Medical Image Denoising Classification on Machine Learning System

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Abstract

Advances in medical imaging technology continue to create new possibilities for the collection of medical data that are important in timely and accurate diagnosis, in monitoring progress, and in the treatment of various diseases and in medical research. The capabilities of the new skills arise mainly from the technologies depicted in the vivo interior of the human body. Thus the study of the morphology and function of the various organs and the detection of any pathogens is achieved in a very direct way. The "source imaging data" provided by them is important information, but their large number is constantly growing, but their nature also creates the need for further processing with the help of computers. The primary purpose of processing images is to use denoising that includes the elimination of noise due to technical errors and feature preservation. Following noise reduction, the image segment, i.e. the location or areas of interest in an image, is the central objective of the process. In addition, usually, the complexity of the data in large volumes and charts requires a lot of time to study and a lot of experience to do their interpretation correctly. Therefore, in many cases, its automation using machine learning seeks out the partitioning process, but also categorizes images, i.e. classifying an image or parts of an image into specific categories. In most applications, machine learning performance is better than conventional techniques.

Keywords: Neural Network, Denoising, Deep Learning, Machine Learning, Image Processing.

1. Introduction to Medical Imaging

Developments in medical imaging technology have created and continuously create new possibilities for collecting medical data, which contribute important in timely and valid diagnosis, in monitoring progress and the treatment of various diseases, as well as in medical research. The new capabilities arise mainly from technologies that depict in vivo interior of the human body. This is achieved in the most direct way by the examination of the morphology and function of the various organs and the detection of any pathogens. The "raw imaging data" give by themselves important information, but their large number is constantly growing, but also their nature, create the need for their further elaboration with the help of computers. Thus, almost as a rule, its first stage application of various techniques and procedures for the collection of illustrations data, follows a second stage, that of their digital processing and of their interpretation. Computer-supported analysis of medical imaging data, but also the integration of relevant information when it comes from multiple sources, is now a broad and ever-evolving field of scientific research that creates prospects for the faster and more complete interpretation and utilization of this data.

1.1 The Medical Imaging Technology Systems

By the general term, Medical Imaging Systems characterize the set of techniques and procedures for both productions of images of the internal structures of the human body (pathological information), as well as for its visual representation function (functional information) of the various organs or tissues of the human body.

Today there are and are widely used various medical systems imaging that is basically distinguished depending on the type of radiation that interacts with biological tissues. The main imaging systems (known by their English acronyms) are CT, MRI, ULTRASOUND, OCT, PET, SPECT, with their various variants. In some cases, in medicine in practice, two or more different techniques are combined and Hybrid systems have also been developed for this purpose. The composition of the data from different imaging techniques ultimately aims at the most comprehensive image of the examined organ or tissue and in the most reliable export conclusions. Combined application is made for the utilization of comparators' advantages of certain techniques.

1.2 The digital processing of the medical image

- Image processing is the general framework of the approaches that apply to the present dissertation. It is a complex computational process and refers to the plethora of mathematical and algorithmic techniques that apply to images (considered as two-dimensional or three-dimensional signals) and their result can be "new images" where what we want is clearer to observe and/or a series of parameters that highlight or "reveal" the information needed to solve specific problems. The main goal of processing is always fast and accurate export essential information about the objects of interest. Here the peculiarity of the medical images must be pointed out, since

- Concern the internal structures and function of the human body, ie the representation of complex and dynamic biological systems and
- Arise, mostly after reconstitution or reconstruction of images reconstruction) of imaginary sections of tissues and organs from their multiple projections. Yet, the medical images obtained by applying the various techniques, usually present distortions - alterations, errors (artifacts) that related to the additional information entered by the user equipment or technique, but also in the presence of unwanted residues in examined tissue or end to patient movement. The initial purpose of processing images is the removal of noise due to these technical errors. Noise reduction is followed by image segmentation that is, locating in an image the area or areas of interest, a process which is the central objective of the processing. In addition, the large volume usually and the complexity of the illustrations data require a lot of time to examine and a lot of experience to properly their interpretation. Thus, in many cases, its automation is sought partitioning process, but also the categorization of images classification), i.e. the classification of an image or areas of an image into specific categories.

