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Image Denoising For Medical Image Analysis

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Abstract
The aim of this work is to identify the optimal Machine Learning (ML) techniques for image denoising in radiological medical applications. MRI diagnosis of brain tumors, X-ray analysis of the chest, MRI imaging for breast cancer, US Computer Aided Diagnosis (CAD) and detection of skin and breast abnormalities, and Medical Ultrasound (US) for prenatal development are the six specific radiology areas examined in the examination. The machine learning methods that demonstrate remarkable accuracy in radiologists' medical diagnoses are the main topic of this report. Among the picture denoising techniques discussed are curvelet algorithms, wavelet-based medical denoising, basic filtering techniques, and optimization strategies. Often, machine learning outperforms traditional picture denoising techniques. To get fast and efficient results, radiologists are increasingly applying machine learning techniques to MRI, US, X-ray, and skin lesion images. The paper also discusses the challenges researchers have when applying machine learning and image denoising techniques in clinical contexts, as well as the features and contributions of various machine learning methodologies.
Keywords: *Image denoising, ultrasound, filtering techniques, classifiers, wavelets*

1. INTRODUCTION

The scientific community faces a major research challenge in the fields of diagnosis, detection, and disease prediction due to the increasing volume of patient data in medical imaging [1]. Currently, radiologists are increasingly focused on medical data mining to enhance patient care. Medical data mining and image denoising represent cutting-edge challenges for researchers [2]. This rapid advancement is driven by the need for cost-effective, accurate, rapid, and sustainable treatment options. Technological advancements are facilitating easier detection and prediction in imaging [9].

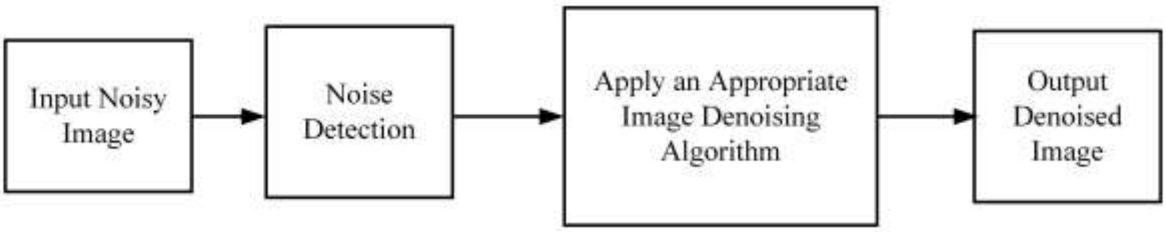

Figure 1: Basics of preprocessing

Examples include radio astronomy, medical imaging, natural picture processing, and more [3]. Every application might be predicated on unique needs. In other words, because denoising may result in the loss of tiny details like edges, textures, etc., because they share the same high frequency spectrum as generated noise, it is important to approach noise reduction in natural photos with particular caution.
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2. REVIEW OF LITERATURE

According to Fatima and Pasha (2017), decision trees yield high variance and minimal bias [10]. Lower bias indicates that the model can fit and accommodate the training data well, while high variance indicates that the test dataset performs poorly while the training data set performs well [13]. While high variance is not a good thing, low bias is; this random forest adds some flexibility and turns the high variance element into a low variance [5]. Because classification problems are difficult to solve with a single decision tree, the random forest is preferred over the decision tree [6]. Since the random forest depends on a large number of trees, some flexibility and unpredictability will be included [11]. According to Ul Hassan et al. (2018), the Random Forest classification approach is a bootstrap data set that is created by selecting the data at random and including duplicates from the data; this is known as random sampling with replacement [4]. The final decision in a classification problem is COPD disease; we have the original training set for COPD, so we will use it as a bootstrap data set to build a random forest. Next, Make use of the bootstrap dataset to build a decision tree. Select the candidate that goes to the root while building the decision tree. The candidate who divides the data well will go to the best root out of those with many qualities. With the aid of the Gini index, we chose the root node. When there are several qualities, we select two at random, determine which is the best, and designate that as the root. This is the second randomness that will enter the random forest algorithm's creation [7]. The decision tree technique is constructed similarly in the end: two candidates are chosen at random, and the best candidate is then used to create a decision tree for the bootstrap data. Step three would be to repeat repeatedly in order to produce a larger number of decision trees.

