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# A Performance Review for Hybrid Region of Interest-based Medical Image Compression

**SUHAILA AB AZIZ[1], (Member, IEEE), SURIANI MOHD SAM[1], (Member, IEEE), NOOR HAFIZAH HASSAN[1], HAFIZA ABAS[1], (Member, IEEE), SITI ZALEHA ABDUL RASID[2], MUHAMMAD FATHI YUSOF[1] AND NORLIZA MOHAMED[1], (Senior Member, IEEE)**

[1]Razak Faculty of Technology and Informatics (RFTI), Universiti Teknologi Malaysia, Kuala Lumpur (UTM), 54100 Kuala Lumpur, Malaysia
[2]Azman Hashim International Business School (AHIBS), Universiti Teknologi Malaysia (UTM), Kuala Lumpur 54100, Malaysia

Corresponding author: Suriani Mohd. Sam (e-mail: surianikl@utm.my).

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**ABSTRACT** In this modern era, medical image sharing has become a routine activity within hospital information systems. Digital medical images have become valuable resources that aid health care systems' decision-making and treatment procedures. A medical image consumes a significant amount of memory, and the size of medical images continues to grow as medical imaging technology progresses. In addition, an image is shared for analysis to support knowledge sharing and disease diagnosis. Therefore, health care systems must ensure that medical images are appropriately distributed without information loss in a timely and secure manner. Image compression is the primary process performed on each medical image before it is shared to ensure that the purpose of sharing an image is accomplished. The hybrid region of interest-based medical compression algorithms reduces image size. Furthermore, these algorithms shorten the image compression process time by manipulating the advantages of lossy and lossless compression techniques. A comprehensive review of previous studies that utilized this approach was conducted. Sample studies were selected from published articles in an open database subscribed to by Universiti Teknologi Malaysia for ten years (2012 to 2023). This work aims to critically review and comprehensively analyze previous types of algorithms by focusing on their main performance results: compression ratio, mean square error and peak signal-to-noise ratio. This article will identify which type of algorithm can give optimal value to the primary performance metric for compressing medical images.

**INDEX TERMS** DICOM, Hybrid Image Compression, Medical Image, Performance Review, Region of Interest-based,

## I. INTRODUCTION

Medical images are critical resources that assist physicians and facilitate monitoring of a patient's health condition, providing a wide range of information that doctors and specialists need to make accurate diagnoses. Moreover, medical images are among the most critical assets of a health care information system (HIS). Health care practitioners utilize these images to electronically detect, diagnose, treat and evaluate various diseases.

In the current technological era, image files occupy a significant amount of memory. The same issue applies to medical images. Each medical image consumes a vast amount of memory and storage space. Therefore, an HIS administrator must ensure sufficient memory space for storing medical images. In addition, the records of many patients must be retained for an extended period, consuming more space for storing images [1], [2].

The primary operation that involves medical images in an HIS is medical image sharing. With the challenges that we are currently facing due to the Coronavirus disease 2019 (COVID-19) pandemic, the need for image sharing has become particularly evident as movement is restricted in many places worldwide. In many clinical cases, diagnostic planning requires collaboration between referring physicians and radiologists to share their knowledge and experience. Especially in complex cases, high-quality communication is essential to further enhance patient care [3]. Medical practitioners must exchange data, particularly medical images, views, ideas and knowledge, to diagnose and analyze diseases. Medical image sharing must be accurately, precisely and safely implemented. Therefore, medical files must be transferred through a network with high bandwidth requirements to ensure that shared images are secure and accurate[4].

Compression has elicited considerable attention in the field of medical images. Medical image compression is utilized in applications to increase transmission speed, obtain more reliable data and reduce storage costs [5]. The primary objective of medical image compression is to reduce the transmitted data volume to preserve bandwidth without substantially influencing data quality by deleting redundant information [6]. Compressing medical images is essential as efficient storage and data transfer through high-bandwidth digital communication networks are decisive. Furthermore, image compression enables a picture archiving and communication system (PACS) to minimize file size in an HIS while retaining critical diagnostic information in its storage requirements [7].

Image compression is classified into lossy and lossless compression [8]. In lossy compression, the resultant image is a near duplicate of the original image with minimal data loss. In contrast, the recovered data are identical to the original data in lossless compression [9], [10]. Both compression types exhibit substantial advantages and disadvantages. Thus, hybrid image compression approaches have been developed by combining the advantages of the two techniques to maximize their effects [11].

Accordingly, a hybrid technique addresses image compression by dividing the original image following the region of interest (ROI). First, a medical image is divided into ROIs and non-ROIs. Subsequently, a hybrid approach is adopted to ensure that a suitable compression technique is utilized to compress the appropriate region [12], [13]. Lossless compression techniques compress the ROI, while the non-ROI is compressed via lossy compression.

However, measuring the performance of compression algorithms remains a challenging task. The effectiveness of an algorithm is evaluated based on its performance in compressing images. Commonly employed measuring metrics include the compression ratio (CR), mean square error (MSE) and peak signal-to-noise ratio (PSNR). These metrics can evaluate the quality and effectiveness of a compression algorithm. In addition, they establish a specific value that provides a particular effect and objective.

The current work comprehensively reviews previous studies that compressed medical images using an ROI-based hybrid method. This review focuses on evaluating the performance of the algorithms proposed by each author. First, comparisons are made among the evaluation metric values of the CR, MSE and PSNR. Second, the relationship among the algorithm, research objectives and evaluation metric values are discussed to measure the quality and effectiveness of the presented algorithm. The analysis results of this review paper will obtain an ROI-based hybrid compression algorithm that gives optimum performance values for the CR, PSNR and MSE for medical images.

This paper is structured as follows: Section 1 presents a brief overview of the study's primary idea. Next, Section 2 summarises digital medical images and their modalities. Section 3 discusses medical image compression based on an ROI-based hybrid medical image compression approach. Section 4 analyses and discusses the performance reviews of hybrid ROI-based algorithms from selected papers. Section 5 concludes this study.

## II. DIGITAL MEDICAL IMAGE

Medical imaging has become a significant and essential tool for successfully and appropriately treating an individual's health-related challenges in this modern world. Medical imaging generates visual representations of the body's interior for clinical diagnosis and medical procedures. Although medical evaluation may be required before treating many diseases, the use of diagnostic imaging services is critical for detecting, accurately assessing and documenting the courses of many diseases and evaluating treatment responses. The number of worldwide image processing operations has significantly increased due to enhanced health care systems and the increased availability of medical technologies. Medical images are significant for surgery, diagnosis, treatment and research; they are a critical component of computerized patient data. In addition, many medical decisions require efficient, safe and high-quality imaging to reduce the incidence of unnecessary procedures. Accordingly, the usage of medical imaging has experienced significant growth in recent years [1], [14].

