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GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

MEDICAL IMAGE COMPRESSION BASED ON VECTOR QUANTIZATION AND DISCRETE WAVELET TRANSFORM

MSc THESIS

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Thesis Advisor: Prof.Dr. Ahmet ZENGİN

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The thesis work titled “MEDICAL IMAGE COMPRESSION BASED ON VECTOR QUANTIZATION AND DISCRETE WAVELET TRANSFORM” prepared by Azhar ABDULHASAN MUHAMMED ALI AJAM was accepted by the following jury on 14 /07/2023 by unanimously/majority of votes as a MSc THESIS in Sakarya University Graduate School of Natural and Applied Sciences, Computer Science department.

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Sakarya University

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(14/07/2023)

Azhar ABDULHASAN MUHAMMED ALI AJAM

To those who gave my life, hope and ambition: my parents,

To the person who believed in me and helped me to reach my goal, my dear friend, my beloved husband,

To my children who supported me and endured the hard times with me, my heartbeat and my Darlings,

To everyone who helped me, even if it was just a word:

I dedicate this work to you with great thanks and gratitude.

ACKNOWLEDGMENTS

After completing the preparation of this thesis, we could not continue unless I express my sincere thanks and great gratitude to Prof. Dr. Ahmet Zengin, who kindly supervised this research, supported me fully and advised me during the preparation period. To him, all my thanks.

I also express my thanks and gratitude to Dr. Ahmed Al-Baghdadi, who gave me his valuable time and extensive experience, which constituted a great addition to the research work.

I also express my thanks and gratitude to my family for their support and assistance throughout my studies.

Azhar ABDULHASAN MUHAMMED ALI AJAM

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ABBREVIATIONS

AC	: Arithmetic Coding
BPP	: Bits Per Pixel
CR	: Compression Ratio
CT	: Computed Tomography
DCT	: Discrete Cosine Transform
DICOM	: Digital Imaging and Communications in Medicine
DWT	: Discrete Wavelet Transform
FMRI	: Functional Magnetic Resonance Imaging
LWT	: Levitation Wavelet Transform
MAF	: Moving Average Filter
MRI	: Magnetic Resonance Imaging
MSE	: The Mean Square Error
MSSIM	: Mean Structural Similarity Index for Measuring image
RMSE	: Root Mean Square Error
PSNR	: Peak Signal to Noise Ratio
PSO	: Particle Swarm Optimization
SSIM	: Structural Similarity Index for Measuring Image
VQ	: Vector Quantization

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MEDICAL IMAGE COMPRESSION BASED ON VECTOR QUANTIZATION AND DISCRETE WAVELET TRANSFORM

SUMMARY

Due to the prevalence of chronic diseases, diagnostic imaging procedures are increasing annually. However, storage is challenging because storage capacity is limited to accommodate these ever-increasing medical images. As a result, it has become important to develop new ways to compress these images due to their large sizes. Therefore, there is a need for a compression method that preserves medical diagnoses and has a high compression ratio. Image compression aims to significantly reduce the size of different types of images while preventing distortion and harmful distortion during reconstruction. The medical image compression system is an important topic in image processing systems to reliably compress and decompress various types of medical images since image compression has become the latest emerging trend all over the world. This can be accurately implemented for both lossy and transparency techniques, such as discrete waveform transform (DWT), discrete cosine transform (DCT), fractal-based and wavelet-based notation vector quantization (VQ), predictive coding, and so on. Although these techniques are used to design the compression system, they face some challenges, such as reducing the original size, level of computational complexity, and minimum square of compression errors. This thesis addresses these critical challenges to improve medical image compression performance.

There are two main ways to compress images, each of which is determined by whether or not the original image can be reconstructed from the compressed image. Lossless compression is where no information is lost in compression or decompression operations, and this is used with medical images to keep all image information. Lossy compression is where the entire image cannot be decompressed because it uses a lossy compression method where some information has to be deleted. To compress digital images without losing quality, they are widely used along with JPEG.

The purpose of this thesis is to introduce a simple and effective image compression technique that increases the efficiency of the compression system and improves the performance of compression methods based on discrete waveform transform (DWT) while maintaining the mean structural similarity (MSSIM) and Peak signal-to-noise ratio (PSNR) at an acceptable level. Medical images represented by MRI, CT, and ultrasound are the data sources for this thesis.

We used MATLAB (R2022b) to formulate the necessary coding. To accomplish this work and to take advantage of the capabilities of the program in the field of image processing, this thesis proposes a combination of Discrete Wavelet Transform (DWT) and Vector Quantization (VQ) to process complex medical images while preserving the diagnostic content.

Medical images inevitably suffer from salt and pepper noise; in this method, filtering removes them during pre-processing. We use [3×3] Gaussian algorithm to determine the value of each pixel in the output image based on the value of its associated pixel and adjacent pixels in the input image. Then wavelet analysis (DWT) can divide image information into approximate and detailed partial signals. A close-up sub-signal shows the general direction of the pixel value, and three detailed sub-signals show vertical, horizontal, and diagonal details or changes in the image. If this detail is small, it can be set to zero without significantly changing the image. There are two types of filters, high pass filter and low pass filter. Thus, the signal is effectively divided into a detailed high-frequency part and a rough low-frequency part.

A Discrete Wavelet Transform (DWT) is applied to preserve the edges of the images (horizontal, vertical and diagonal) as the image is divided into four bands, and the sub-band conversion is repeated with the highest level of specificity. Vector Quantization (VQ) technique is used for data compression, correction, pattern recognition, density and clustering estimation. Missing data from some ranges is retrieved by finding the closest set, including the available data ranges. It will get the same value as the midpoint VQ applied to all the parameters generated by the previous step except for the sub-range. This contains the most important details for image recovery since the basis of VQ work is to represent pixel arrays by an index in the codebook. Many improvements are made to reduce the computation time for image compression.

The experiments performed at this point are different codebook sizes within different-sized windows for each image. Performance efficiency was evaluated with different sizes of codebooks and windows and for increasing the pressure by arithmetic coding. Then we use the threshold principle between the two methods that generate wave coefficients and exclude the value less than the specified threshold. The best combination of hybrid technology was found at two levels of DWT before quantification. This thesis tested the images by applying three separate analytical levels of the wavelet transform.

The resulting wave coefficients were then encoded using image coding techniques based on wavelet transform, which is arithmetic coding. With this proposed hybrid technology, we achieve a good performance, and by adding an operation optimization algorithm, we achieve even better performance.

The proposed compression scheme achieved better results than the referenced studies and increased the compression ratio. The test showed that decomposing the wave into three levels achieved the best compression ratio and the best encoding technique used with the previous wave. Several factors affect the results of the previous tests, the most important of which are the type of encoding technique for wavelet coefficients and the optimization algorithm used. Tests showed that decomposing the wavelets into three levels achieved the best compression ratio and the best encoding technique used with the previous wave.

To compress images, we use the arithmetic coding (AC) algorithm, which uses fractions between 0 and 1 to generate a unique string of characters. A data code encoding and decoding algorithm repeatedly processes and encodes (decodes) a single data code, making it symbolically iterative. When the algorithm iterates, it divides the period between 0 and 1 into smaller and smaller parts, keeping one of these pieces as a new period. The technology runs on layered time slots, each of which contains a sequence of code that is evaluated for size. Code stream size comparisons are used to reconstruct the data stream, indicating how the encoder divides and stores overlapping subintervals, unlike well-known compression methods such as prefix Huffman symbols.

Then we turn to artificial intelligence, using the particle swarm optimization (PSO) algorithm. The particle swarm development method is almost certain to find a globally optimal solution. The global search ability is also great, and the computational performance is much faster than traditional methods.

The test was done using the Compression Ratio (CR) parameter, the Mean Square Error (MSR) parameter, and the Peak Signal to Noise Ratio (PSNR) parameter. Experiments were performed with different codebook sizes and window sizes for each image. A test was performed to evaluate the efficiency of the measuring tool with different sizes of codebooks and windows. Experiments at both levels confirm the larger size of the codebooks. The best are chosen to maintain image quality and thus a suitable choice of the hybrid algorithm because image quality is critical in medical imaging.

At the end of the work, we compared it with a reference study where the fine image details were used in terms of extension, dimensions, and pixel depth, which gave better results than the referenced studies and increased the compression ratio. It was found that applying the proposed scheme to compress images using optimization algorithms helps to obtain the best results Providing several proposals to take into account the time and improve performance.

VEKTÖR KUANTİZASYONU VE AYRIK DALGACIK DÖNÜŞÜMÜNE DAYALI TIBBİ GÖRÜNTÜ SIKIŞTIRMA

ÖZET

Kronik hastalıkların yaygınlaşması nedeniyle tanısal görüntüleme prosedürleri her yıl artmaktadır. Bununla birlikte, bu tür görüntülerin depolanması çok zordur çünkü depolama kapasitesi, sürekli artan bu tıbbi görüntüleri barındırmak için yeterli değildir. Sonuç olarak, boyutlarının büyük olması nedeniyle bu görüntüleri sıkıştırmak için yeni yollar geliştirmek önemli hale gelmiştir. Bu nedenle tıbbi teşhisleri koruyan ve sıkıştırma oranı yüksek bir sıkıştırma yöntemine ihtiyaç vardır. Görüntü sıkıştırma kavramı, yeniden oluşturma sırasında bozulmayı ve zararlı bozulmayı önlerken, farklı görüntü türlerinin boyutunu önemli ölçüde azaltmayı amaçlar. Tıbbi görüntü sıkıştırma sistemi, görüntü işleme sistemlerinde çeşitli tıbbi görüntüleri güvenilir bir şekilde sıkıştırmak ve açmak için önemli bir konudur, çünkü görüntü sıkıştırma tüm dünyada en son ortaya çıkan bir trend haline gelmiştir. Bu, ayrık dalga dönüşümü (DWT), ayrık kosinüs dönüşümü (DCT), fraktal tabanlı ve dalgacık tabanlı notasyon vektör niceleme (VQ), tahmine dayalı kodlama gibi hem kayıplı hem de şeffaflık teknikleri için doğru bir şekilde uygulanabilir. Bu teknikler sıkıştırma sistemini tasarlamak için kullanılsa da orijinal boyutu küçültme, hesaplama karmaşıklığı düzeyi ve sıkıştırmada minimum hata karesi gibi bazı zorluklarla karşılaşırlar. Bu tezde, tıbbi görüntü sıkıştırma performansını iyileştirmek için bu kritik zorluklar ele alınmaktadır.

Görüntüleri sıkıştırmanın iki ana yolu vardır ve bunların her biri orijinal görüntünün sıkıştırılmış görüntüden yeniden oluşturulup oluşturulamayacağına göre belirlenir. Kayıpsız sıkıştırma, sıkıştırma veya açma işlemlerinde hiçbir bilginin kaybolmadığı bir yöntemdir ve bu, tüm görüntü bilgilerini tutmak için tıbbi görüntülerde kullanılır. Kayıplı sıkıştırma ise, bazı bilgilerin silinmesi gereken kayıplı bir sıkıştırma yöntemi kullandığından tüm görüntünün sıkıştırılmış halinin açılamadığı yerdir. Dijital görüntüleri kalite kaybı olmadan sıkıştırmak için JPEG ile birlikte yaygın olarak kullanılırlar.

Bu tezin amacı, ortalama yapısal benzerliği (MSSIM) ve tepe sinyalini korurken, sıkıştırma sisteminin etkinliğini artıran ve ayrık dalgacık dönüşümüne (DWT) dayalı sıkıştırma yöntemlerinin performansını iyileştiren basit ve etkili bir görüntü sıkıştırma tekniğini tanıtmaktır. Gürültü oranının (PSNR) kabul edilebilir bir seviyede olduğu MRI, CT ve ultrason ile temsil edilen tıbbi görüntüler bu tez için veri kaynaklarıdır.

Gerekli kodlamayı formüle etmek için MATLAB (R2022b) kullandık. Bu hedefi başarmak ve programın görüntü işleme alanındaki yeteneklerinden yararlanmak için, bu tezde, teşhis içeriğini korurken karmaşık tıbbi görüntüleri işlemek için Ayrık Dalgacık Dönüşümü (DWT) ve Vektör Nicelemenin (VQ) bir kombinasyonunu önermektedir.

Tıbbi görüntüler kaçınılmaz olarak gürültü içerdiğinden, bu yöntemde ön işleme sırasında bunları gidermek için filtreleme kullanılır. Girdi görüntüsündeki ilişkili pikselin ve bitişik piksellerin değerine dayalı olarak çıktı görüntüsündeki her pikselin değerini belirlemek için [3×3] Gauss algoritmasını kullandık ve ardından görüntü bilgisini bölmek için dalgacık analizi (DWT) kullandık. Bir yakın plan alt sinyali, piksel değerinin genel yönünü gösterir ve üç ayrıntılı alt sinyal, görüntüdeki dikey, yatay ve çapraz ayrıntıları veya değişiklikleri gösterir. Bu ayrıntı küçükse, görüntüyü önemli ölçüde değiştirmeden sıfıra ayarlanabilir. İki tip filtre vardır yüksek geçiren filtre ve alçak geçiren filtre. Bu nedenle, sinyal etkili bir şekilde ayrıntılı bir yüksek frekans parçasına ve kaba bir düşük frekans bölümüne ayrılır.

Görüntünün kenarlarını (yatay, dikey ve çapraz) korumak için bir Ayrık Dalgacık Dönüşümü (DWT) uygulanır, çünkü görüntü dört banda bölünür ve alt bant dönüşümü en yüksek düzeyde özgüllükle tekrarlanır. Veri sıkıştırma, veri düzeltme, örüntü tanıma, yoğunluk ve kümeleme tahmini için Vektör Niceleme (VQ) tekniği kullanılır, mevcut veri aralıkları dahil olmak üzere en yakın küme bulunarak bazı aralıklardaki eksik veriler elde edilir ve veri ile aynı değeri alacağı varsayılır. VQ çalışmasının temeli piksel dizilerini kod çizelgesindeki bir dizinle temsil etmek olduğundan, görüntü kurtarma için en önemli ayrıntıları içeren alt aralık dışında önceki adım tarafından oluşturulan tüm parametrelere uygulanan orta nokta VQ ve görüntü sıkıştırma için hesaplama süresini azaltmak için birçok iyileştirme yapılmıştır.

