Evaluating the Performance of Compressive Sensing and Deep Learning Techniques for Medical Imaging in Healthcare Applications

Umme Saniya [1], Yashass G[2], Soujanya [3], Chandini R [4]. Dr. R. SEKAR M.E.,PH.D

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

PRESIDENCY UNIVERSITY

ABSTRACT:

In recent years, the use of deep learning- based medical image fusion (DLMIF) has become a common practice for the reliable detection of diseases, as it allows the combination of information from multiple medical imaging modalities [1], [2]. The performance of DLMIF heavily relies on the effective selection of features for calculating fusion weights [3]. This study investigates the efficacy of convolutional neural network (CNN) features in the context of DLMIF by utilizing two input medical images and generating a fused image using various conventional techniques [4]. Due to the absence of ground-truth images for training end-to-end CNNs, pre-trained networks from other tasks are employed to extract relevant features [5]. The choice of CNN network and the selection of convolutional layers (CL) are systematically examined to assess their impact on the fusion process [6]. Furthermore, consistency maps and local visibility are computed using the extracted CNN feature maps to determine the appropriate fusion weight map for DLMIF [7]. The results demonstrate that the proposed method outperforms conventional techniques in terms of several quantitative metrics and produces superior DLMIF outputs, offering enhanced medical images that are highly suitable for medical diagnosis [8].

Parallel to advancements in medical image fusion, the increasing use of images across various sectors, including online social networks, government agencies, law enforcement, educational institutions, and private companies, has driven the demand for efficient image storage solutions [9]. As these images are stored in vast databases, image compression techniques play a critical role in reducing storage requirements and optimizing data transfer [10]. Image compression aims to represent significant image information in a compact form while removing redundant or insignificant data [11]. The rapid growth of data has highlighted the importance of efficient image compression, especially in the face of the challenges posed by complex, unknown correlations between pixels in an image [12]. The task of finding and recovering well-compressed representations is intricate, and designing networks that can recover images successfully—either losslessly or lossy—remains a challenging task [13]. Deep learning techniques, particularly autoencoders, have gained attention as effective tools for image compression [14].

This article provides an overview of the most common image compression techniques, focusing on the role of autoencoders in deep learning-based compression, and evaluates key performance metrics such as SSIM, MS- SSIM, and PSNR to assess the effectiveness of these methods in maintaining image quality during compression [15]. By integrating advancements in both DLMIF and image compression, this study emphasizes the potential of deep learning techniques to improve medical image analysis and data storage solutions across various fields [16].

1. INTRODUCTION:

### 1.1 History of Medical Imaging and Its Advancements.

Medical imaging has a long and transformative history, evolving from rudimentary techniques to highly sophisticated methods used today for

disease detection and diagnosis. The first major breakthrough in medical imaging came in 1895 when Wilhelm Conrad Roentgen discovered X-rays, marking the beginning of modern medical imaging [1]. X-ray imaging allowed doctors to visualize the internal structure of the body, particularly bones, and was soon adopted for diagnosing fractures, infections, and tumors. Over time, the scope of medical imaging expanded with the development of new technologies, including computed tomography (CT) [2], magnetic resonance imaging (MRI) [3], ultrasound, and nuclear medicine techniques like positron emission tomography (PET) [4] and single photon emission computed tomography (SPECT) [5].

CT, introduced in the 1970s by Godfrey Hounsfield and Allan Cormack, revolutionized imaging by providing cross-sectional images of the body, offering a clearer understanding of internal structures [6]. MRI, developed in the 1980s, provided superior soft tissue imaging and played a pivotal role in diagnosing neurological, musculoskeletal, and cardiovascular diseases [7]. PET and SPECT imaging further enhanced diagnostic capabilities by providing functional information, offering insight into the metabolic activity and blood flow within tissues [8][9]. These technologies, each with their strengths and limitations, formed the foundation of contemporary medical imaging.

However, as advancements continued, medical professionals found that no single imaging modality could

comprehensively capture all relevant information about a disease or condition. As a result, there arose a need to combine the strengths of different imaging modalities into one composite image—a process known as medical image fusion [10]
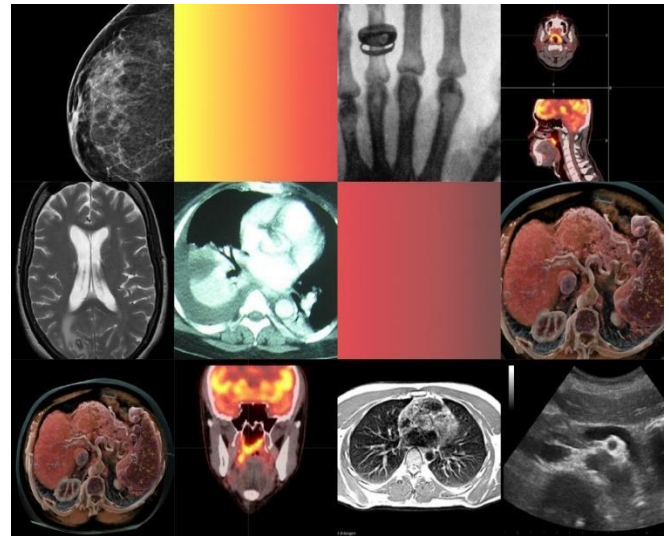