The image file format is frequently an important issue among medical image processing practitioners. Image file format provides a structured approach for delivering computer files with image-related information. The file format specifies how image data are stored in an image file and how a computer system can effectively interpret pixel data to load them and make them presentable [15]. Commonly used standard medical imaging file formats include Analyze, Neuroimaging Informatics Technology Initiative (Nifti), MINC and Digital Imaging and Communications in Medicine (DICOM).

DICOM theory is generally recognized and routinely utilized in the medical setting. DICOM is the established standard, and technical improvements in medical imaging and network infrastructure integration will be employed for many years. DICOM is an international standard for archiving and transmitting medical images, enabling secure medical image communication across networks. DICOM is

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widely utilized to store and disseminate restorative medical images in devices, including many manufacturers' scanners, servers, workstations, printers, appliances and PACS [2]. In addition, the DICOM file format contains image data and metadata that convey essential image information, such as patient characteristics, equipment and acquisition details [15]. DICOM is the most comprehensive standard in digital medicine, and advances in computer technology have significantly improved how hospital images are viewed [16].

Different modalities for various medical assessment purposes have been presented. A doctor will select a suitable modality based on a patient's illness. The assessment is then delivered through several modalities, including magnetic resonance imaging (MRI), computed tomography (CT) and radiography (X-Ray) [17].

### *A. CT*

CT is an X-ray scan that uses a narrow beam of X-rays to perform a computerized X-ray imaging process. A CT machine is pointed towards a patient and rapidly spun around his or her body, creating signals that are analyzed by the machine's computer to produce cross-sectional pictures or 'slices' of the body. These slices are tomographic pictures as they provide more comprehensive information than traditional X-ray images. After the computer in the machine gathers multiple sequential slices, the slices may be digitally 'stacked' to produce a 3D picture of the patient, allowing for better identification and localization of fundamental structures and suspected tumours or anomalies [18]. These cross-sectional pictures of the human body are then viewed on a computer screen, printed or copied to a CD [19]. Thus, CT scans are occasionally known as computerized axial tomography scans.

CT scans help detect disease or damage in many parts of the body. For example, CT has evolved into an effective screening technique for detecting potential malignancies or abdominal injuries. For example, a heart CT scan may be performed to detect various heart diseases or conditions. CT scans of the head can detect injuries, tumours, and clots that cause stroke, bleeding and other disorders. In addition, CT can examine the lungs to identify malignancies, pulmonary embolisms (blood clots), excess fluid and other diseases, including emphysema or pneumonia. CT is particularly effective for imaging complicated bone fractures, badly degraded joints or bone malignancies as it frequently provides more information than traditional X-ray images [7].

### *B. MRI*

MRI is a noninvasive and commonly employed imaging technology that creates exact 3D anatomical images and provides diverse and detailed images of the body's interior for medical purposes. Similar to a CT scan, an MRI produces a cross-sectional picture. The MRI technique is based on a scientific phenomenon known as nuclear magnetic resonance (NMR), which is a spectroscopic approach that is used to gather small physical and chemical data about molecules. MRI scanners utilize radio frequency (RF) and a high magnetic field to monitor the magnetic moments of protons and to create images of different body regions [20].

MRI scans are frequently utilized to identify knee and shoulder problems. MRI is beneficial for imaging soft tissues and nonbone body components. MRI is distinct from CT as it does not use potentially hazardous ionizing X-rays. The brain, spinal cord, nerves, muscles, ligaments and tendons are more apparent on MRI than on traditional X-ray images and CT scans. MRI can distinguish between the white grey matter and grey matter in the brain and detect aneurysms and tumours. MRI does not use X-rays or other forms of radiation; it is the method selected when frequent imaging is needed for diagnosis or therapy, particularly of the brain [7].

### *C. X-RAY*

X-ray is the most basic and widely utilized method for medical imaging. X-ray is frequently used to identify foreign soft tissue items, diagnose bone fractures, locate injuries or infections and diagnose bone fractures. Furthermore, specific X-ray techniques may use iodine or barium-based contrast agents to increase the visibility of specific organs, blood vessels, tissues or bones. Medical radiography is a broad phrase that refers to various studies that involve X-ray imaging of interior organs. This process of producing and capturing an X-ray photograph presents the user with one or more static images after exposure. Thus, radiography involves a single image preserved for subsequent assessments [7].

Computer radiography (CR) is an indirect method that replaces traditional film radiography. The hard or soft cassette has a memory plate, allowing it to be used in various applications. Digital radiography (DX) is a more sophisticated X-ray examination technique that creates a digital X-ray image on a computer. This technology collects data during an object examination using X-ray sensitive plates; the data are instantly transmitted to a computer without requiring an intermediary cassette [21].

## III. MEDICAL IMAGE COMPRESSION

Medical imaging has become an essential and necessary technology for successfully and correctly diagnosing and treating various diseases. However, medical imaging demands considerable storage and involves the transmission of images over a high-speed network. Moreover, the medical images contain sensitive patient information, and their transmission over the internet requires secure communication channels to protect the privacy of the patient. Therefore, the compression of medical images is an excellent solution to storage and transfer challenges. Medical image compression not only saves storage space but also facilitates fast, secure image transfer via networks.

Image compression is a process that reduces the number of bits used to display, store and transmit data as fast as possible to decrease and minimize data. Redundant and irrelevant information is identified and exploited to reduce the storage size of an image [22]. Unnecessary data are deleted to reduce irrelevance information and to increase the compression rate. Irrelevance is not essential while working with medical images as health care workers aim to ensure that every detail in an image is either visible or not visible. Redundancy reduction refers to the elimination of redundant data. Given that neighbouring pixels will probably be linked, duplicate information may exist. Such redundancy is one of the three types known as the redundancy of interpixels. The two other redundancy types are coding and psychovisual redundancies [23].

The motivation for studying medical image compression stems from the need to reduce storage space, improve image transmission speed, secure sensitive patient information transmission, and enable real-time access to the images for efficient patient care. In addition, developing efficient compression techniques will significantly impact the healthcare industry by improving the overall management and accessibility of medical images, thereby aiding in the early diagnosis and treatment of various medical conditions [24]. As the volume of medical images increases, the need for efficient compression methods will become even more critical. Medical image compression is a rapidly evolving field, with new research being conducted all the time to develop better compression algorithms [25], [26].

### A. IMAGE COMPRESSION IN DICOM

DICOM is a comprehensive international standard. The drafting committee of standards is already aware of the importance of DICOM image compression and has assigned a particular working group to address this issue. Therefore, the committee has developed and maintained the compression transfer syntaxes used in the standards. DICOM provides a mechanism for supporting the use of JPEG 2000 image compression through the encapsulated format in PS3.3 (Information Object Definitions). Annex An in PS3.5 (Data Structures and Encoding) defines several transfer syntaxes following the JPEG 2000 standard and provides lossless (bit-preserving) and lossy compression schemes. A transfer syntax is a collection of encoding rules that may clearly express abstract syntaxes [2], [27].

