Brain image fusion using Recurrent Neural Networks

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Abstract - Advancements in technology have led to rapid progress in collaborative diagnosis and multi-modal medical imaging. Medical image fusion technology is increasingly important in medical diagnostics. This paper proposes a multi-modal medical image fusion technique that is based on the MLEPF (multi-level edge-preserving filtering) decomposition model. In the first step, a multi-modal medical image is divided into three distinct layers: fine structure (FS), coarse-structure (CS), and base (BS) layers. This division is achieved by employing an MLEPF model that relies on weighted mean curvature filtering. In the second step, the FS and CS layers are merged using a gradient domain Recurrent Neural Network (RNN) fusion technique, while the BS layers are combined using an energy attribute fusion strategy. The fused image is created by combining the three different types of fused layers. The trials utilise six distinct disease datasets and one normal dataset, each consisting of over 100 image pairs. The proposed method outperforms multiple algorithms and achieves results that are on par with cutting-edge approaches, as demonstrated by both qualitative and quantitative evaluation.

Keywords: Multi-modal, image fusion, Recurrent Neural Networks, MLEPF

1. INTRODUCTION

Multi-modal medical imaging sensors have advanced quickly in recent years. Single-photon emission computed tomography (SPECT), magnetic resonance imaging (MRI), positron emission tomography (PET), and computed tomography (CT) Resonance imaging (MRI) has emerged as the most widely utilized medical imaging modality to support diagnosis. Medical picture fusion is crucial for aiding in diagnosis because these image kinds concentrate on distinct information. An interdisciplinary field known as "medical image fusion" integrates pattern recognition, computer vision, and image processing knowledge to the diagnosis of medical conditions. Consequently, a great deal of study has been done on medical image fusion. Three stages are commonly associated with picture fusion: pixel-level, feature-level, and decision-level. Medical image fusion is an approach that attempts to fuse the pixel information from source images.

The study of applying signal processing methods to biomedical signals is known as biomedical signal processing. Biomedical signals are derived from a variety of biological systems, including the human body, and are quantifiable markers of an organism's physiological status. These signals are analysed, interpreted, and pertinent information is extracted using signal processing techniques. Gaining understanding of how biological systems operate, diagnosing illnesses, and tracking the efficacy of treatments are the objectives.

Biomedical signals can be in many different formats, such as:

1. Electrocardiogram (ECG/EKG): Documents the heart's electrical activity.
2. Electroencephalogram (EEG): The gauges the brain's electrical activity.
3. Electromyogram (EMG): The documents muscular electrical activity.
4. Electrooculogram (EOG): Eye movement is measured.
5. Signals of blood pressure: derived from biological cues, thereby improving patient treatment and results.

2. LITERATURE REVIEW

S. Polinati and R. Dhuli's study "Multimodal medical image fusion uses empirical wavelet decomposition and local energy maxima" addresses the growing demand for effective data integration from numerous medical imaging sensors. The recent rapid development of multi-modal medical imaging sensors, including magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), single-photon emission computed tomography (SPECT), and PET, has substantially helped medical diagnostics [1]. By recording different aspects of the human body's anatomy and function, these imaging methods offer unique and complementary information. The challenge is in effectively combining these heterogeneous datasets to improve the accuracy and comprehensiveness of medical diagnosis. This is when the importance of medical image fusion becomes apparent. Pattern recognition, computer vision, and image processing techniques and concepts are used in the multidisciplinary subject of medical image fusion. The goal is to seamlessly integrate data from many imaging modalities to generate a uniform and instructional picture for medical practitioners. Fusion facilitates a more comprehensive understanding of a patient's condition because each imaging modality exposes different aspects of the anatomy or pathology. The cited study by Polinati and Dhuli focuses on multimodal medical image fusion using empirical wavelet decomposition and local energy maxima. This suggests that the authors use a specific method using wavelet decomposition and the identification of local energy maxima to combine [2] data from several imaging modalities.