3. MATERIALS AND METHODS

The wavelet-based approach facilitates rapid computation and effective de-speckling while preserving essential image details for enhanced diagnostic accuracy. Since many research rely on small datasets, which limits their application to bigger datasets, the analysis shows a huge disparity in both the quantity and quality of datasets employed. Furthermore, the system's overall effectiveness and the quantity of patients diagnosed by radiology are impacted by the processing time for detection and classification algorithms.

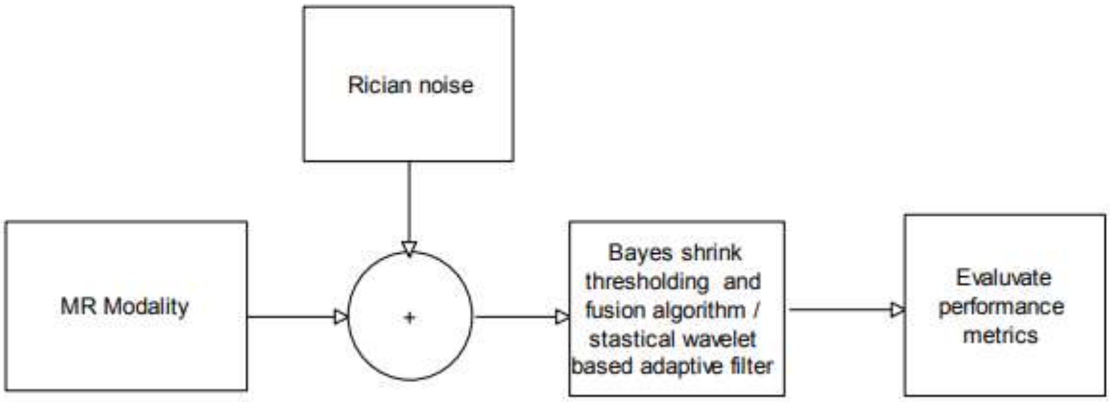

Figure 2: Flow diagram

Meta algorithms are machine learning techniques used in ensembles [15]. It integrated many machine learning methods into a single predictive model in order to accomplish one of three goals: lowering the variance (known as bagging), lowering the bias (known as boosting), and then improving the predictions (known as stacking) [14]. The training data is being separated into different datasets [8]. When all of these predictions are integrated into a single learner or classifier, the results are superior to those of any one of these classifiers alone[12]. Sequential as well as parallel and ensemble methods are the two basic groups into which the ensemble methods fall. One strategy to better the students is to form an ensemble of them. The fundamental tactic of the ensemble method is to put together multiple algorithms or models to produce an ensemble learner. In this instance, we have several models that were trained on the same data. Each model produces its own findings, which are then combined to create the ensemble model's predictions. The outcomes of machine learning can frequently be greatly enhanced by ensemble learning.

4. RESULT AND DISCUSSION

Image quality measurement encompasses two methodologies: a subjective approach and an objective approach. The subjective assessment of image quality (IQA) relies on human evaluation, as the primary users of most multimedia applications are individuals. Consequently, subjective evaluation is deemed the most accurate and reliable method for assessing image quality.