Bu noktada gerçekleştirilen deneyler, her görüntü için farklı boyuttaki pencerelerde farklı kod boyutlarıdır. Performans verimliliği farklı boyutlardaki kod ve pencerelerle ve aritmetik kodlama ile baskıyı artırmak için değerlendirilmiştir. Ardından, dalga katsayıları üreten ve belirtilen eşikten daha düşük değeri hariç tutan iki ana yöntem arasında eşik kullandık. Hibrit teknolojinin en iyi kombinasyonu, ölçümden önce iki farklı DWT seviyesinde bulundu. Bu tez, dalgacık dönüşümünün üç ayrı analitik seviyesini uygulayarak görüntüleri test etmektedir.

Ortaya çıkan dalga katsayıları daha sonra aritmetik kodlama olan dalgacık dönüşümüne dayalı görüntü kodlama teknikleri kullanılarak kodlanmıştır. Önerilen bu hibrit teknoloji ile iyi bir performans elde edildi ve bir operasyon optimizasyon algoritması ekleyerek daha da iyi performans elde ettik.

Önerilen sıkıştırma şeması, referans çalışmalardan daha iyi sonuçlar elde etmiş ve sıkıştırma oranını artırmıştır. Testler, dalgayı üç seviyeye ayırmanın, önceki dalgayla kullanılan en iyi sıkıştırma oranını ve en iyi kodlama tekniğini elde ettiğini gösterdi. En önemlileri dalgacık katsayıları için kodlama tekniğinin türü ve kullanılan optimizasyon algoritmasıdır. Testler, dalgacıkların üç seviyeye ayrıştırılmasının, önceki dalga ile kullanılan en iyi sıkıştırma oranına ve en iyi kodlama tekniğine ulaştığını göstermiştir.

Görüntüleri sıkıştırmak için, benzersiz bir karakter dizisi oluşturmak üzere 0 ile 1 arasındaki kesirlerin kullanıldığı aritmetik kodlama (AC) algoritmasını kullandık. Bir veri kodlama ve kod çözme algoritması, tek bir veri kodunu tekrar tekrar işler ve kodunu çözerek onu sembolik olarak yinelemeli hale getirir. Algoritma iterasyon yaptığında, 0 ile 1 arasındaki periyodu giderek daha küçük parçalara böler ve bu parçalardan birini yeni bir periyot olarak tutar. Teknoloji, her biri boyut açısından değerlendirilen bir kod dizisi içeren katmanlı zaman dilimlerinde çalışır. Kod akışı boyutu karşılaştırmaları, veri akışını yeniden yapılandırmak için kullanılır ve

Huffman ön eki sembolleri gibi iyi bilinen sıkıştırma yöntemlerinin aksine, kodlayıcının örtüşen alt aralıkları nasıl böldüğünü ve depoladığını gösterir.

Ardından, parçacık sürüsü optimizasyonu (PSO) algoritmasını kullandığımız yapay zekaya yöntemi kullanılmıştır. Parçacık sürüsü geliştirme yönteminin küresel olarak optimal bir çözüm bulması neredeyse kesindir. Küresel arama yeteneği de çok iyidir ve hesaplama performansı, geleneksel yöntemlere göre çok daha hızlıdır.

Test, Sıkıştırma Oranı (CR) parametresi, Ortalama Kareli Hata (MSR) parametresi ve Tepe Sinyali Gürültü Oranı (PSNR) parametresi kullanılarak yapıldı. Her görüntü için farklı kod çizelgesi boyutları ve farklı pencere boyutları ile deneyler yapılmıştır. Ölçme aracının etkinliğini değerlendirmek için farklı boyuttaki kod çizelgeleri ve pencerelerle bir test yapılmıştır. Her iki seviyedeki deneylerden, kod çizelgelerinin daha büyük olduğu doğrulanmıştır. Görüntü kalitesini korumak için en iyisi seçilmiştir, çünkü tıbbi görüntülemede görüntü kalitesi kritik öneme sahiptir.

Çalışmanın sonunda, ince görüntü detaylarının uzantı, boyutlar ve piksel derinliği açısından kullanıldığı bir referans çalışma ile karşılaştırma yaptık, tasarladığımız sistem referans çalışmalardan daha iyi sonuçlar verdi ve sıkıştırma oranını artırmıştır. Optimizasyon algoritmalarını kullanarak görüntüleri sıkıştırmak için önerilen şemayı uygulamanın en iyi sonuçları elde etmeye yardımcı olduğu bulundu. Zamanı hesaba katmak ve performansı artırmak için bir dizi öneri sağlanmıştır.

1. INTRODUCTION

Visual data has recently captured the majority of people's attention. Of the many ways to get insight into the human mind, visual representations are among the most informative. There has been an uptick in the number of uses for image processing in the domains of civil engineering and medicine, both of which make extensive use of the transmission and relaying of pictures [1].

In the last two decades, studies have shown an uptick in the use of diagnostic imaging. The fast improvement of imaging-system technology and software is responsible for this change. More precision, faster development, and less anxiety are benefits of switching from analog to digital systems. In addition, telemedicine is a rising field in the medical sector, but its potential is hampered by the industry's currently available bandwidth. To a great extent, these have all accounted for the abundance of photographs available. This results in the annual acquisition of petabytes of such photographs. X-ray, Ultrasound, MRI/FMRI (Functional Magnetic Resonance Imaging), Nuclear Medicine, PET (Positron Emission Tomography), CT (Computed Tomography), and DA (Dual Energy Measurement X-rays) are all examples of imaging technologies [2].

Medical imaging technology has developed to meet the demand for cheap storage and user access to pictures from various sources, allowing for easy archiving, sharing, and retrieval of these images. The enormous pixel resolution of these photographs, however, greatly restricts the storage capacity of the devices. Image compression is used to save space when transferring or storing the image. This data compression tool uses a small number of bits to encode the original image. With the help of picture compression, you may save space on your computer by eliminating unnecessary data or merging similar pixels. One may readily categorize medical picture compression methods as either lossless or loose.

1.1. Lossless Compression

This compression method can completely re-create the original image using the original data. It's a technique for reducing the size of a file by encoding its contents. No information is lost in the compression or decompression processes with this technique. The term "lossless compression" refers to a data compression method utilized for software files and pictures (such as medical X-rays) where any loss of information would be unacceptable. Reducing the size of a picture without sacrificing quality is known as lossless compression. This method is an excellent approach to reducing the size of photos without sacrificing quality. Lossless compression retains an image's information to make the size manageable. Parts of the original image are preserved without any loss in quality, and the compression may be undone if necessary. The output image seems massive, and decoding it might be difficult [2].

1.2. Lossy Compression

The image cannot be fully decompressed because it uses a lossy compression method in which some information must be deleted. To compress digital photos without quality loss, JPEG is widely utilized. Since it discards some of the original image's data, lossy compression can produce smaller files. However, this approach's lack of color and complexity is difficult to see because of how little they are. The compression is decreased, but the picture size is not completely lost since unnecessary sections and tags are eliminated. This technique can produce a significantly reduced-size image with minimal loss of quality [3].

1.3. Related Work

In signal processing, studies have focused on wavelet transformations and vector quantization. Applying DWT and VQ methods in compression is not a new concept. Several different techniques have been developed by researchers and utilized to create compression systems.

In 2023 Xiang, Shao, Qiaokang Liang, and Leyuan Fang [4] used a Gaussian mixture model by discrete wavelet transform (DWTGMM) based on discrete wavelet transform (DWT) and Gaussian mixture model (GMM) for image compression where they used DWT to transform the wavelets and get four separate representations, and then use the proposed DWTGMM to model them separately.

In 2022 Narasimhulu, S., and T. Ramashri [5] submitted a proposal for a research study that includes a hybrid compression technology that is based on the Levitation Wavelet Transform (LWT) with Discrete Cosine Transform (DCT). They used a methodology to obtain a high compression ratio and to preserve the quality of the reconstructed image lossless compression. The MATLAB software tool was used to implement the compression process, and the performance was verified by the compression standards PSNR and MSE.

In 2022 Shyamala, N., and Dr. S. Geetha. [6] used the wavelet transform method and a modified grasshopper optimization algorithm to choose the optimal coefficients for efficient compression and decompression. A hybrid mean filter eliminates the noise and decomposes it using the integer wavelet transform. Then, the compression performance of the proposed method was confirmed by comparing it with known standards in terms of signal-to-noise ratio, mean square error, and average structural similarity index at different compression ratios. It is proved that the proposed method provides good compression with high image quality.

Two methods for compressing images were proposed in 2011 by researchers Katharotiya, Anilkumar, Swati Patel, and Mahesh Goyani [7]. Both the Discrete Cosine Transform (DCT) and the Discrete Wavelet Transform (DWT) underpin the first approach, applying the discrete wavelet transform (DWT) to other pictures to evaluate their respective quality. It is clear from their trials that there are benefits and drawbacks to both methods. Both approaches are quite effective at compressing images to a suitable ratio without losing too much detail. Yet, the results of the studies demonstrate that the DWT method is superior to the DCT method in terms of quality and efficiency.

An example of a hybrid approach picture comparison was conducted by Vijayabhaskar and Raajan [8] in 2013. (DWT and DCT). They estimated compression efficiency using the basic waveform filters developed by Haar. The compression process aims to represent a picture with fewer bits per pixel. Orthogonal wavelets and bi-orthogonal wavelets are the two primary types of wavelet families. The hybrid picture compression method combines three different types of images

(DWT and DCT). The PSNR findings of simulated gray picture compression processes favor Daubechie's (db-9) wavelet family wavelet filters. Bad outcomes are produced by using the "haar" wavelet. Finally, a well-reconstructed image is achieved by combining the Daubechies wavelet (db-9) with the hybrid image compression method.

A new method of picture compression employing VQ was suggested in 2019 by Chatterjee, Rishav, Alenrex Maity, and Rajdeep Chatterjee [9]. Pattern recognition, data mining, computer vision, and human interaction rely on efficient and effective image compression algorithms and approaches. Compression is a feasible method to reduce the number of bits needed to represent a digital image. There is a plethora of picture compression methods available in the literature, each with its own set of advantages and disadvantages.

In Table 1.1, we compare the methodologies used in the research reported here to highlight their respective strengths and weaknesses.

1.4. Motivation

As a result, it's become important to develop new methods of compressing these photographs due to their bloated sizes. Modern technological advancements have made it possible for digital photographs to shrink to fit within the allotted area of data storage media. Some of the criteria for storage should include ensuring adequate quality is maintained. Image compression reduces the quantity of data needed to depict a digital image. Data compression is achieved by removing redundancies in the data, specifically in three ways:

1. Coding redundancy, which occurs when less-than-optimal code words are used,
2. Inter-redundancy, which arises from correlations between pixels in the image and,
3. Psychological visual redundancy occurs when data is ignored by the human visual system (i.e., Visual nonessential information).

Table 1.1. Comparison of the algorithms with the advantages and disadvantages

Previous studies	Algorithm	Advantages	Disadvantages
Xiang, Shao, Qiaokang Liang, and Leyuan Fang, 2023	Gaussian mixture model (GMM)& Discrete wavelet Transform(DCT) (DWTGMM)	Using DWT for four sub-bands, we achieve high precision as well as a Gaussian filter.	Sub-bands take longer to compress.
Narasimhulu, S., and T. Ramashri, 2022	A hybrid compression technology that is based on the Levitation Wavelet Transform (LWT) with Discrete Cosine Transform (DCT)	It allows the generation of several separate biowaves.	
Shyamala, N., and Dr S. Geetha, 2022	Integer wavelet transform (IWT) Grasshopper optimization	(IMT) Computationally faster and more memory efficient. The optimization algorithm increases compression efficiency.	The grasshopper algorithm takes a longer time to reach efficient compression and high image quality.
Chatterjee, Rishav, Alenrex Maity, and Rajdeep Chatterjee, 2019	VQ (vector quantization for Image compression	Vector quantization techniques gave efficient results. The rounded image quality was significantly improved since these techniques assign larger bit ratios to regions: the active image and vice versa to the inactive image areas.	All of these techniques suffer from increased work-in complexity The sender and the receiver because they use more than one encoding directory
Vijayabhaskar, P. V. M., and N. R. Raajan, 2013	Hybrid (DWT & DCT) technique. Standard wavelet filters of Haar and Daubechies (db-9)	Daubechies (db-9) wavelet filter of wavelet family obtain a better PSNR result.	The 'haar' wavelet gives poor results.
Katharotiya, Anilkumar, Swati Patel, and Mahesh Goyani, 2011	Discrete Cosine Transform (DCT) with image and the Discrete Wavelet Transform (DWT). With another image.		

1.5. The Aim of the Thesis

This study proposes a simple and effective picture compression technique that outperforms the current methods. The project relies on an optimization approach to boost the compression system's efficiency, achieve a high compression ratio utilizing Discrete Wavelet Transform (DWT), and maintain a respectable mean Structural Similarity (MSSIM) and Peak Signal-to-Noise Ratio (PSNR).

1.6. Suggested Approach

As ultrasonography images inevitably suffer from salt-and-pepper noise, this method employs filtering to remove it during pre-processing. Even if the image isn't an ultrasound, DWT will still maintain the edge, as this is a necessary step in making any medical diagnosis based on the image. For generated coefficients below the threshold, we substitute a value of zero. We used a Vector Quantization (VQ) and an Optimization technique to get the highest compression ratio and greater performance. The outcome then has a quantitative slant. To save or send a compressed image, the quantum coefficients are mathematically encoded, and the resulting bits represent the image.

1.7. Research Methodology

The research methodology was based on the following principles (Figure 1.1.):

1. Conducting a research study of medical images and the most critical issues related to digital image compression.
2. Conducting a theoretical and mathematical study of wavelet transformation and studying the most crucial coding techniques based on it.
3. Determine the best coding technique to use.
4. Show and discuss the results.
5. The practical application of the studied digital images, the simulation program MATLAB.

1.8. Organization of the Thesis

This thesis contains five chapters organized as follows:

Chapter 1 introduces route planning and reviews the literature on many topics relevant to this study.

Chapter 2 presents basic theoretical information on the essential topics related to this thesis proposal.

Chapter 3 presents the proposed algorithms: Moving Average Filter (Gaussian Filter, Discrete Wave Transform, Arithmetic Coding, PSO Optimization Algorithm).