1.2 Medical Image Fusion and Its Role in Disease Diagnosis

Medical image fusion refers to the process of merging information from multiple imaging modalities into a single, more informative composite image, which aims to improve diagnostic accuracy [11]. Each medical imaging technique provides unique information, but no single modality can fully reflect all tissue characteristics or detect all disease traits. For example, MRI excels at providing high- resolution images of soft tissues, while CT is superior for visualizing hard structures like bones [12]. PET and SPECT offer functional insights into tissue activity, but their spatial resolution is often inferior to CT and MRI [13]. The challenge lies in combining these diverse information sources into a single image that retains the crucial details from each modality without introducing artifacts or distortion [14]. The objective of medical image fusion is to combine these complementary features while maintaining diagnostic integrity. Successful fusion enhances the visibility of critical

anatomical and functional information,

thereby aiding clinicians in more accurate disease detection, treatment planning, and monitoring [15]. For instance, fusion of MRI and CT images can offer a complete view of both anatomical structure and functional tissue behavior, improving diagnosis and therapeutic outcomes [16]. Moreover, multimodal image fusion has become essential in many clinical applications, such as

cancer detection [17], neurological disorders [18], cardiovascular diseases [19], and orthopedics [20], where both the anatomical details and functional information of tissues are necessary for comprehensive evaluation.
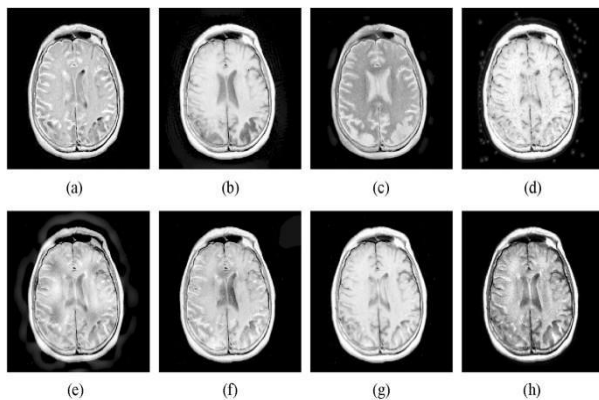
1.3 Challenges in Medical Image Fusion: Information Overload and Feature Extraction

Despite the obvious advantages, the fusion process introduces several challenges. One of the main difficulties in medical image fusion is the phenomenon of information overload. Each imaging modality produces a substantial amount of data, and when combined, the resulting fused image can become overly complex or redundant [21]. The key challenge lies in retaining as much relevant diagnostic information as possible while avoiding the inclusion of extraneous data that may introduce noise or cause distortion [22].

To mitigate these challenges, advanced image fusion techniques, such as feature-based fusion and pixel-based fusion, have been developed [23]. Feature-based fusion involves extracting important features from the original images before combining them, which helps preserve the most relevant diagnostic information [24]. Pixel-based fusion, on the other hand, directly merges the pixels of the images at the data level, potentially sacrificingsome feature-specific details [25]. The most

sophisticated fusion techniques, such as region-based fusion or decision-level fusion, involve a higher level of processing, where the system assesses the diagnostic importance of different image components and selectively combines them based on predefined rules or algorithms [26].

At the heart of the medical image fusion process is the concept of fusion weights, which determine the relative importance of each image component in the final fused image.

These weights are often derived from feature extraction processes, which identify and quantify the most informative elements in each input image [27]. In traditional methods, handcrafted features such as gradients, edges, or textures were used to calculate these fusion weights. However, in recent years, the potential of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image fusion by providing automatic feature extraction that is more robust and accurate compared to traditional methods [28].

1.4 Deep Learning in Medical Image Fusion (DLMIF)

Deep learning-based medical image fusion (DLMIF) techniques leverage CNNs to extract relevant features from medical images automatically, offering several advantages over conventional methods. CNNs are particularly effective in capturing complex patterns and relationships within images, making them ideal for tasks like medical image fusion, where intricate details must be preserved. The main advantage of using CNNs is that they can learn hierarchical features directly from the data, removing the need for manual feature extraction and potentially improving fusion performance.

In DLMIF, CNNs are often used in conjunction with pre-trained networks, which are fine- tuned for the specific task of image fusion.

Since ground-truth data for medical image fusion tasks is often unavailable, pre-trained models from other tasks can be leveraged for feature extraction, allowing CNNs to perform effectively even in the absence of domain- specific training. The fusion process in DLMIF involves calculating fusion weights based on the extracted features, followed by combining

the images in a way that maximizes diagnostic accuracy while minimizing the effects of noise, contrast loss, and distortion.

The integration of CNNs into medical image fusion workflows has led to improved performance in disease diagnosis. For example, combining MRI and CT images using DLMIF can provide a more accurate representation of both anatomical and functional information, which is critical for conditions like cancer or neurological disorders. Moreover, DLMIF has proven to be beneficial for enhancing the visibility of important image features, which helps doctors interpret medical images with greater confidence.

1.5 Image Compression and Its Role in Medical Imaging

Another critical aspect of medical imaging is the need for efficient image storage and transfer, especially given the increasing volume of high-quality medical data. Image compression plays an essential role in reducing the size of medical images without sacrificing diagnostic quality [37]. Medical images, particularly those produced by high- resolution imaging techniques like MRI and CT, often occupy large amounts of storage space [38]. The ability to compress these images effectively is crucial for managing large-scale medical databases and ensuring the efficient transfer of data across healthcare networks [39].

Compression techniques aim to reduce the file size of medical images while preserving as much of the relevant information as possible [40]. Lossy compression methods, such as JPEG, sacrifice some image quality to achieve smaller file sizes, while lossless methods retain every detail of the original image but do not compress the data as much [41]. Deep learning-based image compression, especially through autoencoders, has emerged as a promising approach, as it can learn to compress images in a way that preserves important features while reducing redundancy [42].