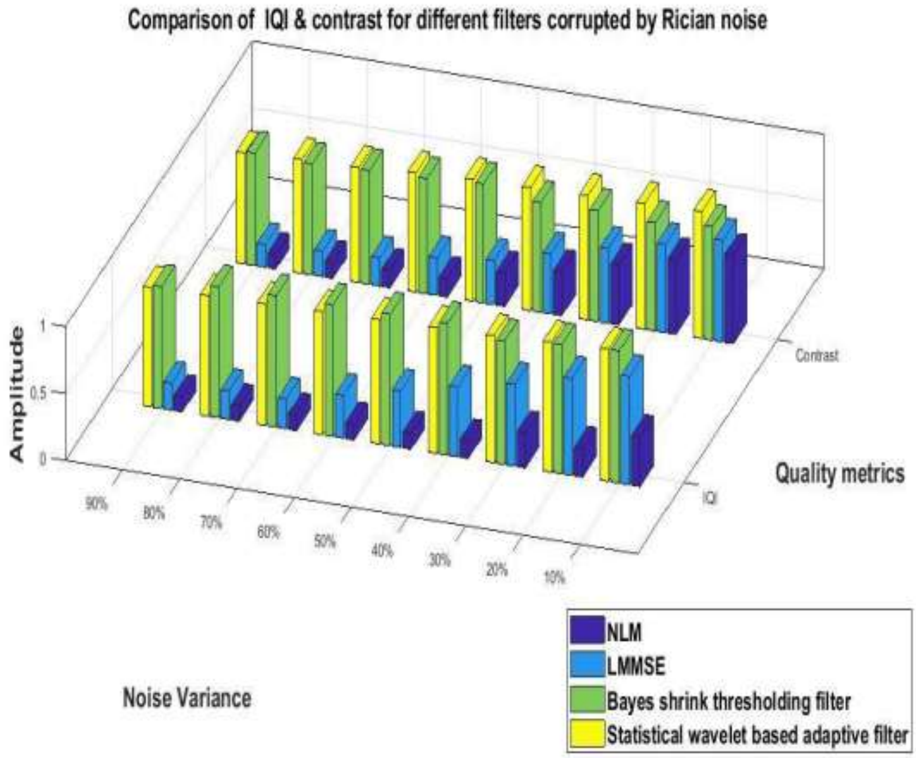

Figure 3: different filters for clinical MR data corrupted by Rician noise

However, this process is often slow, challenging, and costly for practical applications. As a result, objective criteria for image quality that calculate image quality automatically are far more practical. The goal The goal of IQA research is to produce metrics for image quality that closely match subjective assessments.

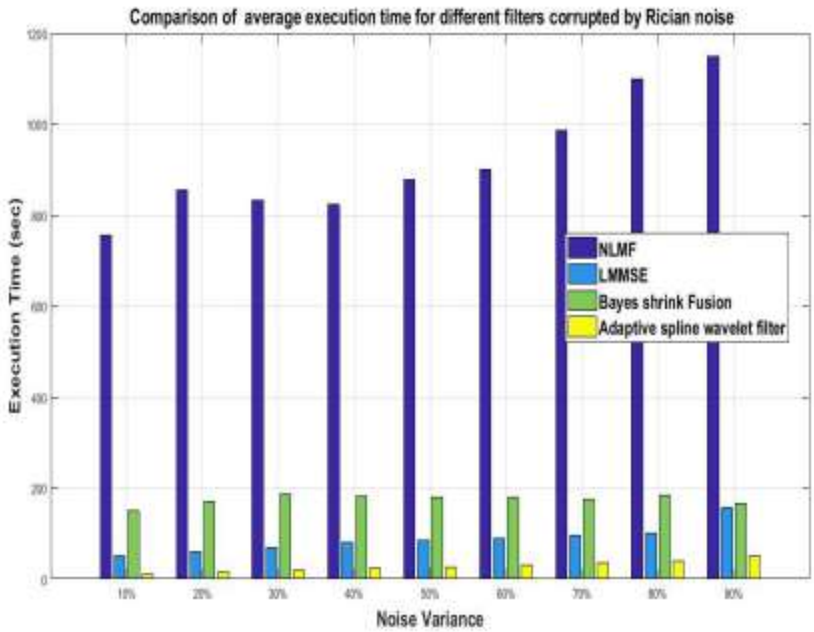

Figure 4: Execution time

The noise in question is of the impulse type, referred to as intensity spikes noise, originating from the transmission channel. It manifests as small black and white dots, where the minimum intensity pixel values appear as black dots and the maximum intensity pixel values as white dots, commonly known as salt and pepper noise. This type of noise is primarily generated due to faults in camera sensors, improper pixel components, and incorrect memory positioning.