It should be emphasized that in general segmentation and categorization are the most basic aspects of image processing and that the application of relevant techniques constitutes its core and the prerequisite for the correct interpretation of medical data. Also that basically, the present research effort is focused and intended precisely in the development and selection of appropriate techniques, starting from the need to address specific problems of diagnostic medicine. Medical image processing, as a scientific discipline, already provides many appropriate techniques and methods but is always a challenge and object research. The question is which specific method is the best with reference to the data type (imaging technology, imaging object) and processing targeting. At the same time, however, medical image processing has its own continuous development. Recent developments in machine learning and against the main reason the use of Neural Networks have created new possibilities in medical image processing [1]. One of the problems in it refers to denoising, which is aimed at recovering an image from the rating. That process involves image pre-and post-processing and filters. This pre-processing stage is usually implemented in image reduction, sharpening, compression, and machine learning tasks. It also allows you to block art events such as definition and sound in the post-image marking process. Currently, with the advancement of machine learning, in specific, in-depth learning, image-representing techniques have made great strides and can capture competitive improvement than model-based denoising techniques [2].

2. Survey on Image denoising and Image Classification

2.1 Image Denoising Filtering Techniqes

Every signal is polluted by noise, so it is to remove the noise from the signal. If the signal is in the form of an image, the phenomenon of noise removal is called image denoising [3]. Image dinosaur encourages researchers to constantly participate and focus on performing better, resulting in the development of current sophisticated art. There is still room for improvement [4]. These distortions include noise, blur, and distortion, which introduce artifacts. Image Restoration rejects these distortions and maintains its excellent details. The main purpose of image recovery is to recreate the original image from its distorted version under unknown properties. Non-linear gate filtering techniques have been shown to be very effective in erasing images, but if the system has unknown dynamics, these techniques will no longer be effective. Therefore, some adaptive control strategies are needed to obtain an appropriate solution. Alternatively, non-linear threshold filtering techniques can be used in the wavelet field to complete a specific task. Wavelet Transform (WT) can accurately estimate any linear function defined in a small package [5]. Because of the inherent properties of limited support and self-alignment, bandwidth is best suited for depicting functions with local linear and rapid variations. WT can approximate any finite energy function. It has a very efficient learning ability and excellent concentration rate and does not require any preliminary requirements [6]. One of the foundations of a large part of denoising methods comes from the reduction of variance linked to averaging. Thus, the greater the number of averaged pixels, the larger the denoising is present. However, averaging pixels that do not have the same amplitude (without noise) introduces bias problems. We, therefore, identify the famous problem of the bias-variance trade-off. It is, therefore, necessary to find a strategy relevant to choose the pixels to average between them. Thus, the most natural idea to carry out denoising consists of averaging the pixels on a neighborhood, typically using a Gaussian kernel. This, therefore, supposes an assumption of regularity on the image: the neighboring pixels look alike. If the nucleus is chosen large enough, it is possible to obtain completely satisfactory denoising for a constant image. However, we understand that the presence of an outline or any pattern in the image will introduce significant bias issues locally.

The method introduced in [7] makes it possible to limit this problem by choosing the pixels to be averaged, not by their spatial proximity, but by their photometric proximity. Thus, an averaging weighted by the photometric distance exhibits content preservation properties (contours, textures, etc.) much more interesting than a spatial average. A compromise between the two approaches is achieved by [8]; the weighting is calculated as the product between a spatial distance and a photometric distance. This method, therefore, obtains a better compromise compared to the two previous ones. We can also classify classical variational methods, such as [9], in this category because they model the images as random Markov fields relating neighboring pixels.

The construction of wavelet theory allowed great advances in denoising methods. The properties of time/frequency localization of wavelets, unlike the Fourier transform which is not spatially localized, were fundamental for the use of the concept sparingly. The representation of a signal in a transformed space is said to be parsimonious if very few coefficients are non-zero. Noticing that the noise in the transformed space is not parsimonious, unlike the signal, it suffices to select the coefficients whose value is too large to be considered as an issue of noise in order to carry out denoising. This thresholding principle is at the heart of methods proposed by [10], which operates gentle thresholding of coefficients, and by [11] who chooses the value of the threshold thanks to a Bayesian approach. Later, the algorithm described in [12] models the dependencies between the coefficients of the wavelet transform by mixtures of Gaussian laws. Introduced in parallel by [13] and [14], so-called non-local methods quickly surpassed wavelet methods. In a way, it is a question of returning to the philosophy of the method of [7] but by using patches instead of pixels. We define a patch as a small window extracted from the image. A patch, therefore, contains richer information than a single pixel, but simple enough to verify the hypothesis. Say self-similarity. Patch methods are based on an image property natural: there are many similar patches in an image.