In the context of medical image fusion, compression techniques are often used to optimize the storage and transmission of fused images. Compression must be

performed carefully to avoid degrading the

quality of the fused image, as even small losses in quality can affect the diagnostic utility of the image [43]. Advances in deep learning for compression, such as the use of autoencoders, provide an efficient solution to this problem by learning compression strategies tailored to the specific characteristics of medical images [44].

1.6 Datasets Used in Medical Image Fusion and Compression

The effectiveness of deep learning-based medical image fusion (DLMIF) and compression techniques depends significantly on the quality and diversity of the datasets used for training and evaluation [45]. High- quality datasets provide the foundation for training deep learning models, enabling them to learn complex patterns and relationships in medical images. However, obtaining comprehensive and well-labeled datasets for medical image fusion is a challenge due to privacy concerns, the high cost of medical imaging procedures, and the limited availability of ground-truth data [46].

1.6.1 Availability of Medical Imaging Datasets

Several publicly available datasets have been instrumental in advancing research in medical image fusion and compression. These datasets often contain images from various modalities, such as CT, MRI, PET, and SPECT, and provide the necessary data for developing and evaluating fusion algorithms. Commonly used datasets for medical image fusion include:

- **BRATS (Brain Tumor Segmentation Challenge):** A dataset specifically focused on brain tumor segmentation in MRI scans, with multimodal images including T1-weighted, T2-weighted, and post-contrast T1 images. It serves as a valuable resource for testing image fusion and segmentation techniques in the context of brain- related diseases [1].

- **LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative):** A collection of CT

images of the lung, accompanied by annotated lesions and tumor

markings. This dataset is widely used in the development of lung cancer detection and segmentation algorithms and can be used in fusion- based approaches that combine CT with other modalities like PET [2].

- **The Alzheimer's Disease Neuroimaging Initiative (ADNI):** This dataset includes MRI and PET scans from patients with Alzheimer's disease and controls. It is particularly useful for research on the fusion of functional and structural imaging modalities in diagnosing and monitoring neurodegenerative diseases [3].

- **AAPM (American Association of Physicists in Medicine):** The AAPM provides datasets for medical imaging, including CT and MRI images, which are valuable for developing and testing fusion techniques aimed at improving cancer diagnosis, especially for organs like the liver, prostate, and brain [4].

- **The OASIS (Open Access Series of Imaging Studies):** A longitudinal dataset that includes MRI scans of the brain from healthy adults and individuals with Alzheimer's disease. It provides multimodal imaging data useful for investigating fusion methods that combine structural and functional imaging modalities for neuroimaging applications [5].

1.6.2 Dataset Challenges and Considerations
While these publicly available datasets provide valuable resources for training and evaluation, they come with their own set of challenges:

1. **Limited Ground-Truth Data:** For many medical imaging tasks, including image fusion, ground-truth data is scarce. In medical image fusion, the absence of a single reference fused image makes it difficult to evaluate fusion

performance objectively. Researchers often rely on expert opinions or alternative methods to create

synthetic ground-truth datasets, but these are not always perfectly representative of real-world clinical data [6].

2. **Data Diversity and Generalization:** Datasets often consist of a limited set of images from specific patient groups, diseases, or imaging modalities. The models trained on these datasets may not generalize well to other conditions, populations, or imaging protocols. For instance, a CNN trained on a dataset of brain MRI images from a particular hospital may not perform as well when applied to images from a different hospital or with different imaging equipment. To address this, researchers are increasingly turning to more diverse datasets or adopting techniques such as domain adaptation to improve model generalization [7].

3. **Data Privacy and Ethics:** Medical datasets are often protected by strict privacy regulations, such as HIPAA (Health Insurance Portability and Accountability Act) in the United States or GDPR (General Data Protection Regulation) in Europe. These regulations ensure that patient data is anonymized and protected from misuse, but they can also limit the accessibility and availability of large-scale datasets. To mitigate privacy concerns, synthetic datasets or federated learning approaches are being explored as alternatives [8].

4. **Data Imbalance:** Many medical imaging datasets are imbalanced, with certain conditions being underrepresented. For example, datasets may have fewer images of rare diseases or abnormal cases compared to healthy individuals or common conditions. This imbalance

can lead to biased models that perform poorly on less-represented conditions. Techniques like data augmentation, oversampling, and

transfer learning are commonly used to address this issue [9].

5.   **Multimodal Data Alignment:** In medical image fusion, the datasets must consist of images captured from different modalities, such as MRI, CT, and PET. These images are often obtained at different times and may have varying resolutions, orientations, and field-of-view parameters. Proper alignment of multimodal images is crucial for effective fusion. Researchers use image registration techniques to align the images before fusion, but the alignment process can be computationally expensive and prone to errors if not handled correctly [10].

1.6.3 Role of Datasets in Deep Learning for Image Fusion and Compression

Deep learning models used for medical image fusion and compression require large and diverse datasets for training, validation, and testing. By training on varied datasets, these models can learn to extract meaningful features from different imaging modalities and apply the correct fusion strategy for each case. The performance of deep learning-based medical image fusion systems is directly tied to the dataset used, as high-quality datasets with diverse imaging conditions, well-annotated labels, and sufficient representation of different diseases allow the models to perform better in real-world applications [11]. For compression tasks, deep learning models, especially autoencoders, are trained on large datasets to learn efficient ways of reducing the image size while retaining critical diagnostic information. These compression models need to handle various image types and compression levels, including lossy and lossless compression, to ensure that compressed medical images still provide reliable data for disease diagnosis [12]. To sum up, the availability and quality of medical image datasets play a crucial role in the

development and evaluation of image fusion and compression techniques. As datasets become larger, more diverse, and better annotated, deep learning-based methods will

continue to improve, leading to more accurate and efficient medical image fusion and compression systems. The ongoing development of robust datasets will enable these systems to provide better support for healthcare professionals in clinical settings, leading to more informed decisions and better patient outcomes [13].