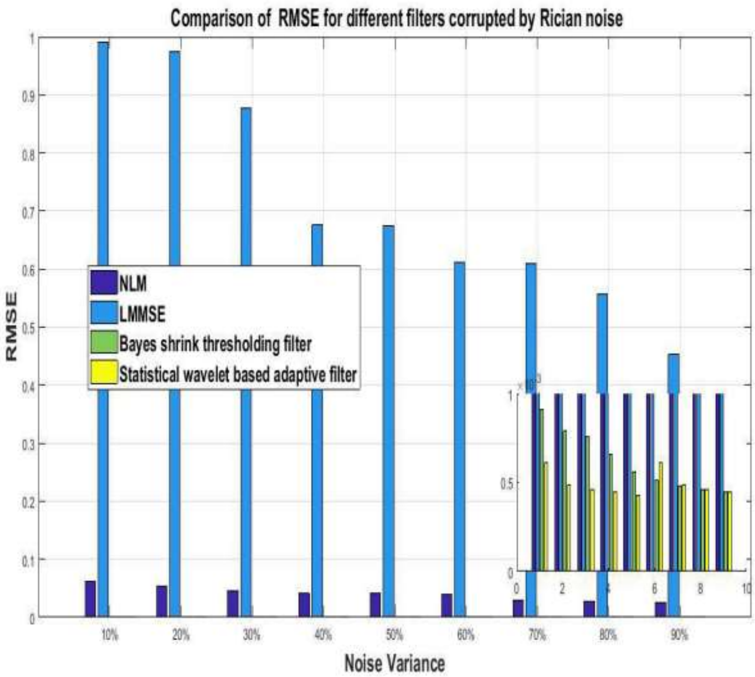

Figure 5: Comparison of RMSE values of different filters

Figure 6 illustrates the appearance of salt and pepper noise. Additionally, it encompasses periodic noise, Brownian noise, speckle noise, white noise, and shot noise, each with distinct sources of generation.

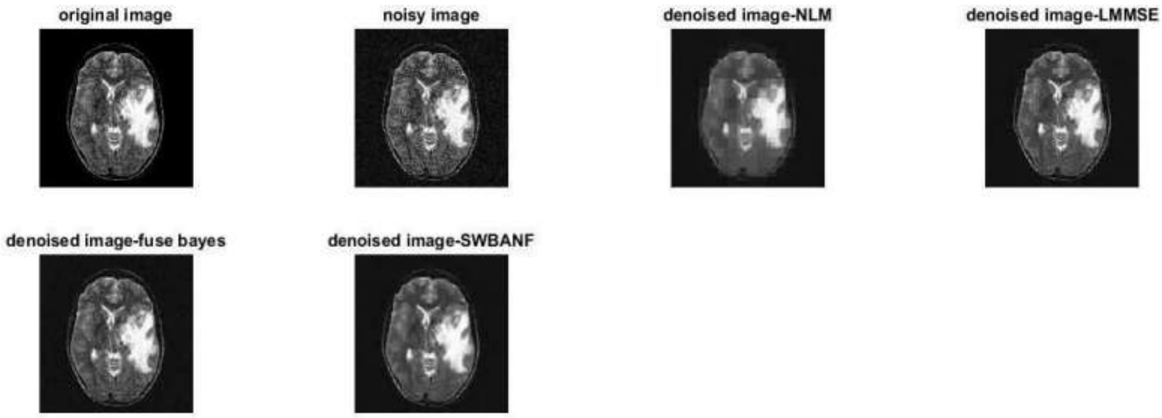

Figure 6: Restoration results of T1 weighted MR brain image

Periodic noise arises from electrical interference, typically occurring during image acquisition, especially in the presence of a strong mains power signal. Multiples of a particular frequency define its space-dependent, often sinusoidal nature, and it is recognized as a conjugate spots pair in the frequency domain.

5. CONCLUSION

To provide a methodical strategy for the diagnosis and prediction of medical pictures, this research looks at a variety of denoising approaches in conjunction with machine learning strategies. It takes into account a number of machine learning techniques that concentrate on making predictions using known traits obtained from training data. An analysis of the literature shows that present approaches' accuracy is insufficient, requiring improvements to attain higher consistency, since Naive Bayes outperforms kNN and SVM in terms of accuracy. A critical requirement is the availability of a benchmark database of ultrasound scanned images to facilitate the dynamic comparison and evaluation of different algorithms within the context of CAD systems.

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