In general, DICOM images are compressed using the JPEG 2000 technique. The JPEG 2000 standard is a compression technique that can cover the compression of medical images [6], [14]. The JPEG 2000 coding stream can be specified for lower-resolution or lower-quality images before transmitting the entire image. This coding stream significantly aids in browsing applications and implies that only one file is required for many applications.

In addition, comprehensive metadata may be provided with an image near the connection, implying that files may be sent to recipients and processed or indexed in an existing database. Some applications, such as those based on DICOM standards, have specialized techniques for handling such metadata. JPEG is collaborating with the DICOM committee to ensure that the two essential standards may be readily merged [7], [12].

### B. LOSSY MEDICAL IMAGE COMPRESSION

Lossy image compression algorithms are implemented when human observers cannot detect image data loss or when information loss is acceptable [28]. Lossy compression algorithms involve information loss. Consequently, information is missing, and the original image is not recovered exactly as it was before it was compressed. Some information in an image may be lost during a lossy compression process; hence, this technique allows for more data compression. Accordingly, shrinking the image size to its most diminutive dimensions is possible. Furthermore, the compression ratio of these approaches is high.

A lossy approach strives for maximum compression ratios, allowing for appropriate degradation in the reconstructed image. This approach eliminates the duplication of less valuable and unnecessary materials and applies algorithms to reduce the input to shallow output data with minor details. This technique's output comprises information that differs from the input; hence, a gap exists between input data and output data. This approach is appropriate for applications in which conserving bandwidth or space is critical without sacrificing data quality. MP3 audio files, JPEG pictures and MP4 movies are products of lossy compression methods [8].

Since no information loss in medical images may lead to a false diagnosis and cause catastrophic effects, the methods are lossy; less priority has been given to medical data compression, even if they achieve higher compression ratios than lossless techniques [29]. For example, enhancement operations may cause further lossy compression impairments. Moreover, doctors are reluctant to utilize lossy compression as any information loss or error induced by the compression process may alter clinical diagnosis judgement and constitute a legal challenge [9], [10].

### C. LOSSLESS MEDICAL IMAGE COMPRESSION

An image rebuilt after decompression during lossless compression is identical to the original image. Such a result is preferable as no information is jeopardized. However, lossless compression can only achieve a maximum average compression ratio of 15% [8], [11]. Therefore, lossless image compression is preferable in sensitive applications, such as medical imaging, military applications and astronomy.

In a lossless image compression technique, reconstructed data from compressed data are comparable with the original input data. Compared with lossless data compression techniques, data loss is relatively minimal. Consequently, this method is applied where dependability and data security are critical. As the original image is accurately recreated, lossless and reversible compression methods are suggested for legal and ethical considerations. The data in the output are identical to those in the input in this method. This compression technique produces a ratio near 1:1, with a low compression rate; therefore, it is appropriate for applications wherein data loss is not allowed, such as information backup and record archiving. Accordingly, lossless compression is widely employed in compressing medical images [13], [30]–[32].

Lossless image compression aims to represent an image with as few pixels as possible to maximize the compression ratio while maintaining clinical relevance without information loss. Compared with lossy compression, data loss in the lossless data compression approach is negligible. Accordingly, this technique is adopted in sectors wherein dependability and data security are critical. Furthermore, lossless compression techniques are desirable for legal and ethical reasons as they perfectly recreate the original picture [33], [34].

### D. HYBRID ROI-BASED MEDICAL IMAGE COMPRESSION

The pros and cons of both types of compression techniques have been presented. Current lossless compression methods exhibit limited usefulness, and only lossy methods allow us to achieve highly significant compression rates. However, compression techniques employed in medical imaging should allow for a high compression ratio, and more importantly, retain the diagnostic usefulness of an original image. The current study shows that lossless and lossy compression methods exhibit significant advantages and disadvantages in data compression. Table 1 presents the comparison between the lossless compression method and the lossy compression method.

Bairagi developed a compression spectrum based on different compression techniques: lossy, lossless, and hybrid. Figure 1 illustrates this compression spectrum, which indicates that the lossy compression technique provides the highest compression ratio, i.e., an average of 85%. However, Table 1 shows that this technique has low image output quality because of an extremely high data loss rate [35]–[37].

In contrast with the lossy method, the lossless compression rate is low, but the image quality is excellent and similar to that of the original image. Moreover, this method provides a low data loss value. Therefore, this method is a crucial element that should be considered when compressing medical images.

Hybrid image compression techniques have been introduced by manipulating the benefits of the two techniques to achieve the maximum effect [38]. Compression that uses a hybrid technique provides a higher CR value than that in a lossless method, with CR averaging 65%. Moreover, the data loss rate of a hybrid technique is lower than that of a lossy compression technique. These results show that a hybrid method can provide the optimal solution for compressing medical images.

**TABLE 1**
**COMPARISON BETWEEN LOSSLESS COMPRESSION METHOD AND THE LOSSY COMPRESSION METHOD**

| *Factor* | *Lossless Compression* | *Lossy Compression* |
|---|---|---|
| **Definition** | The compression algorithm allows the original data to be entirely reconstructed from the compressed data. | An encoding method that uses a rough approximation to represent content. The method reduces data size for storage, handling and transmitting content. |
| **Uses** | Text or programme, images and sound | Images, audio and video |
| **Advantages** | High output quality<br>Low data loss | High compression ratio |
| **Disadvantages** | Low compression ratio | High data loss<br>Low output quality<br>Complex algorithm |

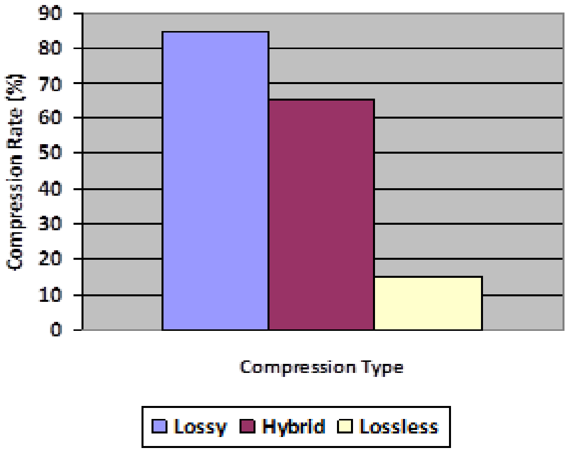


**FIGURE 1. Compression Mode Spectrum** [9], [39].

Figure 2 depicts a medical image compression process block diagram that utilizes a hybrid ROI-based methodology. The image compression procedure begins with the initialization input. Next, the original medical image input diagram is divided into ROIs and non-ROIs using a segmentation procedure. Image segmentation is the process of dividing an image into numerous regions. This process is crucial in describing, recognizing or classifying a processed image or its constituents [40]. The fundamental objective of image segmentation is to make images easier to analyze and interpret while maintaining image quality. This approach is also used within images to trace the boundaries of objects. Pixels are then labelled under their intensity and properties by using this approach. These sections reflect the original image and gain attributes, such as intensity and similarity [41], [42].