Chapter 4 shows the result of all proposed algorithms, selects the best one and makes a comparison with previous studies.

Chapter 5 includes the conclusion and future work of this thesis.

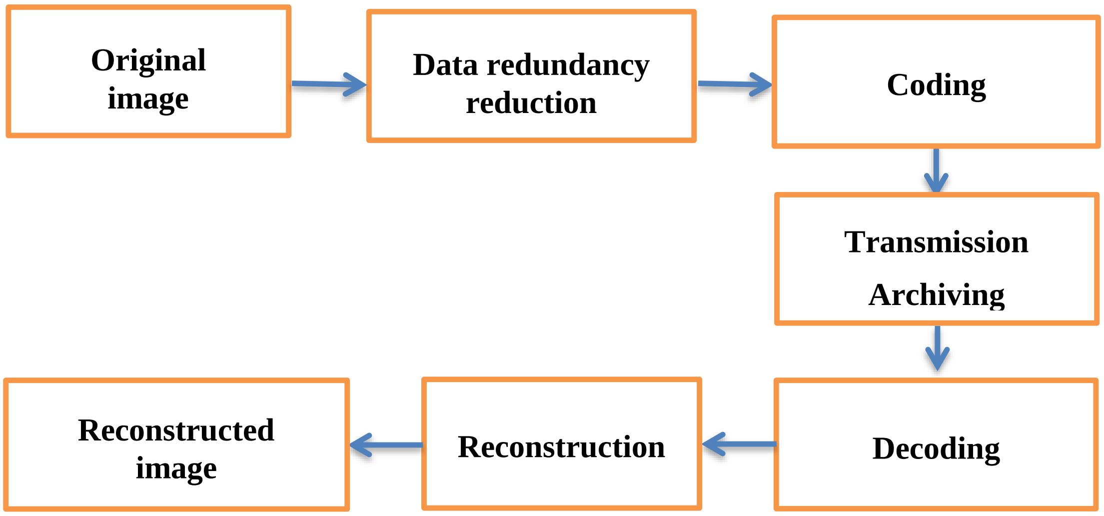


Figure 1.1. Data Compression & Image Reconstruction Methodology

2. MEDICAL IMAGES COMPRESSION

2.1. Medical Images Overview

As matrices, the magnetic resonance and computed tomography pictures comprise rows and columns. Pixels are the squares that make up each column and row. These squares distribute the body's signals to appear in the same order as they do inside the body. The collected signal intensity is used to assign a color to the grayscale. A two-dimensional grayscale image is at our disposal. Computed Tomography (CT) is a technique for obtaining three-dimensional images from a series of two-dimensional images using specialized computer algorithms.

2.2. Fundamentals of Image Compression

Image compression is the technique of minimizing photo files. Source coding is a term used in picture transmission and communication systems (encoding is done at the source of the data before it is stored or transmitted). By reducing the data size, you can save space in a storage medium, bandwidth during transmission, and even radio waves. This additional processing places computational or other cost limits on the decompression process [12], as the compressed data must be decompressed before it can be used.

To compress data is to reduce the quantity of data needed to express the same amount of information. One feature shared by the vast majority of photographs is the existence of correlation and redundancy between neighboring pixels. The primary objective is to discover a less correlated visual representation. To compress data, it is necessary to eliminate unnecessary information and duplicates. The goal of redundancy suppression is to eliminate any extra copies of the original signal (image or video). Irrelevance reduction eliminates data irrelevant to the signal's intended receiver, such as the human visual system (HVS) [10].

2.3. Techniques of Image Compression

Many techniques have been developed to compress these images. Still, the most sought-after innovation is the hybrid imaging technique, where the wavelet transform (DWT) and optimization Vector Quantization (VQ) both lossy [11] are most (see Figure 2.1.).

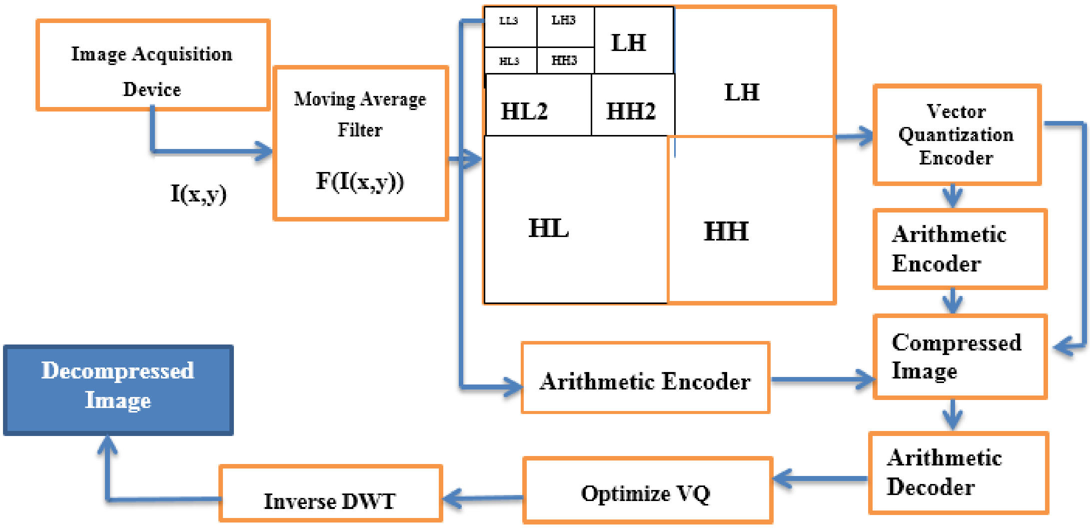


Figure 2.1. Model of proposal method

2.4. Moving Average Filter (MAF)

One of the most common methods for making photographs appear free of noise is the digital filter process, which does so by preserving the image's edges while smoothing out the rest of the picture.

Optimization methods for digital photographs aim to remove noise, or distracting details, from an image so that the final product is better suited to its intended use [13,14].

Additional noise sources are introduced during the capturing and sending of an image. Environmental parameters during the picture acquisition process, sensor quality, light levels, sensor temperature, and image transmission channels and exposure can all affect the performance of imaging sensors.

There are several common sources of noise in digital photographs, including:

1. Periodic noises: They are caused by an issue with the imaging instrument.

2. A dark or bright inaccuracy in transmitting digital image data is the cause of the so-called "salt and pepper" effect.
3. Natural noises: noises produced by the image acquisition system during the process of converting the continuous electrical signal to a digital format that can be read by the computer [15].

MATLAB allows for using many filters on an image, reducing the visible impact of the random noise. The Moving Average Filter (Formula 2.1) is one such filter; it works by first applying a window with the picture with a fixed size (nn), then performing a convolution operation between the window and the portion of the image used by the filter. By applying the filter on the image's edges, the total of the light (intensity) in each light point (pixel) within the window range is divided by the window size, and zero frames are proportionally added around the image to the window size [16].

$$MAF = \frac{1}{N} \sum_{(r,c) \in W} d(r,c) \tag{2.1}$$

N: Represents the number of sham cells within the filter window.

W: Represents the filter window.

R: Represents the image cells within the filter window.

2.4.1. Wavelet transform

As part of signal processing, wavelet transformation has emerged in recent decades. It takes the incoming data and reformats it to eliminate unnecessary repetition between pixels. Transform coding methods translate the pixel values into a set of coefficients, quantized and encoded via a reversible linear mathematical transform. Many of the resulting coefficients for most natural images have tiny magnitudes, making it possible to quantize them for compression purposes without significantly distorting the decoded image [17]. This is a key reason for the success of transform-based coding methods.

The Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT) are the two most common kinds of wavelet transformation (DWT). The first is made for functions specified across the complete real axis, while the second works with functions defined over a range of common integers. There is an excess of data provided by the continuous wavelet transform. Comparatively, the discrete wavelet transform requires much less calculation time but yields useful results. It is possible to execute continuous and discontinuous wavelet transformations using various wavelets [1].

2.4.2. Discrete Wavelet Transform (DWT)

Several iterations of the discrete wavelet transform are applied to the filtered image. The image is enhanced for output, and frequency module information is presented thanks to the multi-level wavelet transform. More so, it provides the opportunity for improved reconstruction following compression. Therefore, later levels have less unnecessary detail and more useful data. One-dimensional processing is used because it is faster and more efficient when applied to a 2D image. After then, the rows and columns are broken down. The desired transformation can be attained by applying filters to both the rows and columns of the 2D image simultaneously [18].

2.4.2.1. DWT technique

Wavelet analysis can be used to split the information of an image into approximation and detailed partial signals. The approach sub-signal shows the general trend of the pixel value and three detailed sub-signals show vertical, horizontal and diagonal details or changes in the image. If these details are tiny, they can be set to zero without significantly changing the image. There are two types of filters [20]:

1. High-pass filter: high-frequency information is preserved, and low-frequency information is lost.
2. Low-pass Filter: Right-frequency information is preserved, and high-frequency information is lost [19].

Thus, the signal is effectively split into a detail part (high frequency) and an approximation part (degree frequency). Level 1 detail is the horizontal detail, Level 2 detail is the vertical detail and Level 3 detail is the diagonal detail of the image signal (see Figure 2.2).

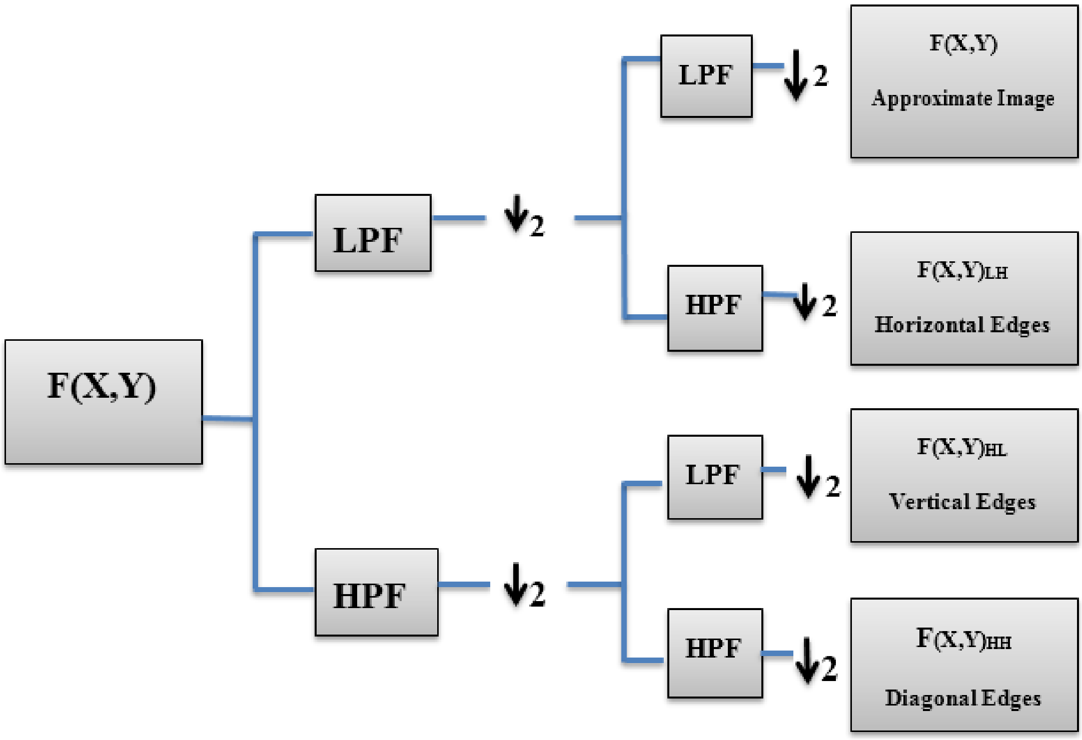


Figure 2.2. DWT technique diagram

The coefficients that fall below a certain threshold are replaced with zero values to determine results over large image data samples. The threshold value is determined by Formula 2.2 [23].

$$t = \frac{\theta\ (f(x,y))}{4 \times \theta(x,y)} \tag{2.2}$$

Where t is the threshold, f (x, y) is the wavelet coefficients, x and y is the dimension of the image and θ is a function that measures the coefficients generated.

2.4.3. Vector quantization

Since the advent of modern computing, large amounts of image data have become a major obstacle in various scientific and technical fields, making the investigation of efficient image compression technologies imperative. It has been extensively used in the development of numerous picture compression methods. Vector Quantization (VQ) seeks to find a fixed length for the most suitable codebook to provide an image representation as close as feasible to the original. The best feasible accuracy is maintained, and no changes were made to the original image during compression if an ideal codebook is learned from the training image.

The goal of the VQ procedure with a selected code vector is to find the set of codebooks that best fits the given data. Once all picture training patterns have been indexed according to the nearest code vector, coding can be considered complete. The condition describes that the codebook can represent the image's information. Codebooks are typically substantially smaller than the initial image dataset [24].

2.4.3.1. Fundamentals of vector quantization

If the data to be quantized has any underlying structure, it can be used effectively using a vector quantization technique. Separate rendering vectors are calculated for each quantization zone, which is achieved by partitioning the space of input vectors into smaller parts. Each data vector is assigned a quantization area based on its location. Instead of transmitting or storing a specific vector of data, the replica vector for that region is used as a representation [25].

To compress images, we use vector quantization, which is analogous to scalar quantization but works with vectors instead of numbers. When dealing with scalar quantization, a huge set of numbers is reduced through actions like rounding to the nearest integer. The quantization levels, however, can't only be integers or equally spaced in time. Rendering vectors are what we use to refer to the quantization steps. The collection of rendering vectors and a rule to map input vectors to rendering vectors are required to define a vector quantize. A vector quantifier that operates on groups of pixels within an image. Various methods for segmenting the input image are used, but the most commonly use larger squares, rectangles, and other forms. For an image originally captured at 8 bits per pixel (bpp), the input block must include 4 * 8 = 32 bits. An 8-bit index represents each of the 256 code words in a fixed-price code. This means that the compression ratio is 32:8, or 4:1. The decoder is essentially a lookup table and comes equipped with its copy of the codebook [26].

2.4.3.2. The algorithm of vector quantization

Step 1: we load the image coefficients that will be quantized. The coefficients are broken down into frequency ranges following a bilinear decomposition. The first level has three sub-bands (LH, HL, HH), the second level has three sub-bands (LH, HL, HH), and the third level has three sub-bands (LH, HL, HH). The second-level LL sub-band is missing.