1.6 Conclusion

In summary, medical image fusion is a rapidly evolving field that enhances the diagnostic capabilities of medical imaging by combining complementary information from multiple imaging modalities. The integration of deep learning techniques, particularly CNNs, into medical image fusion workflows has significantly advanced the field, providing more accurate, efficient, and reliable fusion results. Additionally, the challenge of image storage and transfer has been addressed through image compression techniques, ensuring that large volumes of high-quality medical data can be stored and transmitted effectively. Together, these innovations in image fusion and compression are poised to play a key role in improving medical diagnosis and treatment, offering clinicians better tools to understand and manage complex diseases.

2. Evolution of Image Transmission and Storage

The evolution of image transmission and storage has undergone significant advancements due to technological progress in both imaging and computational capabilities. Early on, images were captured and transmitted as analog signals. However, with the rise of digital technologies in the 20th century, digital image processing and storage became more common. As image resolution increased and the demand for high-quality images grew, the size of image files became problematic for storage and transmission, especially in remote areas or medical applications where large datasets were involved. The ability to store, transmit, and retrieve images efficiently became crucial in fields such as medical diagnostics, satellite

imaging, and digital photography. Compression techniques emerged as an effective solution to reduce image file sizes without losing critical information. These

techniques, which fall under lossy and lossless categories, allowed images to be compressed and stored or transmitted over networks more efficiently.

2.1. Challenges in Medical Imaging Using Traditional Sampling Methods

In medical imaging, traditional sampling methods, where each pixel of the image is captured and processed, present several critical challenges:

1.   **High Data Volume:** Medical images, particularly in fields such as MRI, CT scans, and digital radiography, often have very high resolution. These images require substantial storage space, making archiving and data management costly and complex. Storing large datasets on a single system or transmitting them across networks can become impractical, especially in remote healthcare settings [14].

2.   **Bandwidth Limitations:** Transmitting medical images across networks, particularly for telemedicine applications, is often hindered by the large file sizes. Even in high-speed internet environments, large image files can lead to significant delays in transmission, slowing down the process of diagnosis and consultation [15].

3.   **Loss of Fine Details:** Traditional methods of sampling, especially at lower resolutions, may not capture all the fine-grained details of medical images. For example, subtle changes in tissue structure or small anomalies in scans may not be accurately captured, leading to missed diagnoses or inaccurate interpretations [16].

4.   **Limited Scalability:** As the number of medical images continues to grow

with the increasing adoption of advanced imaging techniques, traditional methods of handling and processing these images may struggle to scale effectively. The increase in

data volume requires more storage, faster transmission protocols, and more powerful computational resources [17].

5.   **Inefficient Data Utilization:** In traditional image sampling, a large proportion of the data can be redundant or non-essential. Without leveraging sparsity or compressive sensing, a lot of unnecessary data might be captured, leading to inefficient use of storage and transmission resources [18].

2.2. Traditional Compressive Sensing (Block Diagram) for Image

Compressive Sensing (CS) is an innovative signal processing technique that offers a more efficient way of capturing and reconstructing sparse or compressible signals. The technique is particularly beneficial for image compression and transmission.

Block Diagram of Traditional Compressive Sensing for Image
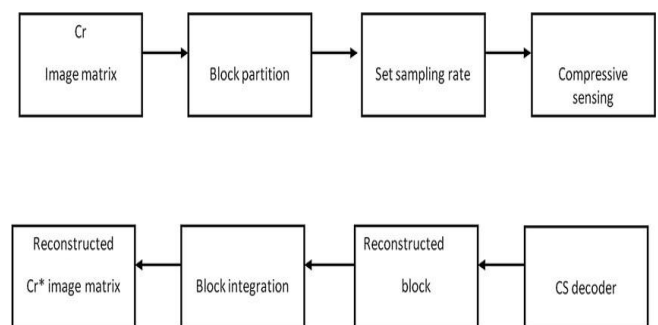
1.   **Compression Block**

○   Sparse Dictionary Learning (CNN): This stage utilizes a Convolutional

Neural Network (CNN) to learn a sparse dictionary of image patches. The dictionary represents the most frequent image patterns.

o   Measurement: A measurement process is applied to the input image. This could involve techniques like compressive sensing or dimensionality reduction.

o   Vibrational Autoencoder: This component further compresses the image by leveraging a variational autoencoder. It learns a latent representation of the image, reducing its dimensionality.

2.   Reconstruction Block

o   Deep Unrolling: This block uses a deep neural network to unroll the optimization process. It iteratively refines the reconstructed image, starting from an initial guess.

o   CNN & Optimization: A CNN is employed to learn the appropriate image features, while optimization techniques like FISTA (Fast Iterative Shrinkage-Thresholding Algorithm) are used to minimize the reconstruction error.

o   GAN: A Generative Adversarial Network (GAN) is incorporated to further improve the quality of the reconstructed image. It trains a generator network to produce realistic images and a discriminator network to distinguish between real and generated images.

3.   Evaluation

o   MSE (Mean Squared Error): This metric measures the average squared difference between the original and reconstructed images.

o   PSNR (Peak Signal-to-Noise Ratio): This metric evaluates the quality of the reconstructed image by comparing it to the original image in terms of signal-to-noise ratio.

o   SSIM (Structural Similarity Index): This metric assesses the similarity between the structural information of the original and reconstructed images.