An ROI-based compression algorithm has been determined to reduce the size of medical images. ROI selection is essential for health practitioners as specific parts of an image have more symbolic contents than other parts [14]. This approach can increase the amount of available storage space by segmenting an image into ROIs and non-ROIs. Furthermore, this method allows each image segment to be compressed using an appropriate technique to maximize the potential for best outcomes [15].

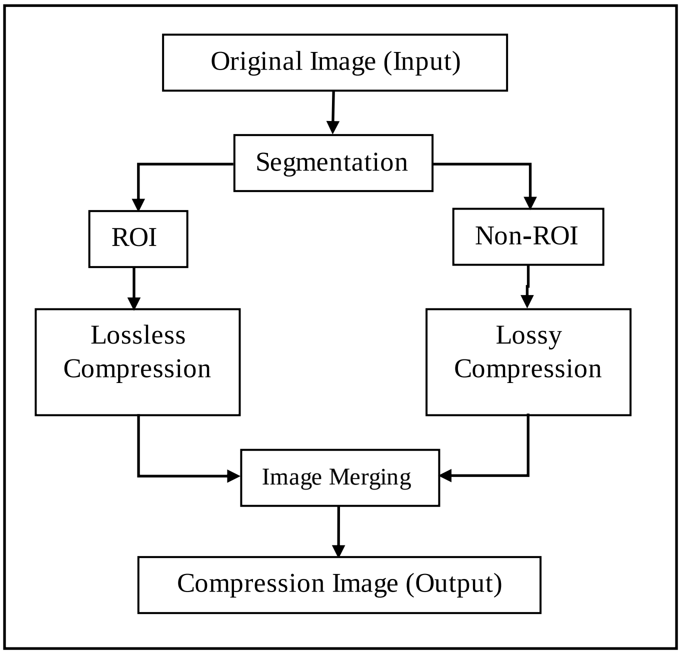


**FIGURE 2. Hybrid ROI-based Data Flow Diagram [41]-[45]**

A medical image consists of three parts: ROI, non-ROI and background. The essential component of an image is an ROI located in small image areas. A non-ROI is also added to rapidly determine an essential region of an entire image. The background, which is the most disregarded area of an image, comprises another element of information. Concerning health, these critical elements must be compressed with high-quality compression without loss compared with other image portions [43]. Figure 3(a) presents a sample of MRI images. Figures 3(b) and 3(c) show the ROI and non-ROI of the sample image, respectively [13].

The appropriate compression algorithm is implemented based on the segment category [22]. Next, the ROI is compressed using a lossless approach, whilst a lossless algorithm is applied to compress the non-ROI. After completing the compression process, the images are combined, and the resulting image is produced. Previous studies are reviewed to determine the use and outcomes of this approach in medical image compression.

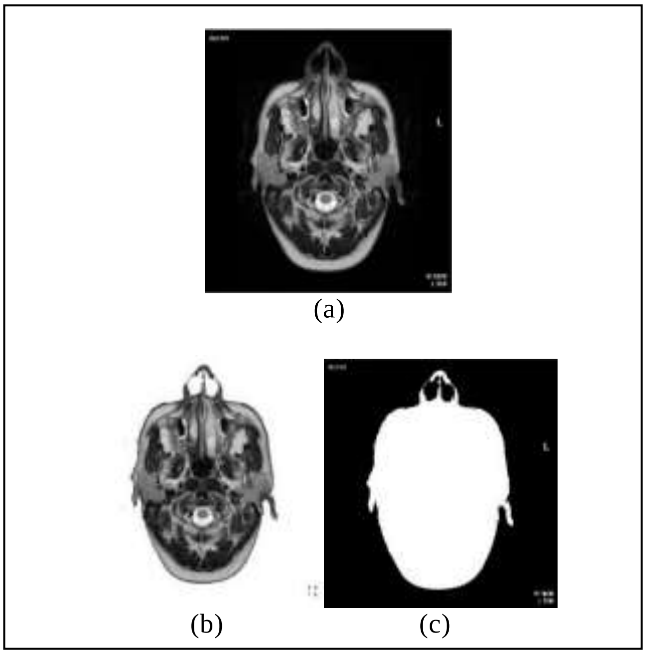

**FIGURE 3.** **(a) Original MRI scan, (b) ROI of the image and (c) non-ROI of the image** [12]

## I. HYBRID ROI-BASED MEDICAL IMAGE COMPRESSION ALGORITHM

This section provides an analysis of ROI-based hybrid medical image compression. Prior studies on image compression that employed medical images in DICOM file format were selected. These papers were published more than ten years ago (between 2012 and 2022) with open access provided only by University Teknologi Malaysia (UTM). As shown in Figure 2, all the selected publications were carefully examined and classified to establish their relevance to data flow diagrams. The focus of this article is on performance evaluation by concentrating on the CR, MSE and PSNR applied to analyze an algorithm's performance with the presented results.

Recently, Dankan Gowda V and colleagues generated an ROI-based near-lossless image compression method for medical images which features Set Partitioning in Hierarchical Trees (SPIHT) and Vector Quantization coding. The proposed method begins by extracting the ROI from the input medical image using the bounding box method. The SPIHT coding method is then used in the ROI portion. Conversely, the non-ROI part is encoded simultaneously, employing the Vector Quantization encoding method. MRI images are used to test the proposed method. This method yielded 49.1 of CR and 38.13db of PSNR, accordingly [44]

Abdellatif and his colleagues presented a hybrid compression approach to improve the compression efficiency of mammography images while preserving vital data. The threshold approach is implemented in this research to accomplish segmentation. The ROI of mammography images is compressed using edge-directed prediction lossless compression, whereas the non-ROI is compressed using fractal lossy compression. The proposed hybrid approach is tested using mammogram images from the mammographic image analysis society (MIAS) database. The metrics used to evaluate compression quality are encoding time, PSNR, and CR. Integrating algorithms using this technique yielded a CR of 36.75, an MSE of 2.701, and a PSNR of 43.85. The results demonstrate that the proposed framework is reliable and provides numerous advantages over other recent mammogram image compression techniques [45].

Prakash Tunga P and Vipula Singh proposed compressing brain MRI images based on automatic tumour extraction. First, the authors use support vector machine (SVM) classification to separate the tumour, followed by automatic region extraction. Second, the ROI area is compressed using arithmetic coding (AC), whereas the non-ROI area is compressed using a combination of the DWT, SPIHT, and AC algorithms. The simulation for this study is run on a computer with an Intel i7 processor and 8 GB of RAM using MATLAB 9.2.0 (2017a) software. The MSE, PSNR, and bpp metrics are utilized to evaluate the algorithm's performance. Last, the images are effectively compressed, yielding a CR of 25.07, an MSE of 0.905, and a PSNR of 50.36 [46].