This method can be considered as close to the learning methods called the dictionary. A dictionary is a family of vectors called atoms, generally small, which allow a signal to be represented by combinations linear. Dictionaries can be seen as a generalization of the concept of basis in mathematics by relaxing the constraints of having a free and generative family. Indeed, the choice of a redundant dictionary (and therefore a non-free family) allows obtaining very useful parsimony properties for denoising. In addition, the choice a dictionary that generates only relatively smooth images makes it possible to avoid encoding the noise once the image has been represented in the transformed space. It can therefore be interesting to have a family that is not generative. The wavelet methods that we have seen previously fall within this framework theoretical, each wavelet being considered as an atom of what is commonly called a dictionary of wavelets. Here, it is no longer a question of analytically defining the atoms like regular functions, but to learn these atoms over a collection of natural images or the noisy image itself. The popular method named K-SVD was introduced by [15] and is inspired by the K-means algorithm. From a training data set, K-SVD learns a dictionary that best represents that data while by imposing a constraint of parsimony using an L norm on the coefficients.

Finally, the Piecewise Linear Estimator (PLE) method proposed by [16] applies an expectation-maximization algorithm for denoising. A dictionary of Gaussian models representing patches is initialized using images of synthetic outlines. Then, the method iterates between steps of expectation, where the patches are denoised in accordance with their closest Gaussian model, where the Gaussian models are updated with the denoised patches. The EPLL method introduced in [17], and which also models patches by Gaussian models. Using a dictionary learned on the image more recently, it has been noticed that learning dictionaries directly on the noisy image give interesting results. Indeed, even if the data learning is then noisy, the information they contain is much more relevant. This is the principle used by the Non-Local Bayes (NLB) method [18]. This method remains very similar in idea to that proposed in [16]. One of the main differences being the initialization of the dictionary with synthetic images for PLE then that it is initialized with the noisy image only for NLB. The work described in [19], which is an extension of the method introduced for a Gaussian noise in [20], propose to use a PCA to learn a patch dictionary on an image corrupted by Poisson noise. We are now interested in the BM3D method which is described as the reference state of the art for almost a decade. First presented in [21], this algorithm uses many ingredients that have shown their potential for denoising. An iterative method: like NLB, BM3D performs denoising in two steps. The method performs coarse denoising which is then used to better estimate parameters in a second iteration. Self-similarity of the image is by a grouping of patches like NLB. Classification of objects is a predominant research area and offers real-life applications in different fields, such as pattern identification, artificial intelligence, and vision analysis [22-24]. There are commonly two kinds of classification. One is referred to as unsupervised classification and the other is referred to as supervised classification. Unsupervised classification is the recognition of natural groups, or structures, within multi-spectral data

2.2 Machine learning methods

Machine learning is related to the creation of algorithms that, based on data, improve their ability to provide assessments based on the knowledge representations they develop. Deep learning is a rapidly evolving field of machine learning. In deep learning, it is done use of computer architectural Technical Neural Networks, with multiple layers of neurons. The computing Experience has shown that deep learning architectures can discover the complex internal (non-obvious) structure in a large amount of data. The methods of deep learning have found in recent years an ever-increasing application in the field of medical informatics in the field of medical processing images.For an introduction to the methods used in this research work, there will be a very brief presentation of its basic principles and concepts of machine learning and neural networks. The basics of a machine learning method are an optimization algorithm, a function cost, a model, and a data set [47]. The projects are usually classification, regression, noise reduction, and price estimation missing in one signal as well as others. For example, object recognition in pictures is best achieved with deep learning [25]. The performance of one machine learning algorithm can be measured accurately, i.e. the ratio of the correct outputs to all inputs. Otherwise with the error rate set is the ratio of errors to all inputs. In terms of experience, algorithms are generally categorized into unsupervised and supervised. Those without surveillance algorithms gain experience over a set of data with characteristics. But there are no labels, whenever they determine which properties are specific to that data set. Those with supervision algorithms gain experience on a data set with features that are associated with a specific tag.