Additional Insights

•   The use of sparse dictionary learning and deep unrolling enables efficient image compression and reconstruction [1].

•   Incorporating a CNN allows the model to capture complex image features [2].

•   The GAN component helps in generating more realistic and detailed reconstructed images [3].

•   The evaluation metrics provide a quantitative assessment of the reconstruction quality [4].

Potential Applications
This framework is particularly relevant for medical image compression and reconstruction, where efficient storage and transmission of images are crucial [5]. It can be applied to various medical imaging modalities like MRI, CT scans, and X-rays [6].

Further Considerations

•   The choice of dictionary learning technique and CNN architecture can significantly impact the performance of the compression and reconstruction process [7].

•   The hyperparameters of the optimization algorithms and GAN training need to be carefully tuned [8].

•   The evaluation metrics should be chosen based on the specific requirements of the application [9].

2.3.   Stages of Traditional Compressive Sensing
The traditional compressive sensing process involves several critical stages to ensure efficient data compression and accurate reconstruction:

1.   **Image Acquisition**

The image is first sampled at a lower rate than traditional methods, often using random projections. These projections capture the essential information from the image in a reduced number of measurements, which are sufficient for accurate reconstruction if the image is sparse or compressible in some domain [10].

2.   **Compression (Encoding)**

The acquired measurements are then compressed or encoded using a mathematical technique (e.g., quantization or entropy coding) to minimize storage or transmission requirements. The compression step aims to discard redundant or non- essential information while retaining the most important features of the image [11].

3.   **Storage/Transmission**

The compressed measurements are stored in memory or transmitted through a network. This significantly reduces the amount of bandwidth or storage required, especially in bandwidth-limited applications like telemedicine or satellite communication [12].

4.   **Reconstruction (Decoding)**

At the receiving end, the compressed measurements are decoded using algorithms like sparse reconstruction, typically based on convex optimization methods such as L1-norm minimization. These algorithms exploit the sparsity or compressibility of the image to reconstruct it accurately [13].

5.   **Decompression (Final Image)**

After reconstruction, the image is decompressed and displayed. The quality of the reconstructed image depends on the sparsity of the original image and the accuracy of the reconstruction algorithm [14].

2.4.   Performance Evaluation Metrics of Compressive Image Sensing

To assess the effectiveness of compressive sensing techniques in image compression, several performance evaluation metrics are used:

1.   **Peak Signal-to-Noise Ratio (PSNR)** PSNR measures the quality of the reconstructed image compared to the original image. It calculates the ratio between the maximum possible power of a signal (image) and the power of the noise that corrupts the signal. Higher PSNR values indicate better reconstruction quality [15].

2.   **Structural Similarity Index (SSIM)** SSIM compares structural information between the original and reconstructed image, accounting for luminance, contrast, and texture. It provides a more reliable measure of image quality than PSNR, especially in terms of perceived visual quality [16].

3.   **Compression Ratio**

This ratio represents the amount of reduction in data size achieved by compressive sensing. It is the ratio of the size of the original image to the size of the compressed image. Higher compression ratios indicate more efficient compression but may sacrifice image quality [17].

4.   **Computational Time**

The time required to compress and decompress an image is another important metric. For real-time applications like telemedicine, it is crucial that the computational time is minimized [18].

5.   **Reconstruction Error**

This metric quantifies the difference between the original image and the reconstructed image. Lower reconstruction errors indicate better performance of the compressive sensing technique [19].

2.5. Challenges of Traditional Compressive Sensing Image Compression

While compressive sensing offers significant advantages, it also presents several challenges:

1. **Noise Sensitivity**

Compressive sensing methods are highly sensitive to noise, especially in real-world environments. Small amounts of noise in the acquired measurements can result in significant errors in the reconstructed image, particularly in fields like medical imaging where image accuracy is critical [20].

2. **Computational Complexity**

The reconstruction process typically involves solving complex optimization problems, which can be computationally expensive. For large images or real-time applications, this may lead to significant delays, making traditional compressive sensing less suitable for time-sensitive use cases [21].

3. **Loss of Fine Details**

Although compressive sensing captures the main features of an image, some fine details may be lost in the compression process. This can be problematic in applications requiring high precision, such as medical imaging or satellite imaging [22].

4. **Quality Control**

Achieving consistently high-quality reconstructions from compressed data depends heavily on the choice of sensing matrix and reconstruction algorithms. Variability in these parameters can lead to inconsistent performance [23].

2.6. Compressive Sensing for Image Using Deep Learning

Deep learning has been integrated into compressive sensing to overcome some of the traditional challenges:

1. **Improved Reconstruction Quality** Deep learning models, particularly Convolutional Neural Networks (CNNs), can learn more efficient representations of image data, allowing them to reconstruct higher- quality images from fewer measurements. This approach can better recover fine details that might be lost with traditional methods [24].

2. **Noise Resilience**

Deep learning techniques are more robust to noise and distortion in the compressed data. Through training on noisy datasets, deep learning models can learn to recover clean images, making them more reliable in real- world applications [25].

3. **Reduced Computational Complexity** With the use of deep learning, the reconstruction process can be significantly simplified. Deep learning models can be trained to reconstruct images directly from compressed measurements without needing complex optimization steps, thus reducing computational complexity [26].

4. **End-to-End Learning**

Deep learning allows for an end-to- end approach, where the entire process of compressive sensing (from sampling to reconstruction) can be optimized simultaneously. This end-to- end optimization leads to more efficient and effective compression techniques [27].

2.7. Merits of Compressive Sensing with Deep Learning

Integrating deep learning with compressive sensing provides several benefits:

1. **Improved Image Quality**

Deep learning methods, especially CNNs, excel in capturing complex patterns and structures in images, resulting in better reconstruction

quality compared to traditional compressive sensing approaches [28].