An ROI-based image compression method for MRI scans, which addresses the frequency components in the finalized medical image, is anticipated by Bindu PV and Jabeena Afthab. The region of interest and nonregion of interest are distinguished using the fuzzy C-Means clustering method. The capsule autoencoder approach is used to compress the non-ROIs. Discrete cosine functions and the Huffman transform with run-length encoding are selected to compress the region of interest. The proposed technique is analyzed using the BRATS-2018 dataset. The suggested brain MRI image compression system is implemented using MATLAB R2021a. Ten brain MRI images from the BRATS 2018 dataset are applied for the performance evaluation. The algorithm's performance is measured using the PSNR, CR, and MSE. The proposed algorithm achieved a CR of 7.49, an MSE of 13.64, and a PSNR of 43.04 [47].

Using intelligent approaches, P. Sreenivasulu and S. Varadharajan developed a narrative medical image compression strategy. Their technique begins by dividing an image into ROIs and non-ROIs using the modified region growing (MRG) algorithm. Next, the ROI area is compressed using the discrete cosine transform (DCT) model and the set partitioning in hierarchical trees (SPIHT) encoding method compression. In contrast, the non-ROI is compressed using a discrete wavelet transform (DWT) and merge-based Huffman encoding techniques. This previous study primarily utilized optimization for selecting filter coefficients from the DWT and DCT techniques. A novel improvised steering angle and gear-based rider optimization algorithm (ROA) was presented for this purpose, modifying ROA. The last decompression step reversed the compression procedure with the same optimized coefficients. The filter coefficient was then adjusted to complete the reduced CR outcome. The resulting image was assessed using the CR and PSNR. The results demonstrated that this approach produced a better outcome, with the best CR and PSNR values of 3.88 and 39.73, respectively [39].

To efficiently convey medical images, C. Peter Devadoss and B. Sankaragomathi employed the block Burrow–Wheeler transform–move to front transform (BWT–MTF) with Huffman and hybrid fractal encoding. The open-source MedPix database, which includes ultrasound, MRI, CT scan and X-ray images, was selected to perform this study. This approach applied a lossless compression technique that combined BWT–MTF and Huffman encoding to the ROI. For the non-ROIs, the author applied lossy hybrid fractal encoding. The compression system's performance was evaluated using PSNR, CR space savings and time consumption. The best results were achieved for ultrasound images, with an average PSNR of 36.166 dB, and MRI, with a PSNR of 34.097 dB. Furthermore, the highest CR (9.621) was determined [48].

A. P. Mukhopadhyay, S. Mohapatra and B. Bhattacharya from India's Vellore Institute of Technology's School of Electronics and Communication eliminated noisy information in the background and revived the image by using a lossless approach. A method based on the DWT and SPIHT was developed for the ROI compression approach. The CR, PNSR and MSE were used to evaluate the performance of this method. The compressed medical image had a decent compression ratio of approximately 31.9995, with an MSE of 74.705 and a PNSR of 30.65 [49].

B. P. Santosh Kumar and K. Venkata Ramanaiah proposed lossy and lossless compression methods for their compression methodology. Their study considered brain MRI, abdominal CT and lung X-ray medical images. The method began by dividing the image into ROIs and non-ROIs. Morphological procedures were then used to segment the brain MRI. Next, the Sobel edge was utilized to segment the abdominal CT. The structured edge detector was employed to segment the lung CT. The ROI was then compressed utilizing lossless run-length encoding (RLE) methods. The non-ROI was compressed using the SPIHT approach. The evaluation metrics MSE and PSNR were used to evaluate the output image's outcome. The results indicated that this method produced improved results, i.e., the best CR and PSNR were 4.2 and 38.16, respectively [38].

Z. Fan, X. Rong and X. Yu introduced an ROI-based medical image compression technique that employed block-to-row bidirectional principal component analysis (PCA). The program initially divided the image into ROIs and non-ROIs using a level-based segmentation approach. The non-ROIs were then subjected to generic PCA. In contrast, the ROI was subjected to block-to-row bidirectional PCA to attain the required image quality while increasing the CR. The experimental findings demonstrated that the proposed technique improved ROI-based block-by-block PCA and ROI-based block-to-row PCA, with a CR of 89.6 and a PSNR of 37.53 [50].

P. V. Joshi and C. D. Rawat discussed this approach to MRI modality during the presentation of their work titled 'Region-based Hybrid Compression for Medical Images' at the International Conference on Signal Processing, Communication, Power and Embedded System. RLE, Huffman and arithmetic coding compressed the ROI. In contrast, the SPIHT method addressed the non-ROI. Preeti assessed the quality of the suggested algorithm by using the PSNR, MSE, structural similarity index (SSIM) and visual information fidelity (VIF). This algorithm's average CR was 0.127, and its PSNR was 10.98 [51].

R. Kiran and C. Kamargaonkar analyzed region-based compression efficacy using block-based PCA. They ran the system through its tests with CT and MRI scans. The automated segmentation technique is applied in this work to trace the necessary ROI on the image. The ROI was primarily treated with block-based PCA, while general PCA covered the non-ROI. This research discovered that region-based PCA outperformed the general PCA method in terms of image quality while producing the same CR. The resulting medical image had a CR of approximately 89.92, an MSE of 2.44 and a PNSR of 44.29 [52].

M. Kaur and V. Wasson developed an ROI-based hybrid medical image compression technique. The approach began by preprocessing medical images, such as X-rays and ultrasound, to eliminate image noise. Consequently, segmentation separated the image into two parts: ROI and non-ROI. Next, compression was applied. In this previous study, the author employed lossy fractal compression for the non-ROI area and context tree weighting lossless compression for the ROI area. Using the CR, MSE and PSNR, the findings were compared with scalable compression approaches utilized by integer wavelet transform and region-based coding. The average CR for this approach was 89.6005, with a PSNR of 53.27 and an MSE of 1.04 [53].

P. Eben, Sophia and J. Anitha suggested a compression strategy for MRI images that used ROI-based compression, boosting the CR compared with the block-based method. They identified the ROI using the split and merge approach and ROI mask creation. The ROI was compressed using a combination of lossless compression methods, including RLE, Huffman, and arithmetic coding. The non-ROI was compressed using lossy compression, which was vector quantization. The success of this algorithm was assessed using the CR, PNSR, MSE and time performance. The reconstructed medical image exhibited an excellent CR of approximately 4.2 and a PNSR of 20.76 [54].

Bairagi et al. suggested two distinct ROI-based compression algorithms. Both techniques compress the ROI by using IWT lossless and the non-ROI by using the SPIHT. The difference was in the segmentation procedure, which produced a CR of 11.43, an MSE of 27.09 and a PSNR of 41.3 when using threshold-based segmentation. Simultaneously, the second approach, which used the Itti–Koch saliency map in segmenting, yielded a CR of 0.151, an MSE of 18.75 and a PSNR of 35.43 [36], [37].