Very recently, the explosion of calculation capacities and the establishment of sets of increasingly comprehensive data have allowed the development of so-called network methods called deep neural networks. These methods, for which very few theoretical results are available, produce extremely high-performance models and have proven to be very flexible. A particularly striking demonstration is made by [26] who propose a denoising method using no a priori. Thus, the authors train a multi-layered perceptron (which is more flexible than Convolutional Neural Network (CNN) architectures) using a large dataset of workouts made up of pairs of noisy and noiseless images. Performances obtained are comparable to the BM3D algorithm introduced in [27] which is however much more complex algorithmically. At the same time, [28] proposes to use another architecture based on auto encoders and obtain equally interesting results. The latest proposed methods still seem to surpass the previous ones. We can in particular cite [29] which learns the residuals following degradation of the image (noise with known or unknown variance, compression, etc.). This method which can be seen as a generalization of the work done by [30] uses a particularly deep CNN architecture. The results appear to greatly exceed the old state-of-the-art for all applications. We can notice that the work presented in this thesis takes up this concept of using the full potential of the residue by removing the learning aspect. The performances are therefore obviously worse, but the theoretical study and interpretation are more advanced. In [30], an automatic method for the detection of arterial lumen and calcareous slab is referred. Arterial lumen segmentation was based on potential shape programming. The calcareous plaque was detected by edge detection and adapted better using an active contour model. In [31] spectral analysis to highlight lipid plate in OCT images is used. In [32], each radial line in IVOCT data as a linear combination of a profile number depth is modeled. After evaluating these profiles through an optimization strategy least squares, classified the tissue types based on morphological characteristics. Their method was tested on ex-vivo data and was effective in identifying fibrous and lipid tissues. In terms of machine learning, there are mixed methods that use either classifier for empirically hand-crafted features or export the characteristics of neural networks (usually for the characterization of pixels). In [33], the features are empirically extracted and SVM, RBF classifiers to detect calcifications, fatty plaques, and fibrous tissue / fibrous plaque are used. In [34], a methodology that makes arterial detection is proposed possible lumen identifies the area of atherosclerotic plaque and classifies four Atherosclerotic tissue types: calcareous (CA), adipose (LT), fibrous (FT), and mixed (MT). The effectiveness of the method was evaluated using labels from 27 sections of arteries taken from 22 patients. In [35], the features are extracted from radial lines using CNNs and classified the parts of the arterial wall into the intima and middle tunic (media) using CNN, random forest (RF), and support vector machine (SVM). They used 26 image series from IVOCT. The object of their research was related to the location of plaques. But their results are not comparable with those of the work to locate the atherosclerotic plaque.

The method of [36] included the export of texture statistical features, application of an algorithm grouping (K-medium) without the oversight of these features, and mapping of grouped areas in the background, atherosclerotic plaque, vascular tissue. There are 3 important tasks with the application of deep learning for the characterization of entire images. The method of [37] used the ResNet and DenseNet to classify the entire OCT image into one of 3 categories: an image without atherosclerotic plaque, an image with calcification, and an image with fibrous / lipid plate. They investigated the use of Cartesian and polar coordinates and used combinations although they found that the images in polar coordinates contribute more to the correct classification. The method of [38] made use of the intensity, the Oriented Slope Histograms, and Local Binary Standards Binary Patterns (LBP) of images to represent them. In the corresponding representations (or features) a linear SVM classifier was applied to the detection of abnormal tissues in 43 patients (distinction in normal and abnormal). The same group in a new post [39] expanded the possibilities of the previous method and used the Fisher vector as well texture features of their previous work for image classification IVOCT in five categories: Normal, Fibrous plaque (FP), Fibro arthritis (FA), plaque rupture (PR) and fibrous calcified plaque (FC). The final ranking was made again with SVM while emphasizing the fact that in this work the images were in polar coordinates. Other works applied deep learning to parts of the images in pursuit of their full semantic interpretation.

The method of [40] implemented the fully-connected network architecture known as SegNet. The data set was 51 images from 13 patients. The image was divided into sections 100x100 in order to detect only the calcareous plaque, which was achieved with an accuracy of 0.7. The method of [41] presented a method of applying a prototype cohesive network in 269 images from 22 patients. Images split into square sections 51x51 and trained the neural network. They chose to classify the tissue into 4 categories, ignoring the fibrous plaque or considering tissue and fibrous plaque in the same category. Nevertheless, the performance of the algorithm in the detection of the calcareous plaque was very low

Dice = 0.22. Finally, the big one's patches did not allow a good resolution of the final result review of IVOCT deep learning methods - the most important of which already mentioned - with a separate reference to the methods of extracting the rates retraction and attenuation.