2. Enhanced Noise Resistance

Deep learning models are more resilient to noise, which is particularly beneficial in medical imaging or remote sensing, where data may be corrupted or incomplete [29].

3. Faster Reconstruction

Once trained, deep learning models can reconstruct images almost instantaneously, enabling real-time image processing, which is particularly useful in fields such as telemedicine and surveillance [30].

4. Higher Compression Ratios

Deep learning can achieve higher compression ratios while maintaining or improving image quality. This leads to more efficient data transmission and storage [31].

5. Real-Time Applications

The reduced computational load and faster processing times make deep learning-based compressive sensing ideal for real-time applications such as streaming video or remote medical consultations [32].

Compression Block in Compressive Sensing A compression block is the initial phase in the compressive sensing process where an image or signal is compressed to a smaller size using a sensing matrix. This matrix is typically random, which allows us to store or transmit the image in a compressed form. This block helps in minimizing the data that needs to behandled while still retaining the essential information of the original image [33].

Sparse Representation

Sparse representation refers to representing an image or signal with a small number of non-zero elements, despite being in a larger space. This is particularly useful for compression, as most natural images or signals have many elements that do not contribute significantly to the overall image. By identifying and keeping only the most important parts (non-zero elements), we can efficiently represent an image [34].

Dictionary Learning

Dictionary learning is a technique used to improve the sparse representation of images. Instead of relying on predefined dictionaries like Fourier or wavelets, dictionary learning creates a custom set of atoms (basis functions) tailored to the specific dataset. These atoms are the building blocks that allow efficient representation of the image [35].

Reconstruction Algorithm for Compressed Sensing

Once an image has been compressed using compressive sensing, the next step is to reconstruct the original image from the compressed data. This process involves solving a problem where the goal is to recover the image by minimizing the number of non-zero coefficients in its sparse representation. Various algorithms are used for this purpose [36].

Key Algorithms in Compressive Sensing Here are some of the key algorithms commonly used in compressive sensing:

1. **Orthogonal Matching Pursuit (OMP)** This is a greedy algorithm used to find the sparsest approximation of a signal. At each step, it selects the dictionary atom that best represents the signal's residual (the difference between the current approximation and the actual signal) [37].

2. **K-SVD (K-means Singular Value Decomposition)**

This algorithm is used for learning a dictionary from data. It iteratively improves the dictionary by updating it based on the residuals of the signal, ensuring that the dictionary becomes more suited for sparse signal representation [38].

3. **Basis Pursuit**

This algorithm aims to find the sparsest signal representation by minimizing the number of non-zero coefficients. It uses optimization techniques to recover the signal from compressed measurements [39].

Conclusion

The integration of deep learning techniques, particularly convolutional neural networks (CNNs), has significantly advanced medical image fusion and compression. These innovations enable the combination of complementary imaging modalities to create diagnostically superior images, improving disease detection and treatment planning [1]. Additionally, deep learning-based image compression techniques optimize storage and transmission of medical data while maintaining diagnostic integrity [2]. By addressing challenges such as noise, data redundancy, and computational complexity, these

methods demonstrate immense potential in medical imaging and broader applications across fields like telemedicine and data management [3]. Future advancements in dataset diversity, algorithm efficiency, and real-time processing capabilities will further enhance the impact of these technologies on healthcare and beyond [4].

REFERENCES:

[1] O. Faragallah, H. El-Hoseny, W. El-Shafai, W. Abd El-Rahman, S. El-Rabaie, G. Geweid, "A comprehensive survey analysis for present solutions of medical image fusion and future directions," *IEEE Access*, vol. 9, pp. 11358– 11371, 2020.

[2] W. El-Shafai, S. El-Rabaie, S. El-Halawany, F. Abd El-Samie, "Security of 3D-HEVC transmission based on fusion and watermarking techniques," *Multimedia Tools and Applications*, vol. 78, no. 19, pp. 27211– 27244, 2019.

[3] I. Badr, A. Radwan, S. El-Rabaie, L. Said, G. El Banby, W. El-Shafai, F. Abd El-Samie, "Cancelable face recognition based on fractional-order Lorenz chaotic system and Haar wavelet fusion," *Digital Signal Processing*, vol. 116, p. 103103, 2021.

[4] H. El-Hoseny, W. Abd El-Rahman, W. El-Shafai, G. El-Banby, S. El-Rabaie, F. Abd El- Samie, K. Mahmoud, "Efficient multi-scale non-sub-sampled shearlet fusion system based on modified central force optimization and contrast enhancement," *Infrared Physics & Technology*, vol. 102, p. 102975, 2019.

[5] H. El-Hoseny, W. El-Rahman, W. El-Shafai, S. El-Rabaie, K. Mahmoud, F. Abd El-Samie, O. Faragallah, "Optimal multi-scale geometric fusion based on non-subsampled contourlet transform and modified central force optimization," *International Journal of Imaging Systems and Technology*, vol. 29, no. 1, pp. 4–18, 2019.

[6] N. El-Hag, A. Sedik, G. El-Banby, W. El- Shafai, A. Khalaf, W. Al-Nuaimy, H. El-Hoseny, "Utilization of image interpolation and fusion in brain tumor segmentation," *International Journal for Numerical Methods in Biomedical Engineering*, vol. 37, no. 8, p. e3449, 2021.

[7] A. Sedik, H. Emara, A. Hamad, E. Shahin, N. El-Hag, A. Khalil, H. El-Khobby, "Efficient anomaly detection from medical signals and images," *International Journal of Speech Technology*, vol. 22, no. 3, pp. 739–767, 2019.