The approach proposed by M. Moorthi and R. Amutha has the advantage that it is not restricted by the size of the blocks used for categorization and does not call for codebook design. The authors manually segmented an image to obtain ROI and non-ROI regions. The ROI area of an image is compressed using an IWT-based compression technique. The JPEG algorithm compresses the non-ROI portion of an image. The presented algorithm's performance is evaluated using quality indicators, including MSE, PSNR, CR, encryption and decryption time. The best CR, MSE, and PSNR were 1.76, 14.17, and 36.61, respectively, showing that this strategy yielded better results [55].

Table 2 provides a detailed summary of the overall methodology applied for all the reviewed articles. The type of image modality used to test each algorithm is specified. The table presents the details of segmentation and the type of lossy and lossless compression algorithms employed in each process, as shown in Figure 2. The performance metrics selected for each algorithm are also presented to show the various metrics to evaluate the algorithm. However, the table only shows the CR, MSE and PSNR results, given that these three values are significant to this analysis.

## iv. PERFORMANCE ANALYSIS OF HYBRID ROI-BASED MEDICAL IMAGE COMPRESSION

This section analyses the findings obtained by previous studies regarding the performance of various types of hybrid ROI-based algorithms in compressing medical images. The algorithm selection is based on journal articles obtained through access to the journal database subscribed to by UTM for ten years (2012 to 2022). In addition, 16 previous studies were manually selected. The researchers used a hybrid ROI-based method to compress medical images, as depicted in Figure 2. The focus of this comprehensive review was to evaluate the performance of each proposed algorithm and to identify the correlation available for each metric.

The essential aspect in ensuring the smooth implementation of an algorithm is to guarantee that all components that support the simulation of the algorithm are neatly prepared and in good condition. The simulation of the algorithm model is developed with the proposed design by using the provided equipment and tools. The development of the proposed algorithm model to support the smooth simulation of the algorithm consisted of three major components: (1) software part, (2) hardware part and (3) digital medical image.

We determined that all 16 prior researchers utilized MATLAB software as a tool to assess the performance of their algorithms. Mathworks (Natick, MA, USA) created MATLAB, a sophisticated program for commercial mathematics. MATLAB is an abbreviation for 'matrix laboratory'; it is primarily used in interactive programming and scientific calculations. Researchers may utilize an ambient interface to analyze matrix equations, display scientific data and perform modelling and various dynamic simulations. MATLAB also provides a comprehensive answer to several scientific fields. For example, MATLAB can simulate all parts of computer vision and data processing for machine learning, such as picture preprocessing, construction and calibration of quantitative and qualitative models, reduction of data dimensionality and data visualization [17], [53].

MATLAB software supports any computer environment, whether Apple or Windows. This software is already on its R2021B version. Nevertheless, developers can still use earlier versions to simulate their algorithms. Thus, an algorithm developer must only ensure that the hardware used for the simulation satisfies the minimum specifications set by the version [42], [56].

Subsequently, the selection of medical image modalities also has a role in algorithm simulation. As stated in Section 2, various medical image modalities are available, and each modality has different characteristics and purposes. A compilation of previous studies determined that all 15 studies used various medical imaging modalities. However, one similarity that was identified was that 13 of 15 researchers selected MRI as one of the image modalities to test the simulation run of their algorithm. This preference was attributed to the benefits of MRI, which is commonly utilized for imaging soft tissues and nonbone body components. MRI scans differ from CT scans as they do not use potentially harmful ionizing X-rays. As a result, the brain, spinal cord and nerves are more visible in MRI than in regular X-ray and CT scans. MRI can also differentiate between the white matter and grey matter in the brain and identify aneurysms and malignancies [57]–[59].

### A. PERFORMANCE METRICS

The performance of the output image results produced by a compression algorithm determines the effectiveness of that algorithm. Therefore, performance evaluation is necessary to check whether the developed algorithm accomplishes its objectives and performs the simulation model by following the anticipated design. The output image is compared with the input image to determine the success of an image compression technique.

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TABLE 2
SUMMARY OF HYBRID METHODS PROPOSED IN PREVIOUS STUDIES, AS SHOWN IN FIGURE 2

| | Document | Modality | Segmentation | Lossless | Lossy | Evaluation | CR | MSE | PSNR |
|---|---|---|---|---|---|---|---|---|---|
| 1. | [44] | MRI | Bounding box | SPIHT | Vector Quantization | CR, MSE PSNR, bpp | 49.10 | 10.08 | 38.13 |
| 2. | [45] | Mammogram | optimal threshold | edge-directed prediction lossless compression | fractal lossy compression | Encoding time CR PSNR | 36.750 | 2.701 | 43.850 |
| 3. | [46] | MRI brain scans. | Support Vector Machine (SVM) classification and region extraction | Arithmetic coding | DWT, SPIHT and Arithmetic Coding | CR, MSE PSNR, bpp | 25.070 | 0.905 | 50.360 |
| 4. | [47] | MRI | Fuzzy C-Means clustering | Discrete Cosine Transform with Huffman-Run-length encoding | Capsule autoencoder method | CR PSNR | 7.490 | 13.640 | 43.040 |
| 5. | [39] | MRI | MRG algorithm. | DCT SPIHT | DWT Huffman encoding | CR, PSNR, average difference, cross-correlation, NAE. | 3.880 | 6.970 | 39.730 |
| 6. | [48] | US. CT MRI X-ray | morphological | BWT and MTF Huffman encoding | hybrid fractal technique. Quadtree decomposition, zero mean intensity level FIC (ZMIL) with Huffman encoding | CR MSE PSNR CoC Space Saving | 7.420 | 23.640 | 38.350 |
| 7. | [49] | MRI, CT, US. | morphological | DWT SPIHT | DWT SPIHT | CR, MSE PSNR | 31.99 | 74.710 | 30.650 |