One of these is the work of [42], who highlighted the importance and modelled it more accurately attenuation index. The categories they tried to identify are h pathological thickening of the inner lining, the necrotic nucleus, and the infiltration by macrophages. The method [43] used the attenuation index to detect lipid plaque in a patient. The method of [44] showed that the estimation of the attenuation factor also contributes to the better of manual labour segmentation by specialist physicians [45] presented a very clear and documented method for estimation of the feedback factor, after estimation of the coefficient absorption. This method was used by [46] for the development of a manual thrombus detection method.

The method of [46] segmented lungs from images using threshold selection. The method of [48] focused on CT images. The authors used binary partitioning for segmentation. Likewise in [49], CT images were aligned with SPECT for the analysis of the ventilation/perfusion relationships of the lung lobes. The method of [50] used SPECT and CT images to demonstrate the ability to perform their classification of diseases. The several denoising methods are also reviewed [51-58].

3. Analysis of Denoising Filtering Techniques

Table 1: A Survey of Denoising Filtering Techniques

Denoising Filtering Techniques	Features	Advantages	Disadvantages
Bilateral filtering, total variation denoising nonlocal means (NLM) denoising local linear SURE based edge-preserving image filtering (LLSURE) and K-singular value decomposition (KSVD) algorithm	Take an advantage of statistical properties of objects in image space	Preserve sharp edges, similarities between neighboring pixels, etc.	Expensive
Homomorphic wavelet	The threshold has been extended to the redundant wavelet representation, which yields better results	Reduce speckle noise	Phase unwrapping and restrictions of sparsity in the reflectivity function
Projection based techniques	Work on raw data or sinogram, where noise filtering is applied on raw data or sinogram and reconstructed image comes in the form of denoised image.	Advantage of using noise statistics directly in the projections during the reconstruction process	High computational cost
DCT Basis and Sparse Representation	From this method which is based on the K-SVD algorithm by learning dictionary from the noisy image itself.	Better to denoise the white noise and keep the edge information,	The computation of this method is slow
Gauss–hermite expansion	This expansion is used in view of the fact that it allows higher order moments to be incorporated in the probabilistic modelling of the wavelet coefficients.	It has a uniform mean square convergence, the parameters can be expressed in terms of higher order moments in closed-form and the polynomials can be estimated recursively.	It is found in particular that pixel variations may be vast in some cases which potentially tend to develop irregularities in the image
Fractal-wavelet	Used to reduce the blockiness and computational complexity that are inherent in fractal image compression.	Computationally less expensive.	A problem with this technique is that only negligible noise smoothing is generally performed in the vicinity of edges
Discrete wavelet transform	Discrete wavelet transform of an image produces a non-redundant image representation that provides better spatial and spectral localization of image formation, compared to other multi scale representation	In this method, translation invariant performed better performance in both PSNR and visual quality than wavelet denoising	Presents oscillations in the vicinity of signal discontinuities
Soft thresholding]	It first sets to zero the elements whose absolute values are lower than the threshold, and then shrinks the nonzero coefficients toward 0	Gives better performance for visual appearance of images.	Soft thresholding has a limitation with large coefficient values which may not be good for more sophisticated CT images
Non homomorphic	Nonlinear mapping to a different domain in which linear filter techniques are applied, followed by mapping back to the original domain	remove multiplicative noise	It is indiscriminate
Wavelet based statistical	The method is based on the generalised Gaussian distributed (GGD) modelling of sub-band coefficients.	Speckle-reduction method	The difficulty in understanding the results obtained
Haar wavelet transform	The algorithm can effectively clean the noise of image and reserve the detail and veins of image, and obtain a good visual of image	The main key point is that the wiener filter is used in this method which can obtain higher PSNR after cleaned the image noise.	Not continuous, and therefore not differentiable.
Curvelet and contourlet	Coutourlet is a real represent method of	Contourlet transform can	Not able to preserve edges