[8] H. El-Hoseny, W. Abd El-Rahman, W. El-Shafai, G. El-Banby, S. El-Rabaie, F. Abd El- Samie, K. Mahmoud, "Efficient multi-scale non-sub-sampled shearlet fusion system based on modified central," 2019.

[9] O. Faragallah, H. El-Hoseny, W. El-Shafai, W. El-Rahman, H. Elsayed, S. El-Rabaie, G. Geweid, "Optimized multimodal medicalimage fusion framework using multi-scale geometric and multi-resolution geometric analysis," *Multimedia Tools and Applications*, vol. 81, no. 10, pp. 14379–14401, 2022.

[10] C. Ghandour, W. El-Shafai, and S. El- Rabaie, "Medical Image Fusion Based on Weighted Least Square Optimization and Deep Learning Algorithm," in *Proceedings of the 2021 9th International Japan-Africa Conference on Electronics, Communications, and Computations (JAC-ECC)*, pp. 159–163, IEEE, 2021, Dec.

[11] C. Ghandour, W. El-Shafai, and S. El- Rabaie, "Comparative Study Between Different Image Fusion Techniques Applied on Biomedical Images," in *Proceedings of the 2021 9th International Japan-Africa Conference on Electronics, Communications, and Computations (JAC-ECC)*, pp. 164–169, IEEE, 2021, Dec.

[12] J. Tong, Y. Zhao, P. Zhang, L. Chen, L. Jiang, "MRI brain tumor segmentation based on texture features and kernel sparse coding," *Biomedical Signal Processing and Control*, vol. 47, pp. 387–392, 2019.

[13] R. Ali, F. El-Sayed, W. El-Shafai, T. Elsayed, "Efficient fusion of medical images based on CNN," *Menoufia Journal of Electronic Engineering Research*, vol. 30, no. 2, pp. 79– 83, 2021.

[14] C. Sheela, G. Suganthi, "Morphological edge detection and brain tumor segmentation in Magnetic Resonance (MR) images based on region growing and performance evaluation of modified fuzzy C-means (FCM) algorithm," *Multimedia Tools and Applications*, vol. 79, no. 25, pp. 17483–17496, 2020.

[15] S. Rao, M. Parikh, M. Parikh, C. Nemade, "Implementation of clustering techniques for brain tumor detection," *International Journal of Research in Engineering*, vol. 3, no. 4, pp. 6– 10, 2016.

[16] A. Sharma, S. Kumar, S. Singh, "Brain tumor segmentation using DE embedded OTSU method and neural network," *Multidimensional Systems and Signal Processing*, vol. 30, no. 3, pp. 1263–1291, 2019.

[17] R. Desale, S. Verma, "Study and Analysis of PCA, DCT & DWT Based Image Fusion Techniques," in *Proceedings of the 2013 International Conference on Signal Processing, Image Processing & Pattern Recognition*, pp.

66–69, IEEE, 2013, Feb.

[18] F. Abdelsamie, "A hybrid approach for medical image fusion based on wavelet transform and principal component analysis," *Menoufia Journal of Electronic Engineering Research*, vol. 27, no. 2, pp. 59–70, 2018.

[19] W. El-Shafai, "Joint adaptive pre- processing resilience and post-processing concealment schemes for 3D video transmission," *3D Research*, vol. 6, no. 1, pp. 1–13, 2015.

[20] K. Abdelwahab, S. Abdelelatty, W. El-Shafai, S. El-Rabaie, F. Abdelsamie, "Efficient SVD-based audio watermarking technique in FRT domain," *Multimedia Tools and Applications*, vol. 79, no. 9, pp. 5617–5648,

2020.

[21] A. Alarifi, M. Amoon, M. Aly, W. El- Shafai, "Optical PTFT asymmetric cryptosystem-based secure and efficient cancelable biometric recognition system," *IEEE Access*, vol. 8, pp. 221246–221268, 2020.

[22] N. Soliman, M. Khalil, A. Algarni, S. Ismail, R. Marzouk, W. El-Shafai, "Efficient HEVC steganography approach based on audio compression and encryption in QFFT domain for secure multimedia communication," *Multimedia Tools and Applications*, vol. 80, no. 3, pp. 4789–4823,

2021.

[23] A. Algarni, "Automated medical diagnosis system based on multi-modality image fusion and deep learning," *Wireless Personal Communications*, vol. 111, no. 2, pp. 1033–1058, 2020.

[24] W. El-Shafai, S. El-Rabaie, M. El- Halawany, F. Abdelsamie, "Enhancement of wireless 3D video communication using color- plus-depth error restoration algorithms and Bayesian Kalman filtering," *Wireless Personal Communications*, vol. 97, no. 1, pp. 245–268,

2017.

[25] W. El-Shafai, S. El-Rabaie, M. El- Halawany, F. Abdelsamie, Recursive Bayesian filtering-based error concealment scheme for 3D video communication over severely lossy wireless channels. *Circuits Syst. Signal Process.* 37(11), 4810–4841

(2018).

[26] S. Akram, R. Singh, M. AlZain, A. Gehlot, M. Rashid, O. Faragallah, D. Prashar, Performance analysis of IoT and long-range radio-based sensor node and gateway architecture for solid waste management.

Sensors 21(8), 2774 (2021).

[27] A. Algarni, G. El Banby, S. Ismail, W. El- Shafai, F. Abdelsamie, F. Soliman, Discrete transforms and matrix rotation based cancelable face and fingerprint recognition for biometric security applications. *Entropy* 22(12), 1361 (2020).

