration the trade-offs between computational complexity, noise characteristics, and denoising quality.

VI. FUTURE SCOPES

Future work in robust image denoising strategies, focusing on methods such as K-Nearest Neighbors (KNN), Principal Component Analysis (PCA), and Wavelet Transforms, can delve into several promising directions. Firstly, integrating these methods with advanced deep learning frameworks could enhance their adaptability and performance across diverse image types and noise levels. Hybrid approaches combining the strengths of KNN, PCA, and wavelet methods with convolutional neural networks (CNNs) may offer significant improvements in preserving image details while suppressing noise. Secondly, exploring real-time implementation and optimization of these methods for edge devices and resource-constrained environments can widen their practical applications. Additionally, extending the evaluation of these methods to address complex noise patterns, such as non-Gaussian or mixed noise, could improve their robustness in real-world scenarios. Finally, leveraging large-scale datasets and transfer learning techniques to fine-tune these methods for specific domains, such as medical imaging or satellite imagery, could further enhance their utility and reliability.

Thereby improving both efficiency and accuracy. Another promising avenue is the development of multi-resolution or multi-scale approaches that combine the spatial and frequency domain capabilities of wavelet transforms with the local adaptability of KNN and the dimensionality reduction strengths of

PCA. These approaches could provide enhanced results in handling high-resolution images and complex textures. Additionally, exploring unsupervised or self-supervised learning strategies could minimize reliance on extensive labeled datasets, which are often challenging to obtain.

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