4. Analysis of Machine Learning Algorithms

Table 2: A Survey of Machine Learning Techniques

Machine learning algorithms	Features	Advantages	Disadvantages
Decision Tree	Predictive model which is a mapping from observations about an item to conclusions about its target value.	Variable transformations are not required and saves data preparation time	Relatively inaccurate
ANN	They have self-learning capabilities that enable them to produce better results as more data becomes available.	Image pre-processing, date reduction, segmentation and recognition are the processes used in managing images with ANN	Disadvantages include its 'black box" nature, greater computational burden, proneness to over fitting, and the empirical nature of model development.
SVM	It is essentially a binary (two-class) classification technique, which has to be modified to handle the multiclass tasks in real world situations	Solve linear and non-linear problems	It does not perform very well when the data set has more noise i.e. Target classes are overlapping.
RF	Several decision trees are created (grown) and the response is calculated based on the outcome of all of the decision trees.	Non-parametric, capable of using continuous and categorical data sets, easy to parameterize, not sensitive to over-fitting, good at dealing with outliers in training data	Large number of trees can make the algorithm too slow and ineffective for real-time predictions
GAN-CNN	The main goal is to train the Neural network to work with unknown noise levels since most of deep neural networks Are trained for certain specific ones.	The model handles noisy though 2 stages For generating noisy model and denoising	Complicated to train
Noise2Noise (N2N)	It has the ability to learn and reduce Noise from unpaired training data.	The training directs the loss function to minimize the predicted pixel estimation Problems separately from corresponding input	Exploits a strategy for recovering degraded Images without using ground-truth images
MWCNN	The aim of MWCNN[43] is to make the balance between neural learning capacity and computational costs by manipulating images in multiple levels of wavelet transform	Enhance the detail patterns And sharp structures from the noisy image	Variations are not taken into account for operation.
BMCNN	It is a denoising method that aims to take the advantages of both NLS and CNN.	Combined the advantages of non-local and learning based Techniques for the enhancement of the visualization performances including irregular And repetitive structures	Lots of training data is required
NN3D	NN3D is a powerful denoising method that is inspired from both NLS and learning based Methods.	Improved performance by integrating pre-trained neural network and preserving image Details	It often leads to hallucinations
BM3D-Net	BM3D-Net is a network inspired by BM3D and allows BM3D algorithm to have the benefits from the learning capacity of a neural network.	Achieves better denoising performance on real images	Challenging To solve arbitrary noise problems
DnCNN	Residual deep CNN architecture for image AWGN denoising.	Tackle the main problems of training Great deep neural networks such as vanishing/exploding problems.	It is inefficient for those networks to improve their performances by increasing the number of learning parameters because of diminishing feature reuse problem that limits the contribution of last several neural networks.

5. Denoising Evaluation

Currently, subjective and objective evaluation is the available approach to evaluate the quality of the denoised image. Former evaluates from a qualitative attitude and the latter evaluates from a quantitative attitude. However, until now there is lack of uniform criteria for assessing the denoise effect. PSNR and SSIM are performed to evaluate the denoise effect of images[29, 30].

Let g(i,j) and F(i,j) represents is the gray value of the input image and the denoised image, the size of the image is M×N. Then PSNR is:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[\mathrm{g(i,j)} - \mathrm{F(i,j)}] \ldots\ldots (1)$$

$$PSNR = 10log_{10}\left[\frac{255^2}{MSE}\right] \ldots\ldots (2)$$

The smaller is the MSE value, the larger the PSNR value. This means that if the difference between the original and denoised image is small, and the denoise effect is excellent.

SSIM is an image quality rating index based on structural similarity. It is given by

$$SSIM = \frac{(2v_1v_2+d_1)}{(v_1^2+v_2^2+d_1)}\frac{(2\delta_{12}+d_1)}{(v_1^2+v_2^2+d_2)} \ldots\ldots (3)$$

where v_1 and v_2 are the pixel means of original and denoised image respectively. σk is the pixel variance, $\delta_{12}$is the covariance, and d_K is a constant. If it is close to 1, it indicates that the denoised image is identical to the input image. This means retaining additional edge details of the input image.

Conclusion

This chapter provided the review on the details associated with image denoising and classification techniques, their challenges in addition to the benefits and shortcomings. It also addressed the detection medical images employing a variety of algorithms. It is very important to learn patch-based dictionaries to learn noise from the medical images using machine learning techniques. This can reduce the noise along with preserving the edges of the images with maintaining their visual quality. The restoration of medical images and overcome from degradation is also a challenge while denoising them. Machine learning approach is better than any other method for image. While using machine learning and specifically decision tree for denoising medical images, the main benefit is low complexity but accuracy of classification depends on the design and features of the classifier. This way, the denoising and classification employing various algorithms has been studied.

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