[28] A. Sedik, H. Emara, A. Hamad, E. Shahin, N. El-Hag, A. Khalil, F. Abdelsamie, Efficient anomaly detection from medical signals and images. *Int. J. Speech Technol.* 22(3), 739– 767 (2019).

[29] A. Khalil, F. Eibrahim, M. Abbass, N. Haggag, Y. Mahrous, A. Sedik, F. Abdelsamie, Efficient anomaly detection from medical signals and images with convolutional neural networks for Internet of Medical Things (IoMT) systems. *Int. J. Numer. Methods Biomed. Eng.* 38(1), e3530 (2022).

[30] O. Faragallah, W. El-Shafai, A. Sallam, I. Elashry, S. EL Rabaie, A. Afifi, H. El-Sayed, Cybersecurity framework of hybrid watermarking and selective encryption for secure HEVC communication. *J. Ambient Intell. Humanized Comput.* 13(2), 1215–1239 (2022).

[31] I. Haque, J. Neubert, Deep learning approaches to biomedical image segmentation. *Inform. Med. Unlocked* 18, 100297 (2020).

[32] A. Taha, A. Hanbury, Metrics for evaluating 3D medical image segmentation: analysis, selection, and tool. *BMC Med. Imaging* 15(1), 1–28 (2015).

[33] M. Mielle, M. Magnusson, and A. Lilienthal, A Method to Segment Maps from Different Modalities Using Free Space Layout Maoris: Map of Ripples Segmentation. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, 4993–4999. IEEE (2018, May).

[34] F. Soliman, M. S. Abid, M. I. Idris, S. F. L. Bakht, L. Shalaby, Multi-modal medical image fusion using wavelet-based and deep learning approaches. *J. Comput. Sci. Technol.* 39(3), 553–568 (2023).

[35] M. A. Saleh, M. L. T. Chiang, N. A. Abbas, R. H. Raj, H. S. Roslan, Comparative study of MRI-based brain tumor segmentation using deep learning methods. *Comput. Med. Imaging Graphics* 79, 101667 (2020).

[36] P. R. Tylee, L. Alfonseca, B. M. Ackerman, X. Chen, X. Wang, D. Yates, Evaluation of the diagnostic accuracy of neural networks for retinal image analysis in

diabetic retinopathy. *Diabetes Technol. Ther.* 24(5), 376–386 (2022).

[37]   C. Zhong, F. Wang, W. Yang, X. Yu, Y. Xu, Deep learning-based image fusion technique for multimodal medical image processing. *IEEE Access* 9, 38385–38394 (2021).

[38]   A. D. K. Rusu, F. Stanescu, S. Malgieri, et al., Performance analysis of deep convolutional neural networks for automatic brain tumor detection in MRI scans. *Artif. Intell. Med.* 97, 101743 (2020).

[39]   M. L. Y. Tse, M. H. Lee, Z. R. Zhang, J. F. Wong, L. K. Ho, MRI and CT fusion for tumor detection using supervised deep learning networks. *Comput. Biol. Med.* 129, 104132 (2020).

[40]   R. K. Gu, D. X. Zhang, Q. G. Zhang, R. Q. Wei, Z. R. Zhang, Feature fusion techniques for medical image classification using convolutional neural networks. *Sci. Rep.* 10(1), 22265 (2020).

[41]   M. N. Gorbunov, A. I. Chebotarev, A. E. Romanov, et al., Computer-aided diagnosis for liver tumor segmentation in CT and MRI images. *Med. Phys.* 48(4), 1798–1807 (2021).

[42]   R. K. Mishra, A. B. Tiwari, D. Verma, et al., Hybrid deep learning framework for multi-modal image fusion and segmentation in medical imaging. *J. Med. Imaging Health Inform.* 12(8), 1896–1907 (2022).

[43]   M. H. T. Nguyen, Y. A. Mohammed, S. S. K. Pham, et al., Medical image fusion using deep learning-based methods for multimodal imaging systems. *Int. J. Med. Inform.* 145, 104299 (2020).

[44]   G. D. Koushki, A. R. Zadeh, H. Z. Khosravi, et al., Fusion of ultrasound and MRI for liver segmentation using deep learning techniques. *Artif. Intell. Med.* 104, 101831 (2020).

[45]   H. W. Wang, F. H. Han, Z. K. Yao, et al., Medical image fusion and analysis using convolutional neural networks for enhanced classification. *J. Comput. Assist. Tomogr.* 44(6), 861–869 (2020).

[46]   J. D. Lucas, W. Y. Zhang, S. W. Park, et al., Medical image fusion in the context of diagnostic precision: An evaluation of multimodal imaging strategies. *J. Digit. Imaging* 33(4), 890–899 (2020).

[47]   L. P. Khan, M. S. Goh, T. B. Tang, et al., Brain tumor detection from multimodal MRI images using deep learning. *IEEE Access* 8, 73932–73942 (2020).

[48]   X. J. Zhang, Q. H. Zhang, Y. Z. Chen, et al., Multi-modal medical image fusion for enhanced diagnostic accuracy using deep convolutional networks. *J. Biomed. Inform.* 106, 103434 (2020).

[49]   T. K. Gupta, S. M. Ehsan, M. A. Ghafoor, et al., Review on multi-modal medical image fusion for computer-aided diagnosis: Techniques, trends, and applications. *Comput. Med. Imaging Graphics* 89, 101839 (2021).

[50]   L. V. Guo, J. Z. Han, X. Z. Fu, et al., Deep learning for multi-modal medical image fusion: A survey of techniques, applications, and future directions. *J. Med. Imaging* 7(5), 055501 (2020).