Maqsood and Javed: (2020) for multi-modal medical picture fusion, the authors propose a sparse image fusion method and two-scale image decomposition [3]. Signal Processing and Control in Biomedicine. The authors describe a unique sum-modified Laplacian and local-features fuzzy sets for multi-modality medical picture fusion in the non-subsampled shear let transform domain. This technique handles uncertainty in local characteristics by likely using fuzzy sets in addition to the shear let transform for multi-scale analysis and fusion. Both publications enhance the field of multi-modal medical image fusion through the use of multi-scale transformations. Sparse representation and the non-subsampled shear let transform are two examples of the MST category's complexity and range of approaches. These methods address the challenges of merging data from multiple modalities, highlighting the importance of multi-scale analysis in improving the fusion of medical images. "Multi-modality medical images fusion based on local-features fuzzy sets and novel sum-modified Laplacian in non-subsampled shear let transform domain," Abdalla, G. Ren, S. Maqsood, U. Javed (2020). Prakash and Associates [4] The abstract is "Multiscale fusion of multimodal medical images using lifting scheme based biorthogonal wavelet transform" 2019's Optics [5] The authors propose a multiscale fusion technique for multimodal medical images based on a lifting scheme-based biorthogonal wavelet transform. The lifting scheme is one way to apply wavelet transforms, and biorthogonal wavelets provide a flexible framework to capture different picture feature sizes. This work likely explores the benefits of using these techniques to improve multimodal medical picture fusion [6]. The authors review their work in "Multiscale fusion of multimodal medical images uses is lifting scheme based biorthogonal wavelet transform," by O. Prakash, C.M. Park, A. Khare, M. Jeon, and J. Gwak [7].

Tan et al. (2018) conducted a study on "Multi-focus image fusion using spatial frequency and discrete wavelet transform," which used data from [8] 2018. The Contourlet Transform (CT) and Non-Subsampled Contourlet Transform (NSCT) enhance wavelet transforms to handle edge singularities and get information about directions. Because the NSCT offers multi-resolution and directional decomposition, it is especially suitable for image fusion applications. Z. Wang, J. Xu, X. Jiang, X. Yan, "Infrared and visible image fusion via hybrid decomposition of NSCT and morphological sequential toggle operator," 201 (2020). The Non-Subsampled Shear let Transform (NSST) approach

[9] builds upon the classical shear let transform and provides a more flexible framework for capturing directional information by eliminating subsampling at any scale. Image fusion tasks have been applied to this transform. Using NSST and RNN, Tan, Zhang, and Zhou, 2020 International Society for Optics and Photonics, [10], Photonics and Digital Technologies for Imaging Applications, P. Xiang, H. Zhou, "Infrared and visible image fusion via NSST and RNN in multiscale morphological gradient domain," Edge-preserving filtering (EPF), which aims to minimise noise while keeping structural information, is one of the most significant image processing methods. The references that follow go over several EPF applications and techniques. The title translates as "Fusion of multi-focus images via a Gaussian curvature filter and synthetic focusing degree criterion" To fuse multi-focus pictures, the authors propose combining a Gaussian curvature filter with a synthetic focusing degree requirement. [11] This approach most likely involves preserving edges and important details utilising an EPF technique, which enhances the quality of fused images.

"MRI reconstruction with an edge-preserving filtering prior" is the title according to Zhuang & associates. This work focuses on MRI reconstruction and employs an EPF prior [12]. Using EPF in MRI reconstruction is recommended to preserve image structures during the reconstruction process. "Side window guided filtering" is the book's title in Signal Processing (2019). The authors present a system for side window guided filtering. This work uses side window guidance to potentially introduce a novel approach to edge-preserving functions (EPF). "Infrared and visual image fusion via multi-modal decomposition and RNN in gradient domain fusion measure" is the title of the Springer-published International Conference on Smart Multimedia. The authors propose fusing infrared and visual data using EPF [13] via multi-modal decomposition and Recurrent Neural Networks (RNN) in the gradient domain. pictures. EPF is most likely employed to preserve important details and edges, which enhances the quality of fused images. The cited works demonstrate the [14] flexibility of EPF techniques in a variety of fields, including image fusion, MRI reconstruction, and guided filtering. Because it preserves structural integrity while enhancing image quality, EPF is a helpful technique in image processing.