Step 2: chopping the picture into uniform, non-overlapping pieces called vectors.

Step 3: we locate the center of the previously generated vectors.

Step 4: Let a tiny offset in regular and random directions and divide each centroid into two centroids (x and y).

Step 5: Group the data by assigning each piece of information to a centroid.

Step 6: we locate the cluster centers and use the square Euclidean distance method to determine the total distance, which we then use to evaluate the degree of distortion [18].

2.4.4. Encoding algorithm

Various techniques are employed for compression having complexities ranging in different degrees. The final step of any compression system is an entropy encoding representing data compactly. This encoding process may complement the outputs for prior stages. Arithmetic coding is the most effective, versatile, agile process of all entropy encoding techniques [27].

2.4.4.1. Arithmetic coding (AC)

Arithmetic coding uses numerical fractions between 0 and 1 to compress information to create a unique string of characters. The algorithm for encoding and decoding data symbols iteratively processes and encodes (decodes) a single data symbol at a time, making it symbolically recursive. As the algorithm iterates, it divides an interval between 0 and 1 into smaller and smaller pieces, keeping one of these pieces as the new interval. The technique operates on layered intervals, each containing the code sequence evaluated for size. Code stream size comparisons are used to reconstruct the data stream, which indicates how the encoder should divide and store the nested subintervals. In contrast to well-known compression methods like prefix (Huffman) codes, Arithmetic Coding is somewhat unique. Error control coding, which aims to find and fix glitches in computer programs, should be considered a separate discipline [28].

2.4.4.2. Encoding and decoding

The encoder only needs to consider three pieces of information:

- The next symbol to be encoded

- The current interval (at the beginning of the encoding process, the interval is set to [0,1], but this changes)
- The probabilities that the model assigns to each of the possible symbols at this stage.

The encoder segments the current interval into smaller intervals, with the size of each interval being proportional to the likelihood of the corresponding symbol. If you encode a series of symbols and then look at the resulting interval, you can tell exactly which symbols made that interval. Those that use the same model and termination interval can figure out what order of symbols must be sent into the encoder to get the desired termination interval. Although the final slot should be transferred, only a portion of the time allotted for the transmission must be sent. To be more precise, only those digits of the fraction (in any base) need to be transmitted that ensure all fractions starting with those digits are contained inside the final range. By doing so, you may rest assured that the generated code will be a prefix [29].

2.4.5. Optimization algorithm

An optimization algorithm is a process that iteratively compares multiple solutions until an optimal or satisfactory solution is found. With the advent of computers, optimization has become a part of computational design activities [30].

2.4.5.1. Swarm Intelligence

In artificial intelligence, swarm intelligence is used to characterize the group dynamics of distributed, self-organizing systems. In 1989, Gerardo Beni and Jing Wang presented it in the context of cellular robotic systems.

Communities of constrained individuals interacting locally with one another and their surroundings are often the setting for the emergence of swarm intelligence. The guidelines that customers follow are simple. As no mastermind directs everyone's behaviors, ordinary intelligence emerges from seemingly random interactions between people. Ant colonies, flocks of birds, herds of livestock, bacterial proliferation, and schools of fish are all examples of this in nature [31].

2.4.5.2. Particle swarm optimization (PSO)

The bird algorithm attempts to simulate the predatory behavior of birds by simulating their random searches for food, with the birds adjusting the search path based on their own prior experiences and those of other flocks to locate the greatest number of potential food sources. The number of food items available at each feeding station is a function, whereas each bird's location and flight path are independent variables. By learning from the experiences of other searches, the search algorithms can track extremes to converge on the best possible result.

Similar to evolutionary algorithms, the developing particle swarm method is almost certain to find a globally optimal solution. Global search ability is also great, and the computation performance is much faster than classic methods [32]. The algorithm can be reduced to three main steps:

1. Calculate the fitness value for each component and the overall fitness value,
2. Update the fit values and
3. Update the speed and position of each item.

Figure 2.3. depicts the schematic diagram of the algorithm.

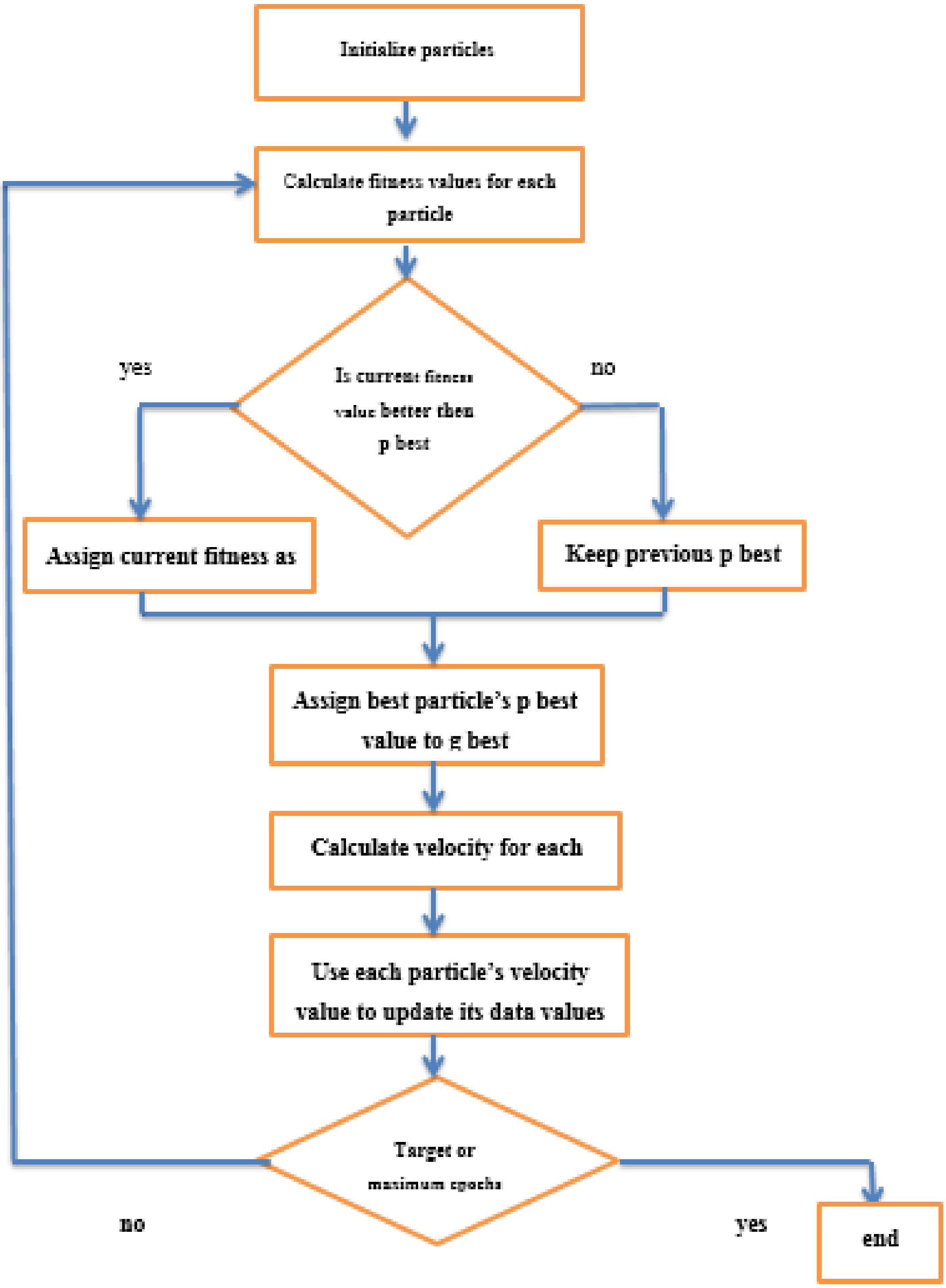


Figure 2.3. Schematic diagram of particle swarm optimization (PSO)

3. PROPOSED METHODOLOGY

3.1. Medical Image Compression

Compressing medical images can drastically reduce their file sizes without sacrificing quality and protect images from being damaged if distortion is introduced during the reconstruction process. A reliable medical picture compression and decompression strategy is required in image processing systems. Both lossy and transparent technologies can be used to implement this system accurately. Although these methods are utilized in the compression system's design, they confront difficulties such as minimizing the originating size, computational cost, and the smallest square of compression mistakes. These significant barriers to acquiring high-quality medical photographs were the focus of the study [1].

The subject of this investigation was medical photographs (Digital Imaging and Communications in Medicine- DICOM). This term refers to a long tradition of work toward establishing a single, comprehensive, and widely adopted norm for the exchange of medical images and data. DICOM is the gold standard when reviewing medical data and processing medical images [32].

The photos all share the trait of having neighboring pixels connected, which causes redundancy (see Figure 3.1.). Finding a representation of the image with a lower correlation is the first order of business. Redundancy elimination and unnecessary data reduction are two key aspects of compression. Reducing redundancy in a picture or video eliminates unnecessary information. Reducing the signal's unrelatedness eliminates information that isn't important for the signal.

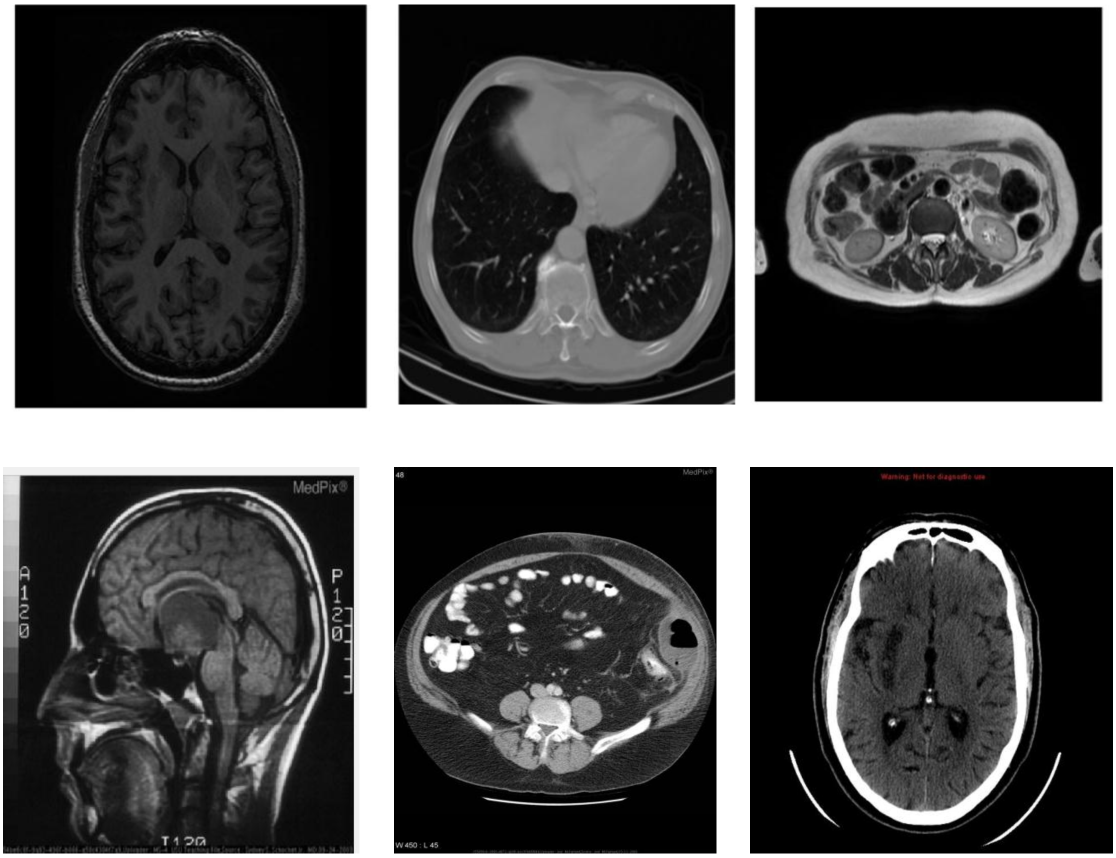


Figure 3.1. Sample Original images

3.2. Methodology

Since the primary goal of this study is to find the highest achievable compression ratio, the work is broken down into two distinct stages: (1) a testing phase, and (2) a proposed strategy for compressing images with adequate no single wavelet pressure. Since no single wavelet can simultaneously produce a high compression ratio and a high quality of restored images, the first step was to select the wavelet that produced the optimum compression ratio. When deciding the encoding method, the ideal wavelet ensures that the recovered images retain their highest possible quality. With the findings from the first step in mind, a multi-stage integrated system was devised to compress high-quality photos. In the suggested technique, the image blocks with the least detail will be compressed using the wavelet with the highest compression ratio. By contrast, the picture blocks containing the most crucial detail will be processed through the primary wavelet that maintains the highest quality of the restored image. The proposed compression algorithm is depicted in a schematic format in Figure 3.2. [1].