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content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2023.3312265



| | Document | Modality | Segmentation | Lossless | Lossy | Evaluation | CR | MSE | PSNR |
|---|---|---|---|---|---|---|---|---|---|
| 8. | [38] | MRI<br>CT | based on modality | RLE | SPIHT | CR<br>PSNR<br>MSE<br>MAE<br>SSIM<br>NCC<br>SC<br>IF | 4.200 | 10.010 | 38.160 |
| 9. | [50] | MRI | based on the level set | block-to-row bidirectional PCA | general PCA | CR<br>PSNR | 0.840 | 11.570 | 37.530 |
| 10. | [51] | MRI | threshold-based | RLE<br>Huffman coding<br>Arithmetic coding | SPIHT | PSNR,<br>MSE,<br>SSIM,<br>VIF | 0.127 | 5229.740 | 10.980 |
| 11. | [52] | CT<br>MRI | edge-based | Block-based PCA | General PCA | CR<br>PSNR | 89.920 | 2.440 | 44.290 |
| 12. | [53] | MRI | Manual | CTW | Fractal lossy compression | CR<br>MSE<br>PSNR | 89.600 | 1.040 | 53.270 |
| 13. | [54] | MRI | Split & Merge Binary mask | RLE<br>Huffman coding<br>Arithmetic coding | Vector Quantisation | CR<br>BPP<br>PSNR | 38.470 | 550.150 | 20.760 |
| 14. | [37] | CT<br>MRI | threshold-based | IWT | SPIHT | CR<br>MSE<br>PSNR | 11.430 | 27.090 | 41.300 |
| 15. | [36] | MRI | Itti–Koch saliency map | IWT | SPIHT | CR<br>PSNR | 0.151 | 18.750 | 35.430 |
| 16. | [55] | CT. | Manual | IWT | JPEG | MSE<br>PSNR<br>CR<br>Encryption time<br>Decryption time | 1.760 | 14.170 | 36.610 |

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The selection of an evaluation metric is critical in the field of data compression to provide an appropriate and accurate evaluation. The compression process's objective determine the evaluation metric to be utilized. Furthermore, other parameters, such as output image correctness and noise content, are considered depending on the topic and research setting [60], [61]. Many evaluation metrics can be applied to measure the efficiency of the performance of a compression algorithm, such as the CR, MSE, PNSR, time and SSIM.

A data compression ratio measures the relative size reduction achieved by a data compression algorithm and is commonly represented as the ratio of the uncompressed size to the compressed size. The CR is calculated by comparing the size of the generated image to the original size and is applied to determine an algorithm's effectiveness by measuring how much an image can be scaled down compared with the original image [4]. Formula (1) is selected to measure the CR.

$$CompressionRatio = \frac{Original\ \mathrm{Im}\,ageSize}{Compress\ \mathrm{Im}\,ageSize} \qquad (1)$$

The MSE and PSNR are used to assess the quality of image compression. The MSE calculates the maximum error between the compressed image and original image. The PSNR is a measure of the total squared error. MSE-based metrics are frequently employed as objective distortion assessments due to their simplicity of calculation. An image with a higher MSE has more visible distortions than an image with a lower MSE. A smaller MSE yields a less noise. The following formula is used to calculate MSE:

$$MSE = \sum M, N[I_1(m,n) - I_2(m,n)]^2 (M * N)\,, \qquad (2)$$

where m and n indicate the numbers of rows and columns, respectively, in the input.

However, image and video compression are commonly used to quantify picture quality reconstructed using the PSNR rather than the MSE. Although the PSNR is extremely useful for comparing images with various dynamic ranges and is utilized for the word length of the signal sample change, the MSE may be interpreted in various ways. The PSNR normalizes the MSE in peak signal levels rather than signal fluctuations, directly comparing the results from different codecs or systems [62]. The PSNR for an image is calculated using Formula (3).

$$PSNR = 10\log_{10}(\frac{R^2}{MSE})\,, \qquad (3)$$

where R is the maximum fluctuation in the input image.

A summary of the selection of evaluation metrics following the objective is provided in Table 3. The CR is used to measure the effectiveness of the algorithm. The higher the CR is, the greater the image can be compressed. Simultaneously, the MSE and PSNR are the measures employed for image quality. The higher the MSE is, the more noise there is in the image. In contrast, the higher the PSNR is the better the image quality. The analysis of the 15 papers that we selected determined that the three commonly utilized performance metrics are the CR, MSE and PSNR. Therefore, we focus on the three types of performance metrics in the current work.

**TABLE 3**
**SELECTION OF EVALUATION METRICS BASED ON OBJECTIVES**

| Evaluation Metrics | Objectives |
|---|---|
| CR | Effectiveness |
| MSE | Quality |
| PSNR | Quality |

## B. ANALYSIS OF CR

The CR is a performance metric that is used to evaluate compression an algorithm's effectiveness. The higher the CR is, the better an algorithm compresses an image. Figure 4 shows the trend result of the CR for ROI-based hybrid medical image compression in previous studies. The graph shows that the algorithm by the researcher [52], [53] generated the best results with the highest CR, i.e., 89.92 and 89.6. In contrast, the algorithm utilized in [36],[50] and [51] produced the lowest CR value, which is less than 1. The results of Bairagi's 2013 study [37] outperformed the CR findings of his 2012 study [36], yielding a CR of 11.43 compared with 0.15 in the previous year. Bairagi utilized the same lossless and lossy compression techniques. He modified the present segmentation method by using a threshold-based segmentation approach.

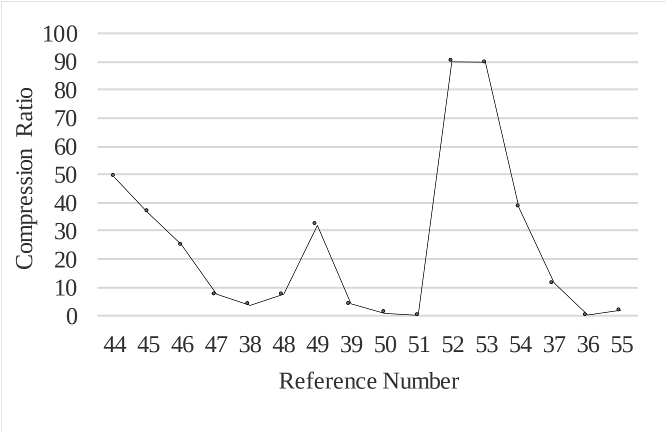


**FIGURE 4.** **Compression Ratio of the Image Compression Trends**

### C. ANALYSIS OF MSE

The MSE is a metric for evaluating the quality of compression techniques. The MSE compares input and output images. The lower the MSE is, the better the meaning when the input and output images are nearly similar. Figure 5 shows a trend line graph of the MSE values for the 16 combinations of hybrid compression algorithms that are being reviewed. The observation results revealed that the average algorithm presents a low MSE value. However, the algorithm produces nearly the same quality as the original image.

The analysis results indicated that the algorithm in [51] provided the highest MSE value of 5229.74. This result shows that this algorithm produces a resultant image that differs from the original image. However, this article states that MSE is not an essential parameter for evaluating the proposed algorithm. Hence, disregarding the high value of MSE is not unexpected. The author only compared his algorithm with the SPIHT algorithm, wherein the results were better than compressing an image using only the SPIHT algorithm.