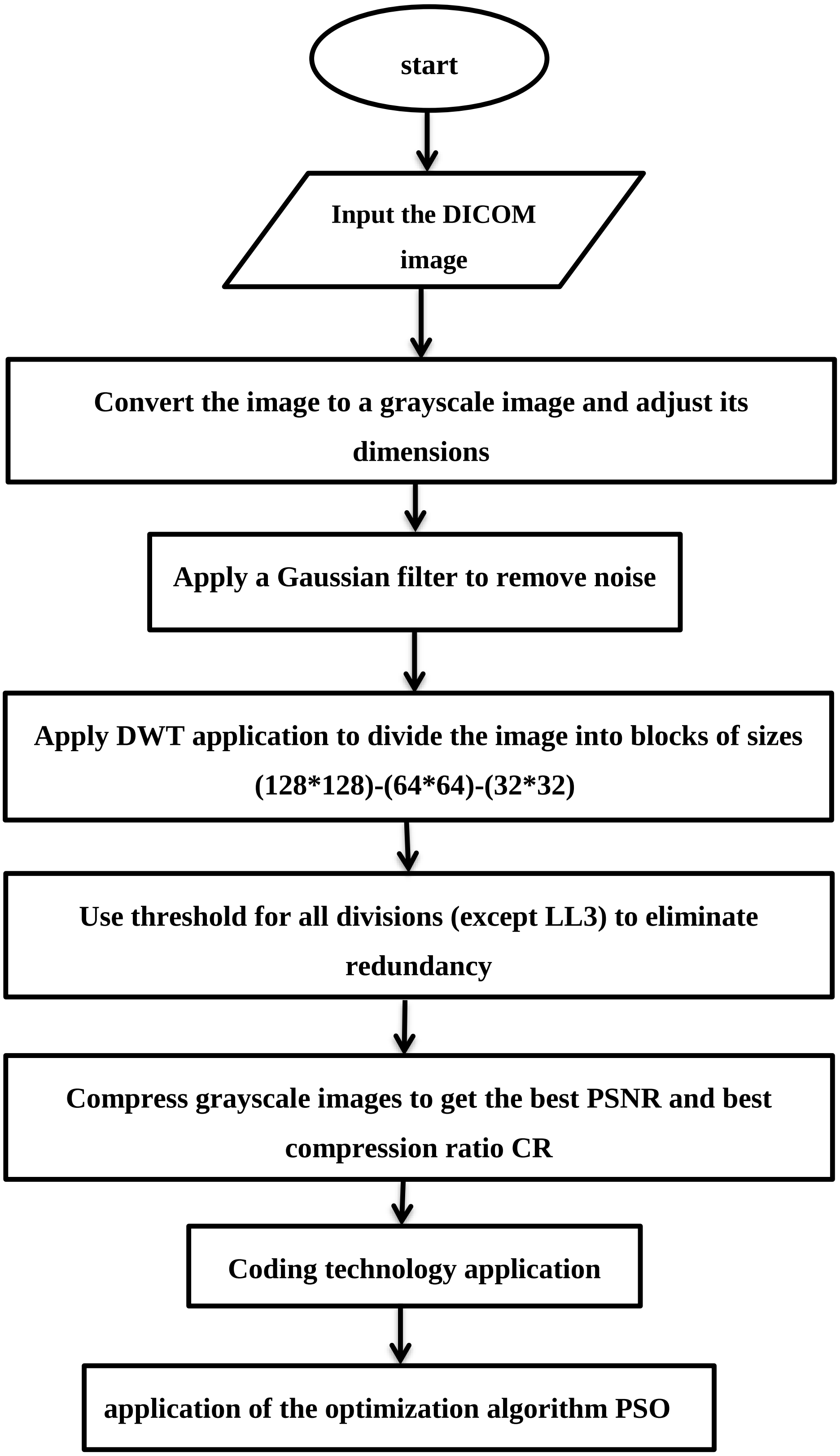


Figure 3.2. Diagram of the proposed compression algorithm

At first, we turn the color image into a grayscale one, with the size set to (512 * 512). After that, we use a filtering procedure to make changes and enhance the image. As part of a neighborhood operation, we use the Gaussian algorithm to determine the value of each pixel in the output image based on the value of its associated pixel and the neighboring pixels in the input image. The noise in a grayscale image can be removed using the Gaussian Filter, which is a linear smoothing filter. It finds extensive application in that domain. The weighted average operation of all pictures is the Gaussian filter (see Figure 3.3.). The value of each pixel is calculated by taking a weighted average of the values of its neighboring pixels. Gaussian filters are used to average gradient values over an entire image, pixel by pixel [32,15]. In other words, the dimensions of the filter matrix (i.e., the filtered dimensions) will be [3×3].

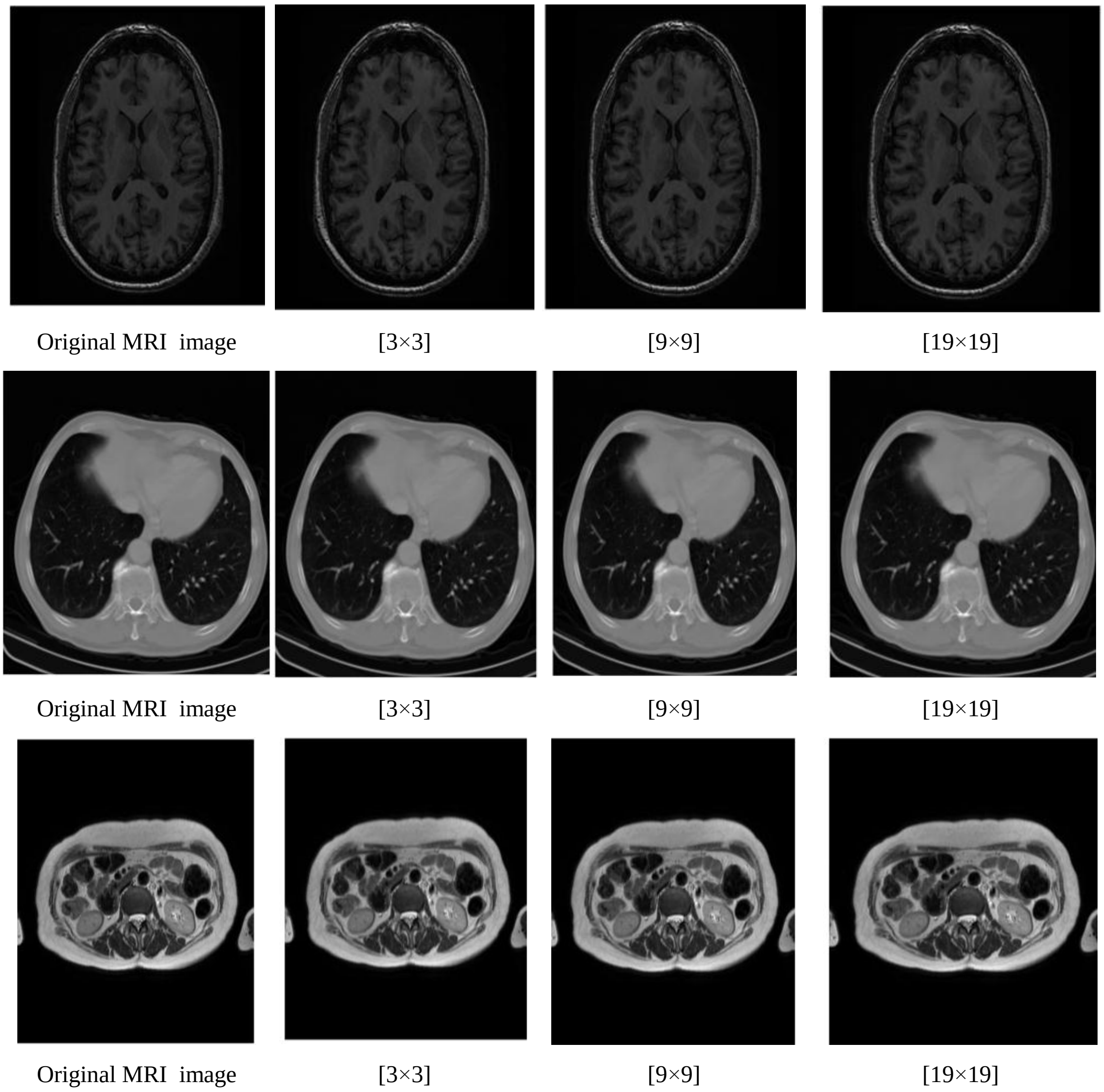


Figure 3.3. Image with different window sizes

3.2.1. Discrete wavelet transformation (DWT)

Wavelets are average zero-valued functions defined on a limited interval. The fundamental principle behind the wavelet transform is that every function (t) may be represented as the superposition of a collection of such wavelets, also known as basis functions. By expanding or contracting (scaling) and translating a single wavelet prototype (the mother wavelet), these fundamental functionalities (baby wavelets) are maintained (shifts). An N-component signal x (n) is subjected to a discrete wavelet transform [33].

The 2D implementation of the DWT method for two-dimensional pictures involves first performing the DWT in the row direction and then in the column direction. The LL is a more substantial representation of the original image; it stores low-frequency proximity information. High-frequency sub-bands LH, HL, and HH include the granular information.

3.2.1.1. Test case (three-level decomposition of image)

After applying the filter, we use the DWT transform on the image to separate it into four bands: LL, LH, HL, and HH. The LL sub-band offers the greatest level of specificity. Repeat the transformation of the LL sub-band to obtain a different set of sub-bands, each of which has a newly transformed LL sub-band. In this way, we know that the image will be broken down into its parts at three distinct granularities. As shown in Figure 3.4, the resulting set of ten sub-bands represents the LH, HL, and HH components of the first level of decomposition, the LH, HL, and HH components of the second level of decomposition, and the LH, HL, and HH components of the third and final level of decomposition, respectively [22,34].

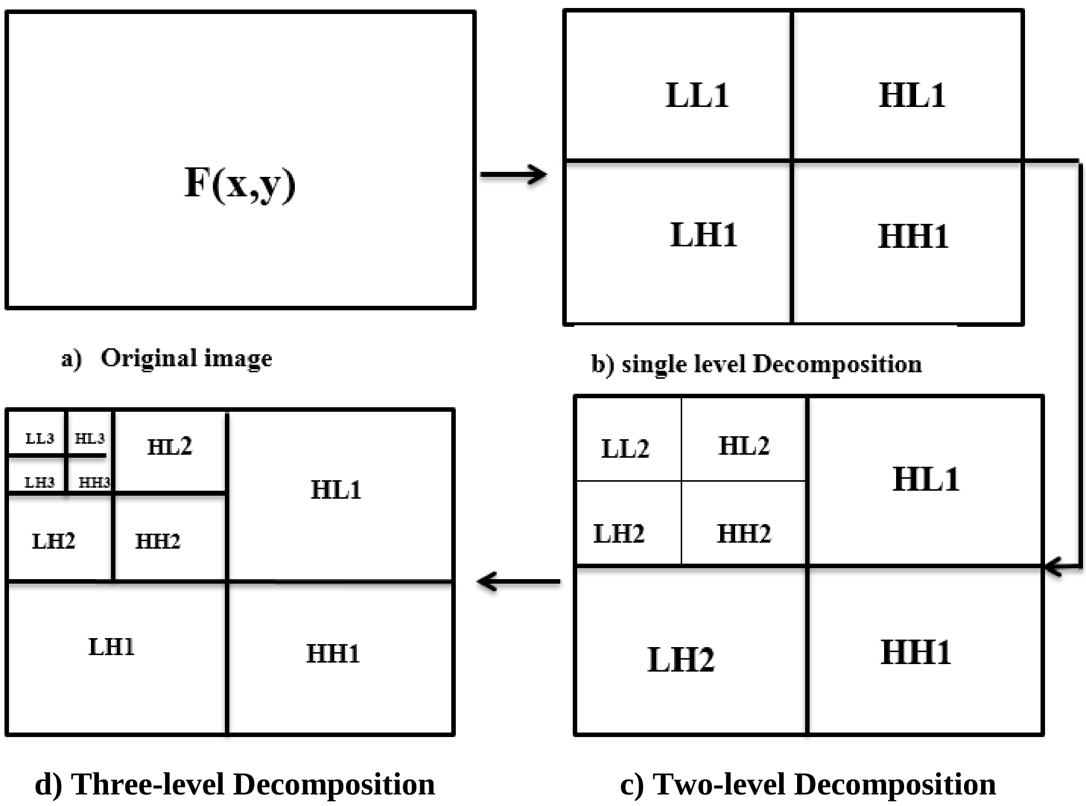


Figure 3.4. Sub-band partitioning of the image after DWT.

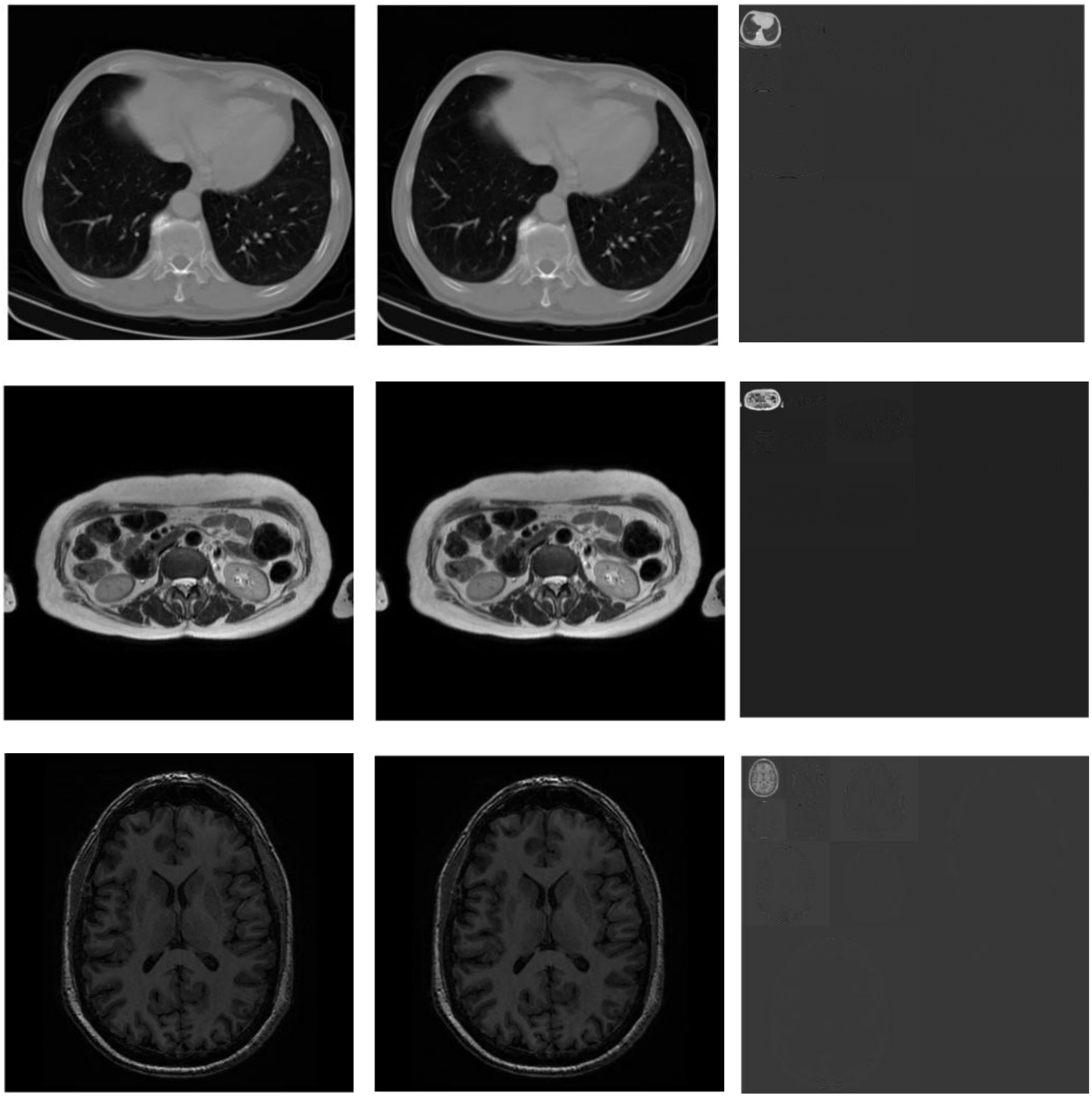


Figure 3.5. Images after processing

3.2.2. Threshold

Following the detection of edges (vertical, horizontal, and diagonal), the threshold applies to all the resultant portions except LL3 (which includes the most precise picture information) to filter out the bulk of the noise. White line images are the result of the edge detection procedure, which itself is a filtering threshold (see Figure 3.5). It conveys the locations of edges in the source picture. Sobel Prewitt, Roberts, Canny, and Roberts are only examples of the various edge detection methods available. By comparing the gray level of each pixel to this threshold, each method's edge detection procedure begins at a different value. This indicates that a binary picture is produced due to the edge detection procedure. If no threshold is given, the edge technique uses a default value. Conventionally, signal and image processing employ the threshold value. It's the smallest detectable signal that has to be handled. In general, if the signal is below the threshold value, the value is zeroed out, and if the signal is over the threshold value, either the signal is taken at face value or the value is assigned [1].