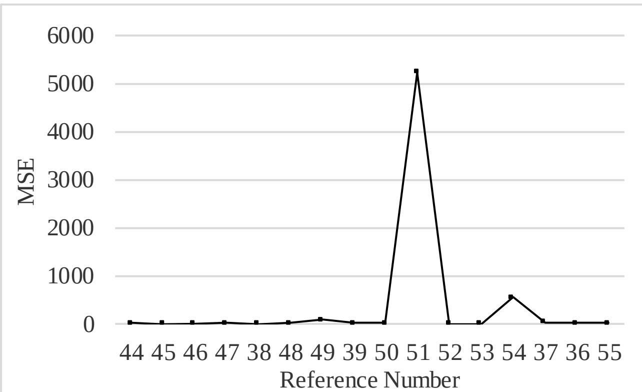


**FIGURE 5.** **MSE of the Image Compression Trends**

### D. ANALYSIS OF PSNR

The PSNR is an evaluation metric for measuring image quality. Assessment is performed based on the noise contained in an image. The lower the PSNR is, the higher the noise content. Thus, the higher the PSNR is, the better the value, i.e., the noise in the image is lower. Figure 6 illustrates the trend line of the PSNR value for the referenced article.

The results of the review revealed that all 16 articles considered the PSNR, which is a parameter for evaluating their algorithm. Therefore, the PSNR values carried out by all the algorithms providing good results are not unexpected. For example, the observation results determined that the algorithms in [46] and [53] presented the highest PSNR values above 50, namely, 50.36 and 53.27, respectively. Other methods consider the significance of this parameter since the average value is higher than 10.

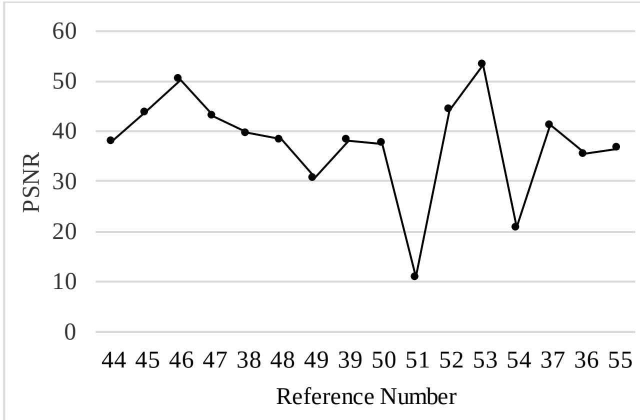


**FIGURE 6.** **PSNR of the Image compression trends**

### E. CORRELATION OF MSE TO PSNR

The results of the analysis of the 16 selected articles indicated that the MSE and PSNR values are highly dependent. Figure 7 shows the correlation between the MSE and the PSNR in the selected articles. The graph indicates that the MSE value is inversely proportional to the PSNR value.

The best resultant image quality has a high PSNR value. Lower MSE values indicate fewer resultant image defects, as indicated by the graph's inverse connection between the MSE and the PSNR; conversely, they result in a high PSNR number. An outstanding compression technique provides a low MSE and high PSNR [63].

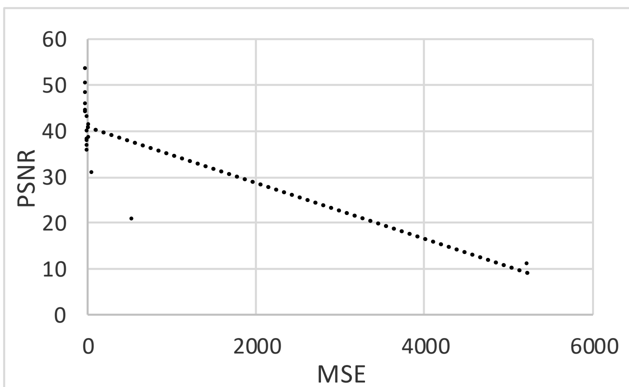


**FIGURE 7.** **Correlation of the MSE to the PSNR**

### F. CORRELATION OF CR TO PSNR

The results of observing the CR and PSNR values for all the investigated algorithms determined that the values of

CR and PSNR are highly dependent. The graph in Figure 8 plots the CR and PSNR values for the entire algorithm. The graph shows that the CR and PSNR values are directly proportional.

The higher the CR is, the greater is the effect of a compression algorithm on an image, that is, the better the compression of an image is, and larger the amount of conserved storage space. A high PSNR value indicates a better-reconstructed image that is considerably closer to the original image. The primary objective of an algorithm developer is to provide the highest CR and PSNR values [35], [64].

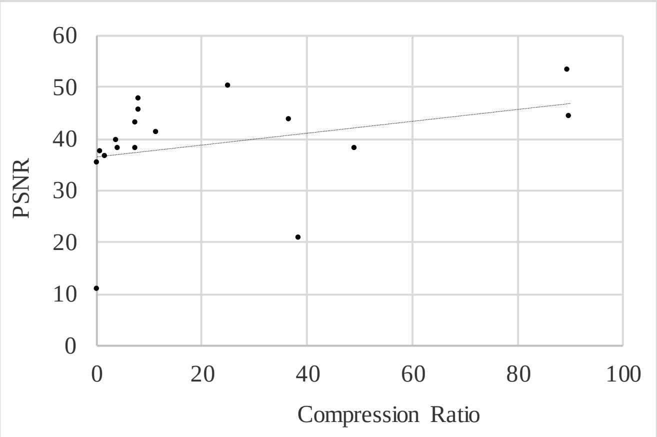


**FIGURE 8.** **Correlation of PSNR to CR.**

## V. CONCLUSION

A hybrid ROI-based compression technique can be applied to compress a medical image. The core idea of this technique is to manipulate the advantages of the classic compression technique, namely, lossless and lossy. This method separates the ROI and the non-ROI from the original image, and then each region is compressed using an appropriate technique to obtain the optimal medical image compression results.

This work analyzed previous studies that used hybrid ROI-based techniques to compress medical images. The articles are selected from a database subscribed to by UTM for ten years (2012 to 2022). The results of manual selection revealed that 16 previous studies adopted this method. The focus of this review is to comprehensively analyze the performance of algorithms proposed by previous researchers. Three primary evaluation metrics are commonly utilized to measure the performance level of compression algorithms, namely, the CR, MSE and PSNR. The CR generally measures the algorithm effectiveness, while the MSE and PSNR measure algorithm quality. Therefore, an algorithm that creates a resultant image will have a low MSE but a high PSNR and CR, which is the optimal compression strategy that image processing practitioners are targeting.

The type of algorithm [53] that gives the best results has been identified as a contribution to the analysis as this method produces the most extraordinary CR and PSNR values, as well as the lowest MSE values. These discoveries open the door for additional creative and innovative researchers to develop these algorithms and achieve higher performance results.

There are many opportunities for future research in this field [65]. Researchers should consider these options to fully realize the promise of blockchain-based ROI compression in medical applications. Integrating blockchain technology into medical image compression can offer several benefits, including enhanced security, privacy, and accessibility. Research can focus on developing blockchain-based ROI-based medical compression techniques that leverage the blockchain's distributed ledger technology to enhance the security and privacy of medical images. By combining ROI-based compression with blockchain, it may be possible to provide secure and efficient sharing of medical images between different entities while maintaining the privacy of patients [66], [67].

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