3.2.3. Vector Quantization (VQ)

Except for the LL sub-band, which has the crucial information for the reconstruction, this process is done to all coefficients arising from the preceding stage. Changes have been made to speed up the computing time required to generate a codebook. Follow these steps to progress the algorithm:

In the first phase, we load the picture coefficients that will be quantized after a discrete wavelet transformation, where a two-level decomposition is performed. There were nine distinct sub-bands that made up the coefficients: three from the first level (LH, HL, HH), three from the second level (LH, HL, HH), and three from the third level (LH, HL, HH). Specifically, the second-level LL sub-band is not included.

Second, we create non-overlapping chunks or vectors of the specified size by dissecting the image.

Next, we locate the center point of the vectors we just made.

The fourth step is to divide each centroid into two new points, x and y. It makes it possible for a minor offset to have a tiny regular and random direction.

Separate data sets may be obtained by following Step 5 and assigning each data point to a centroid.

We next go to Step 6 and locate the cluster centers. Next, we compare the original DWT coefficients to the intended distortion value [18] by calculating the total distance using the square Euclidean distance algorithm. Figure 3.6 depicts the vector quantization process.

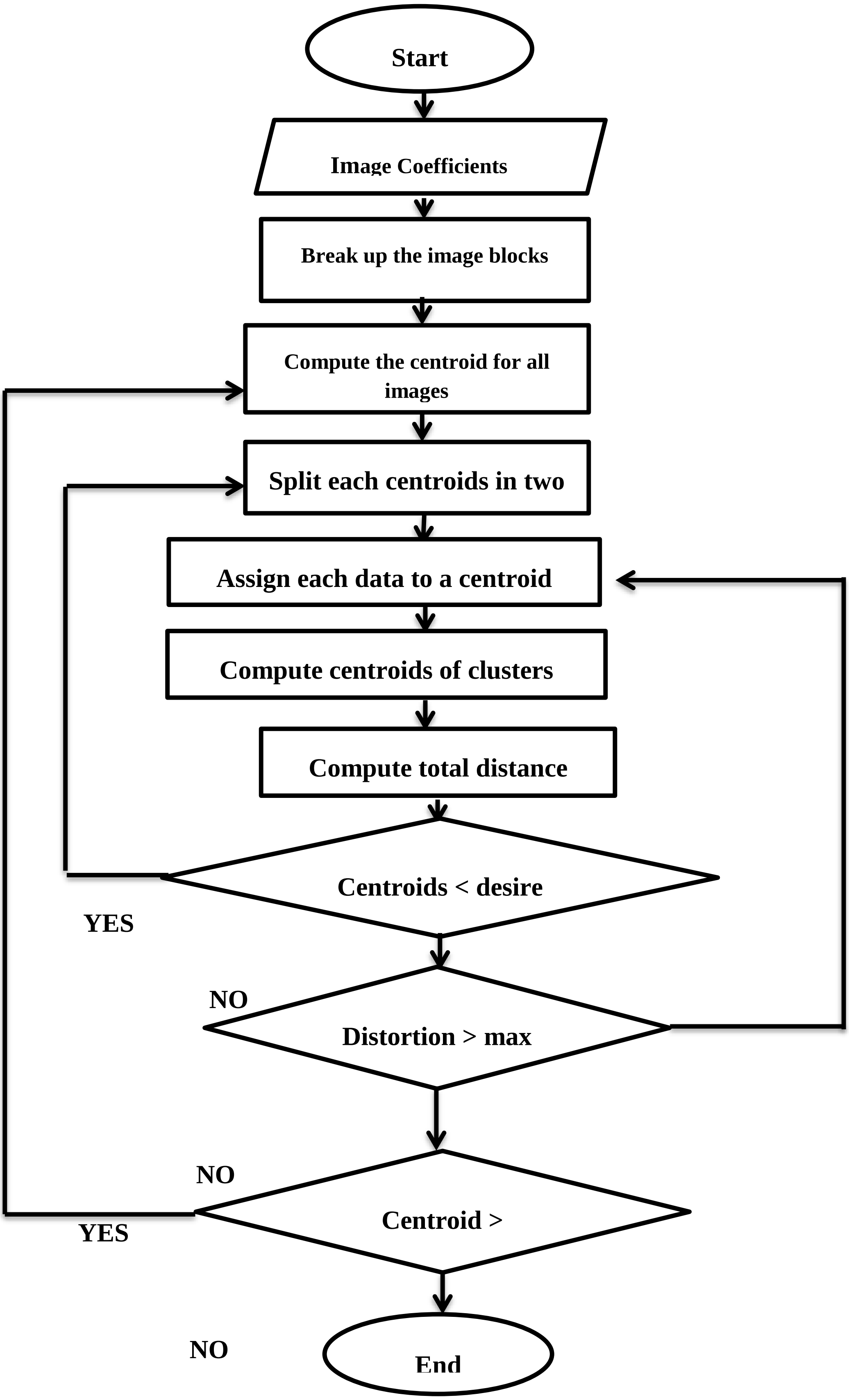


Figure 3.6. Vector Quantization Algorithm

3.2.4. Optimization algorithm

Initially, all elements are defined and given initial values, initial values are calculated, the suitability values are computed for each component, and then the following condition is discussed: Is the current suitability value better than the previous one? If the fit value is better than the last value, we update the old value to the new one. But if the old value is better than the new one, we keep the old value, then put the new fit value of the element. In place of the importance of the swarm's overall fit, we calculate the component's speed and discuss whether a part has reached the ideal solution. If the algorithm ends, but in the event of non-arrival, the algorithm repeats itself from the stage of calculating the value of the new fit. Therefore, the values constantly change slightly when repeating this algorithm repeatedly on the same image to reach the best value. So in this research, we adopted the average of several readings of the same image [29].

4. RESULTS AND DISCUSSION

In this thesis, we chose the medical Image DICOM as a model for testing the results. The image has an extension (.dcm) and a pixel depth of 24 bits (see Table 4.1.).

Table 4.1. The dimensions of all the images

Image	**Dimensions (Pixels)**	**Size**
Brain Image (1)	654×573	100 KB
CI Image(2)	686×605	142 KB
MRI Image(3)	686×605	150 KB
Image (4)	379×394	150 KB
Image (5)	630×630	199 KB
Image (6)	1024×1286	763 KB

And we used MATLAB (R2022b) program to formulate the necessary software coding. To accomplish this work, they benefited from the program's capabilities in the image processing field.

4.1. Evaluation Criteria

The results were tested using objective criteria for evaluating the effectiveness and quality of the compression algorithm [35].

1- Compression Ratio (CR)
2- Mean Square Error (MSE)
3- Root Mean Square Error (RMSE)
4- Peak Signal to Noise Ratio (PSNR)
5- Structural Similarity Index Measure (SSIM)

4.1.1. Measuring the effectiveness of compression

The concept of compression effectiveness expresses how different the size of the compressed image is from the size of the original image. The smaller the size of the compressed image means more efficient or effective the compression algorithm. Several parameters are used to measure the effectiveness of compression, and the Compression Ratio (CR) is the most important parameter. This parameter describes the ability of the compression algorithm used to reduce the space required for data storage and is calculated by Formula 4.1. [36]

$$\mathbf{CR} = \frac{\boldsymbol{I(x,y)}}{\boldsymbol{I'(x,y)}} \tag{4.1}$$

Where I(x,y) is the original image, I’(x,y) is the compressed image, and x, y are the image’s dimensions.

4.1.2. Measuring the quality of compression

Image quality expresses the similarity or closeness of the recovered image after decompression with the original image, and the greater the similarity, the better the compression algorithm used. Several parameters are used to measure the quality of compression. The Mean Error Square (MSE) parameter is the most famous and is calculated by Formula 4.2. [37].

$$\boldsymbol{MSE = \frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N}(I(x,y) - I'(x,y))^2} \tag{4.2}$$

Where I (x, y) represents the pixels of the original image, I (x, y)' represents the pixels of the recovered image after decompression, and N, M represents the number of lines and columns in the image are the dimensions of the image, respectively.

4.1.3. Peak Signal to Noise Ratio (PSNR)

Peak Signal to Noise Ratio (PSNR) has an important parameter in the measurement of compression quality. It is calculated by Formula 4.3. for the image after converting it into a grayscale image [38], [39].

$$\mathbf{PSNR = 10\log 10\frac{255^2}{\boldsymbol{MSE}}} \tag{4.3}$$

Where the value 255 signifies the 8-bit images for grayscale. The value of PSNR approaches infinity as the MSE approaches zero. This shows that a higher PSNR value provides higher image quality. At the other end of the scale, a small PSNR value implies large numerical differences between images.

SSIM is a well-known quality metric used to measure the similarity between two images and is considered correlated with the human visual system's perception of quality (HVS) [40]. SSIM was developed by modeling any image distortion as a combination of three factors: loss of correlation, luminance distortion and contrast distortion. The SSIM is defined using Formula 4.4.

$$\boldsymbol{SSIM} = \left[\frac{2\mu_X\,\boldsymbol{\mu_Y}}{\boldsymbol{\mu_X^2} + \boldsymbol{\mu_Y^2}}\right] \times \left[\frac{2\boldsymbol{\sigma_{XY}}}{\boldsymbol{\sigma_X^2} + \boldsymbol{\sigma_Y^2}}\right] \tag{4.4}$$

$$\boldsymbol{\mu_X} = \frac{1}{K}\sum_{i=1}^{k} \boldsymbol{x_i} \tag{4.5}$$

$$\boldsymbol{\mu_y} = \frac{1}{K}\sum_{i=1}^{k} \boldsymbol{y_i} \tag{4.6}$$

$$\boldsymbol{\sigma_X} = \left\{\frac{1}{K-1} \sum_{i-1}^{k}(\boldsymbol{x_i} - \boldsymbol{\mu_x})\right\} \tag{4.7}$$

$$\boldsymbol{\sigma_y} = \{\frac{1}{k-1}\sum_{i-1}^{k}(\boldsymbol{y_i} - \boldsymbol{\mu_y}) \tag{4.8}$$

4.2. Results

Our analysis depends on the window size [3×3], where the impact of pressure is measured over a range of window sizes. Each feasible window size has a corresponding performance graph. Table 4.2 demonstrates that the PSNR is enhanced by the [3×3] window size, indicating that the filtered picture. Our analysis depends on the window size [3×3], where the impact of pressure is measured over a range of window sizes. Each feasible window size has a corresponding performance graph. Table 4.2 demonstrates that the PSNR is enhanced by the [3×3] window size, indicating that the filtered picture is of greater quality (potential errors are mitigated while edges are preserved). The likelihood of obtaining a median rises as the window size rises. It doesn't accurately depict the relevant pixel. That's why the pixels immediately adjacent to the pixel being processed are the most relevant ones to consider in the intermediate filter. The likelihood of obtaining a median rises as the window size rises. It doesn't accurately depict the relevant pixel. That's why the pixels immediately adjacent to the pixel being processed are the most relevant ones to consider in the intermediate filter.

Table 4.2. Criteria for evaluating the effectiveness and quality of the compression algorithm different window sizes

Window size	MSE	RMSE	PNSR	SSIM	Time	CR
[3x3]	32.9575	5.7409	33.0513	0.8159	167.358855	18.0234
[5x5]	50.8188	7.1287	31.6706	0.7210	170.553260	18.2568
[7x7]	47,9649	6.9257	31.3216	0.7372	170.997976	15.005
[9,9]	50.8187	7.1287	31.0706	0.7210	172.203138	18.2568

Figure 4.1. shows how the image degrades in quality as the window size for the Gaussian filter is increased. From Figure.4.1., it can be inferred that a window size of [3×3] best retains quality.

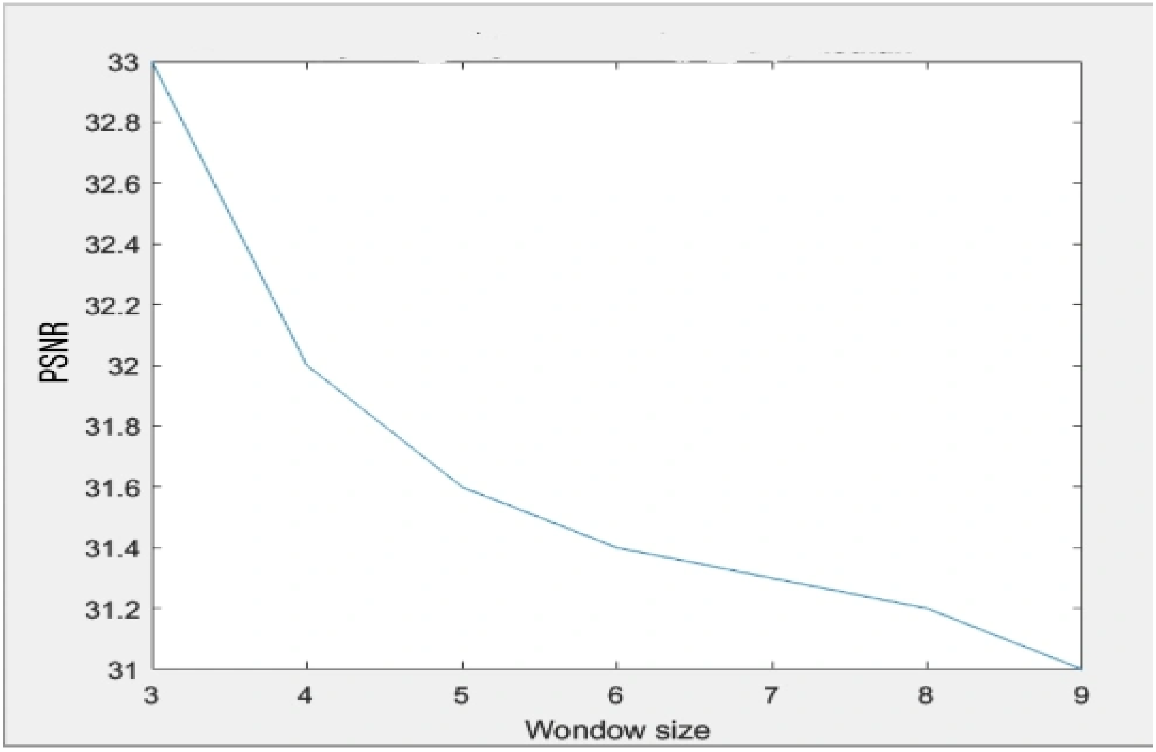


Figure 4.1. The average PSNR by window size using the median filter

Figure 4.2. shows that the error associated with a window size of [3 ×3] is minimal.

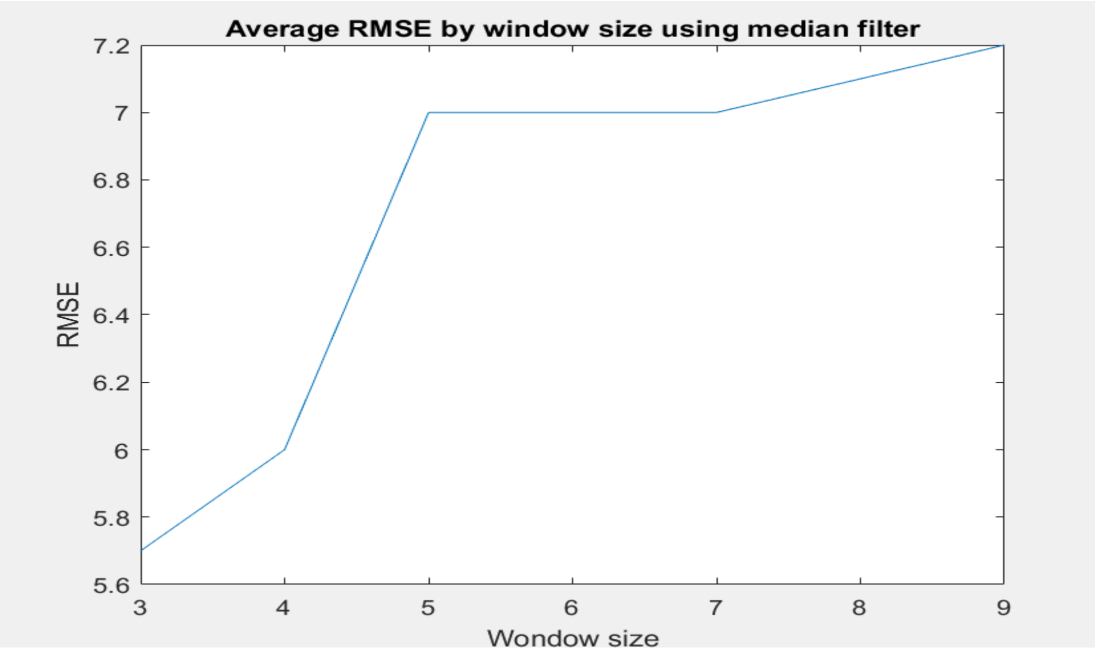


Figure 4.2. Average RMSE by window size using a median filter

This favors applying the [3 ×3] window to the preprocessing step. Considering the amount of time needed to compute the Gaussian Filter, it can be realized from Figure 4.3. that as the window size of the Gaussian filter increases, the time required to perform the preprocessing also increases.

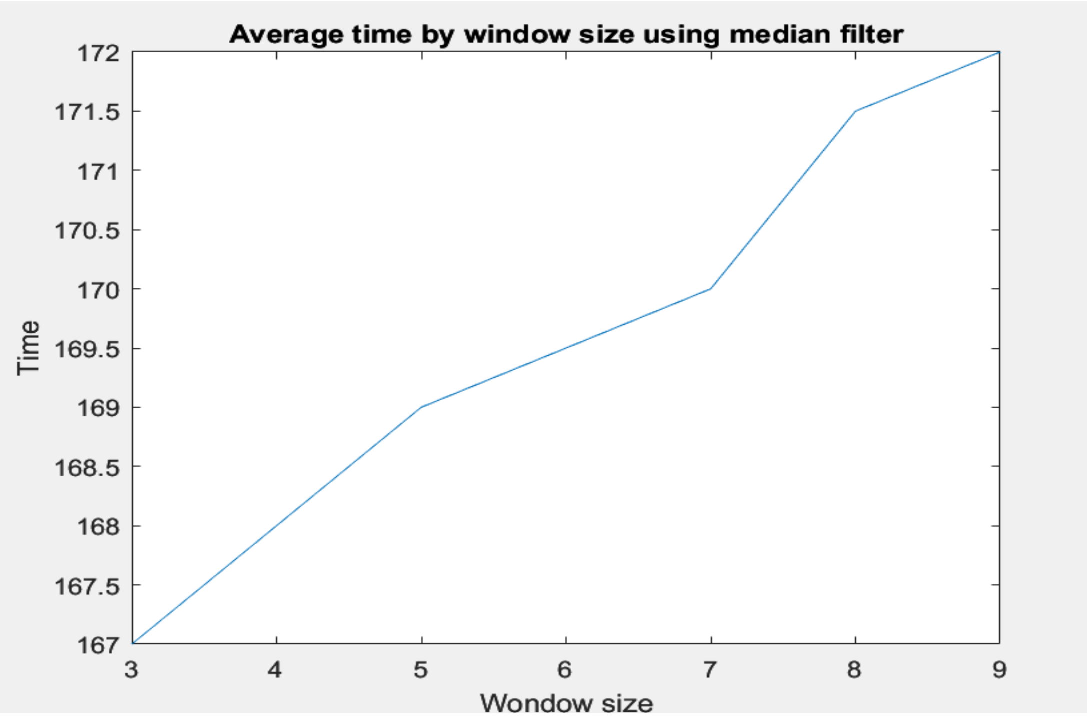


Figure 4.3. Average time by window size using a median filter

And from Figure 4.3. we realize that as the mean filter window size increases, the time required to perform the pre-treatment increases. This is because many pixels are taken into account when finding the median. In the case of a [3×3] dimension, the pixels of significance are nine. The larger window means more pixels are added. The extreme case of a window size of [7×7] means that to determine the median, forty-nine different pixels are taken into account, hence the increase in computation time.

4.3. DWT Operation

After performing a DWT on the filtered image and applying a threshold to the resulting transactions, the performance of using the threshold to the transactions is evaluated. Two different scenarios are taken into account. Two-level decomposition and three-level decomposition (see Figure 4.4.).

Original image Two-level decomposition Tree-level decomposition

Figure 4.4. The image with two different scenarios

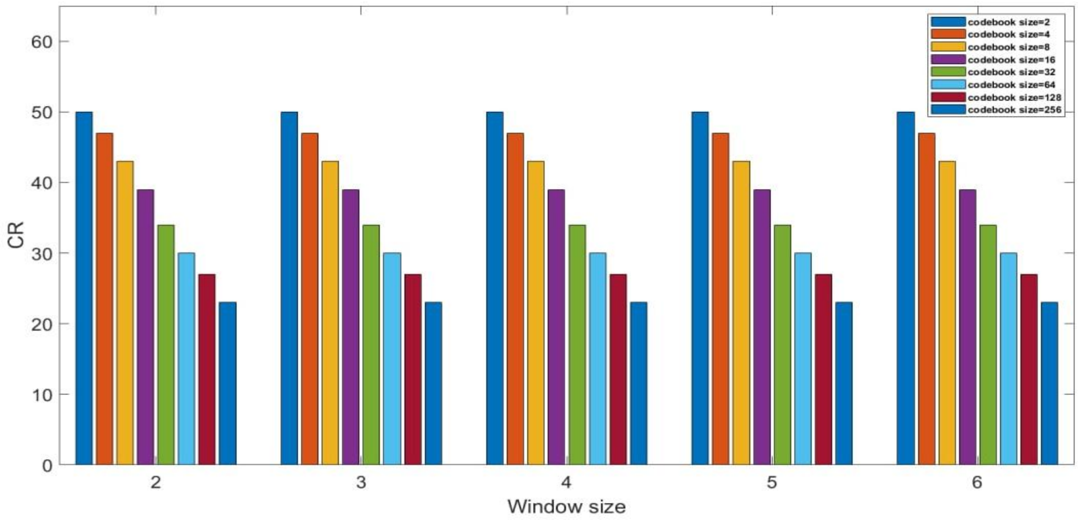
Table 4.3. shows the PSNR, MSE and RMSE results for a reconstructed image sample from DICOM samples. The results concluded that ignoring some parameters did not cause severe distortion in the image. Thus, the image quality remains intact. High PSNR values show this effect.

Table 4.3. PSNR and RMSE and MSE using [3×3] window size

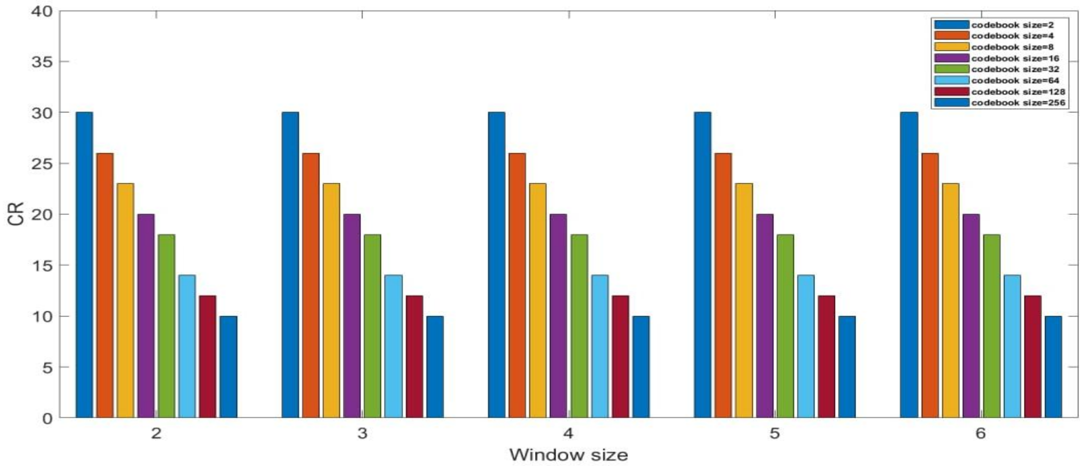
	MSE	RMSE	PSNR	SSIM	Time	CR	Bpp
Image (l) BR	5.5552	5.0552	34.0560	0.7480	198.375437	11.3243	0.1581
Image (2) CI	32.9575	0.7409	32.9513	0.8159	177.358855	18.0234	0.1116
Image (3) MRI1	31.0870	5.5756	33.2050	0.7200	201.616099	22.2860	0.0922
Image (4) MRI2	38.4169	6.1981	32.2856	0.7124	192.373846	20.8704	0.0943
Image (5) CI2	61.9026	7.8678	30.2137	0.6883	166.023659	20.1298	0.0999
Image (6)	43.9224	6.6274	31.7039	0.6813	163.677266	14.9978	0.1370

4.4. Vector Quantization and Encoding

In this step, experiments were performed with different codebook sizes and window sizes for each image. A test was performed to evaluate the efficiency of the measuring criteria with different sizes of codebooks and windows (see Fig. 4.5.). Additional compression by an algorithmic coding algorithm shows the salient results in Fig. 4.5. The graphs indicate the compression ratios (CR) for each codebook size where Fig. 4.5. (a) shows the third level compression ratio, Fig. 4.5 (b) the second level compression ratio, and Figure 4.6. represents the Peak Signal to Noise Ratio (PSNR), where (a) represents the third level while (b) represents the second level.

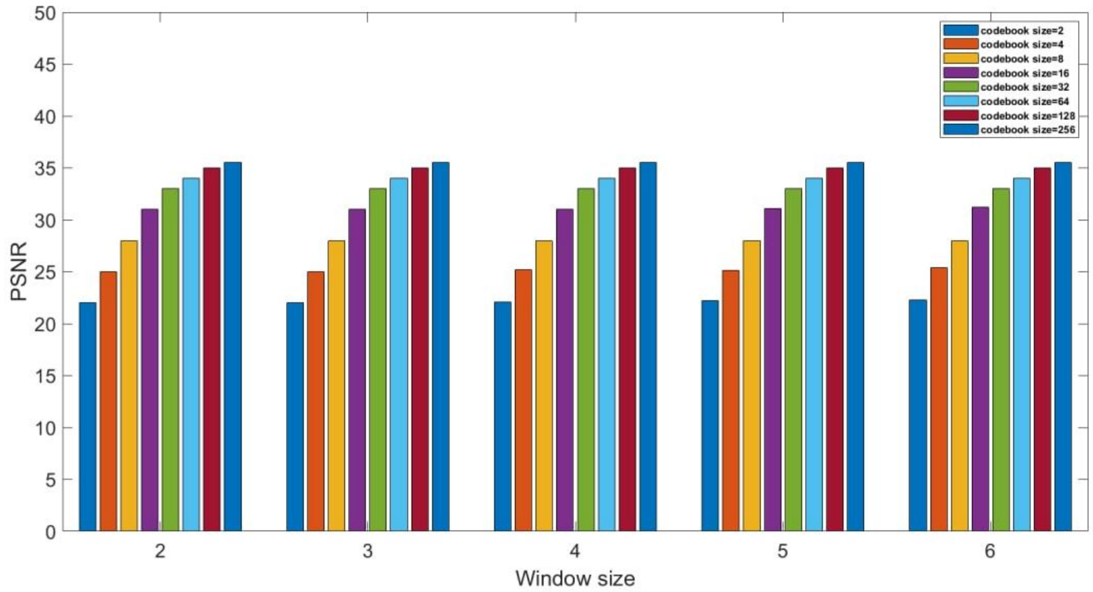


(a)

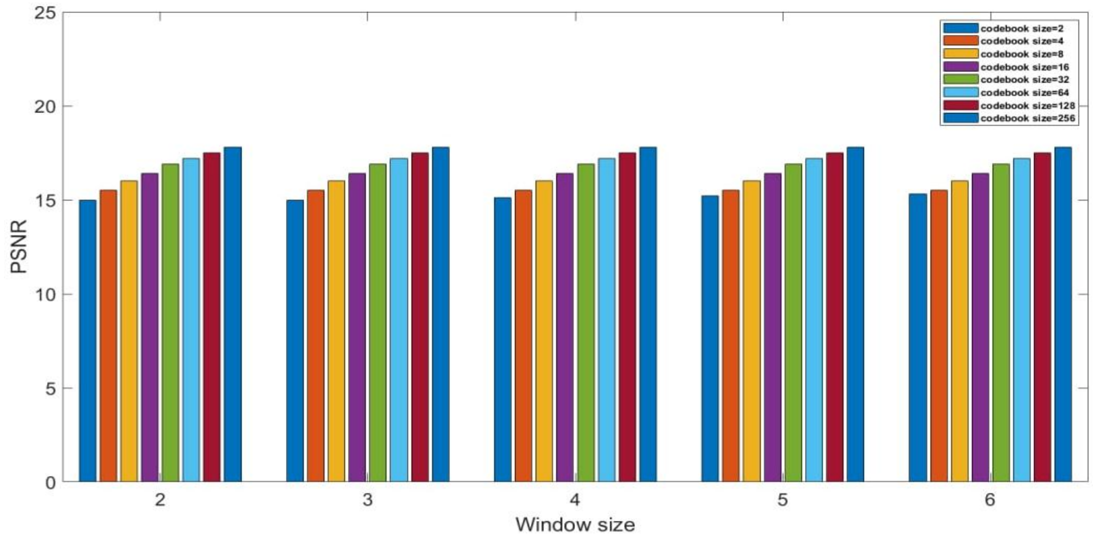


(b)

Figure 4.5. Average compression ratio per window size for different codebook sizes (a) third level and (b) second level



(a)



(b)

Figure 4.6. Average PSNR per window size for different codebook sizes. (a) Third level and (b) second level

From experiments for both levels, the fact that the larger codebook size is confirmed. The best is selected to maintain image quality and therefore a suitable choice of the hybrid algorithm. Because image quality is critical in medical imaging, the pressure was calculated using the Optimization Algorithm (OPS), Figure 4.7. represents the process of descending the curve and reaching the optimization state.

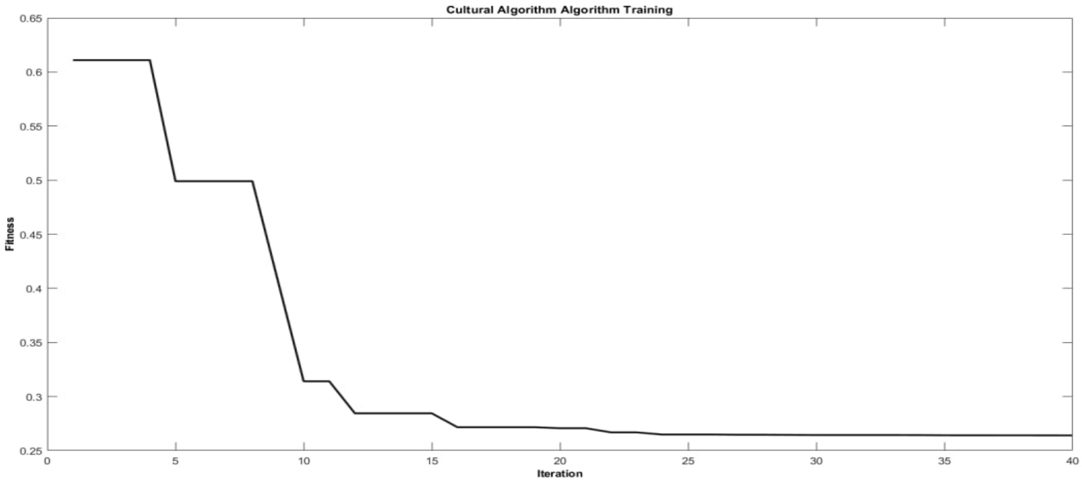


Figure 4.7. Reaching the best state by using an optimization algorithm

At the end of the work, we made a comparison with the reference study [18], where the exact image details were used in terms of extension (. dcm), dimensions (512 * 512), and pixel depth (24 bits). Tables 4.4 and 4.5. show comparisons between PSNR & RMSE & SSIM values achieved in each reference study [18] in which Discrete Wavelet Transform - Vector Quantization (DWT-VQ) technique was used to compress medical images. RMSE and SSIM are achieved by applying the proposed scheme and using the optimization algorithm on the same image quality.

Table 4.4. The results of compression criteria for two different DWT levels of the reference study

Image	Two levels of decomposition			Three levels of decomposition		
	PSNR	**RMSE**	**SSIM**	**PSNR**	**RMSE**	**SSIM**
Image (l)	30.9619	0.5039	0.8732	29.6098	0.6702	0.8010
Image (2)	24.1286	0.9927	0.8697	23. 8722	1.0225	0.7689
Image (3)	27.7495	0.5543	0.8043	27.1934	0.6976	0.7115
Image (4)	26.3682	0.8607	0.8323	25.1994	0.8776	0.7932
Image (5)	28.0147	0.6240	0.8139	26.8572	0.7392	0.7748
Image (6)	27.7434	0.6125	0.8001	27.0192	0.7684	0.7012

Table 4.5. The results of compression criteria for two different DWT levels of the current study

Image	Two levels of decomposition			Three levels of decomposition		
	PSNR	**RMSE**	**SSIM**	**PSNR**	**RMSE**	**SSIM**
Image (l)	32.5687	4.8345	0.7248	34.0560	5.0552	0.7480
Image (2)	33.3052	5.8025	0.8241	32.9513	5.7409	0.8159
Image (3)	33.8840	5.6896	0.7347	33.2050	5.5756	0.7200
Image (4)	33.7830	6.4855	0.7454	32.2856	6.1981	0.7124
Image (5)	31.5158	8.2068	0.7179	30.2137	7.8678	0.6883
Image (6)	32.5536	6.8050	0.6995	31.7039	6.6274	0.6813

Figure 4.8. and Figure 4.9. show the difference between PSNR for both studies and two different levels of dimensions DWT.

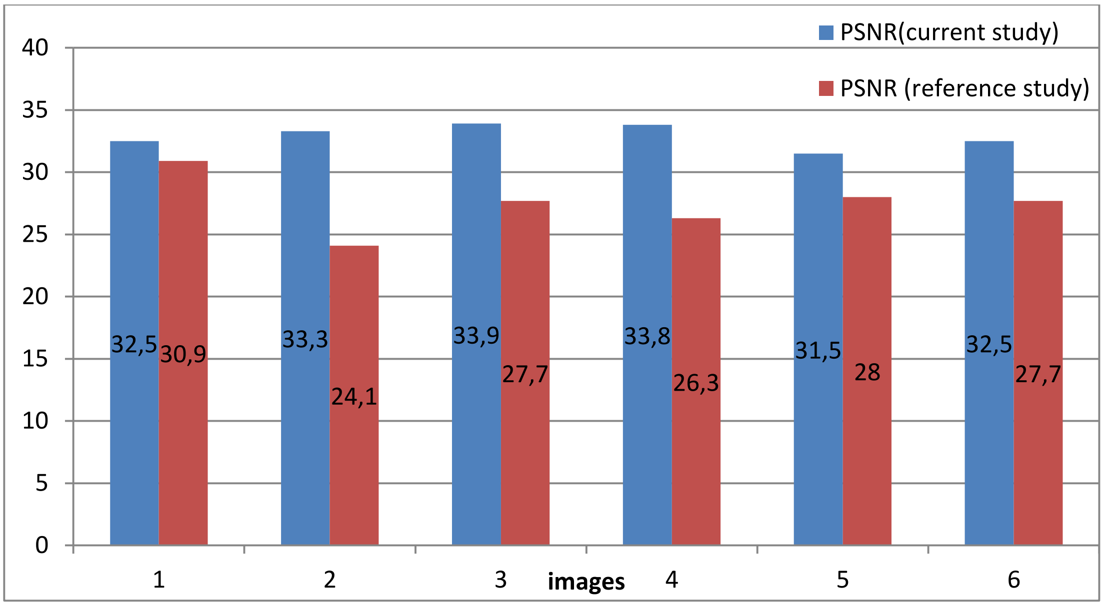


Figure 4.8. Comparison of the PSNR values of the two studies for the second level

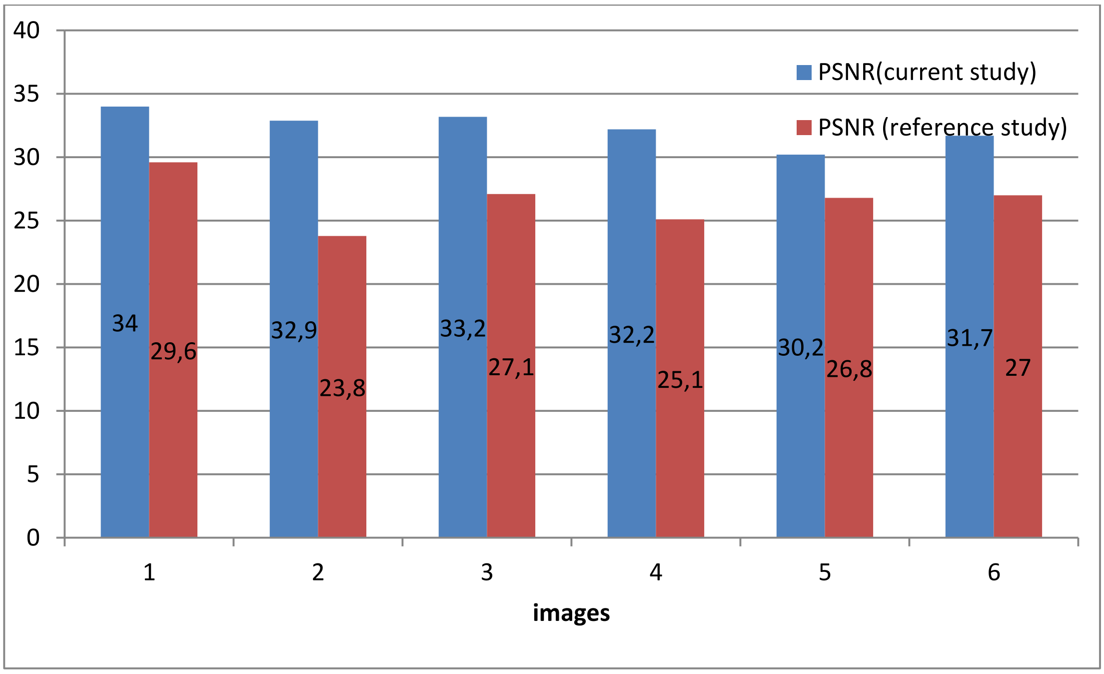


Figure 4.9. Comparison of the PSNR values of the two studies for the third level

5. CONCLUSIONS AND FUTURE WORK

In this study, a combination of Discrete Wavelet Transformation (DWT) and Vector Quantization (VQ) was applied to process complex medical images while preserving the diagnostic content. The threshold principle was used between the two main methods which generate wave coefficients and then exclude the value below the specified threshold because it increases the chance of obtaining a set of zeros. This increases the efficiency of the quantifier. A virtual cipher word is then entered to encode the transactions and encrypted by arithmetic coding. The best combination of hybrid technology was found at two pre-quantification (DWT) levels. With this proposed hybrid technology, we achieve good performance, and by adding an operation optimization algorithm we achieve excellent performance compared to other methods.

In the first phase of this research, we performed a test on images by applying three separate waves transforming the analytical levels. The resulting wave coefficients were then encoded using image coding techniques based on wavelet transform, which is computational coding. These two-stage processes are followed:

1. The test showed that the wavelet level 3 analysis achieved the best compression ratio and encoding technology used with the previous wavelet.
2. The presence of several fundamental factors affecting the results of the previous test, the most important of which are the type of coding technique for wavelet coefficients and the optimization algorithm used.
3. The proposed compression scheme achieved better results than the referenced studies and increased the compression ratio.
4. The proposed scheme was applied to compress images using optimization algorithms.

Hence, at the end of our research.

5. We suggest doing a more in-depth study on the optimization algorithms that include the proposed scheme inside them and comparing their results to get the best results.

6. We suggest applying the work scenario on a broad base of images that differ from the images used in our research.

7. We suggest studying the time coefficient and its consideration during the stages of the proposed scenario to study the effectiveness of using the proposed scheme with time-sensitive applications.

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CURRICULUM VITAE

Name Surname : Azhar ABDULHASAN MOHAMMED ALI

EDUCATION:

- **Undergraduate** : 1992, College of Science, Mathematics & Computer, University of Baghdad
- **Graduate** : 2015, Computer Technology Engineering, AL- Mustaqbal University College, Babylon

PROFESSIONAL EXPERIENCE AND AWARDS:

- (1992-1999) I Worked as Lecturer at Secondary Schools
- (2003-2007) I Worked as an Accountant in an Electrical Contracting Company
- Until Now, I Am Continuing to Work on Archiving and Retirement Programs in the Waqif Office

PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- AJAM, A.A.H, ALBAGHDADI AF, ZENGİN, A. *Medical Image Compression Based On Vector Quantization And Discrete Wavelet Transform*. 2nd International Conference on Engineering, and Science to Achieve the Sustainable Development Goals (ICASDG) 2023. https://icasdg.atu.edu.iq/