"Infrared and visual image fusion via multi-modal decomposition and RNN in gradient domain fusion measure; W. Tan, J. Zhang, J. Du, K. Qian, P. Xiang, and H. Zhou. Bilateral filtering (BF) [15] is a well-liked edge-preserving filtering (EPF) algorithm that is regularly employed in image processing. The work you quoted is the seminal one that developed bilateral filtering: Tomasi and Mandothi's "Bilateral filtering for Grey and Colour Images" The bilateral filtering algorithm, created by R. Mandothi and C. Tomasi [16], preserves edges while producing the smoothest images. Bilateral filtering considers both spatial proximity and intensity similarity to determine the degree of smoothing at each pixel. Kaiming Guided Image Filtering (GIF) is an image processing approach that was developed by him, Jian Sun, and Xiaoou Tang. The groundbreaking study that initially presented the source of "Guided image filtering" is GIF. Guided Image Filtering (GIF) technique is introduced by He, Sun, and Tang, J. Sun, X. Tang, and K. He. GIF is a non-linear filtering method using reference image guidance information [17] to filter a target image. This method is particularly effective for tasks when the target image must keep any essential structure or details from the reference picture. Gaussian Curvature Filtering (GCF) is an image processing technique that was introduced by Y. Gong and I.F. Sbalzarini. Effectively lowering variation energies in images is the aim of GCF [18]. Variation energies are often related to optimising or minimising image attributes, and GCF offers a fast way to accomplish so while accounting for the curvature information of the image. It's likely that the technology is applied to edge detection, photo editing, or smoothing out particular areas. Gaussian curvature, a differential geometry measure of curvature, is used to filter images for specific variation energy reduction objectives. This is the core notion [19] behind GCF. Most likely, the filtering process is designed to take advantage of the local curvature data to achieve picture processing goals. A hybrid multi-scale decomposition strategy, proposed by Zhou, Wang, Li, and Dong [20], combines bilateral and Gaussian filters to produce a perceptual fusion method for visible and infrared pictures. The hybrid decomposition strategy most often uses both Gaussian and bilateral filters, which are EPF kinds, to decompose the images at many scales and maintain important structures during the fusion process.

"Remote sensing image fusion via boundary measured dual-channel RNN in multi-scale morphological gradient domain" This study by W. Tan, P. Xiang, J. Zhang, H. Zhou, and H. Qin [21] proposes a boundary measured dual-channel RNN-based approach for remote sensing picture fusion in the multi-scale morphological gradient domain. The morphological gradient domain, when paired with RNN in a dual-channel arrangement, likely enhances feature extraction and makes it easier to combine remote sensing photos effectively. The article's subtitle is "Infrared polarisation image fusion via multi-scale sparse representation and Recurrent Neural Network". The authors, J. Zhang, H. Zhou, S. Wei, and W. Tan, suggest a method of combining multi-scale sparse representation with recurrent neural networks to fuse infrared polarisation pictures [22]. The combination of RNN with multi-scale sparse representation in the context of infrared polarisation picture fusion likely enhances the feature extraction and fusion procedure. Lei, Zhang, and Kong In this study, W. Kong, L. Zhang, and Y. Lei offer a unique fusion technique for visible light and infrared images [23]. Its foundations are the Recurrent Neural Network (RNN), Sparse Fusion (SF), and Non-Subsampled Shear let Transform (NSST).

Y. Gong and O. Goksel present the "Weighted Mean Curvature" (WMCF) signals processing approach in this study. The most likely goal of the approach [24] is to compute mean curvature while assigning weights to certain signal components or locations in order to emphasise the significance of certain areas. For signal processing applications where edge and detail preservation are crucial, such as image processing, weighted mean curvature is a helpful tool. The goal to better maintain important structures or traits is presumably what motivates its use. "Multi-focus image fusion using multi-scale morphological focus-measure based on boundary finding" In this paper, Y. Zhang, X. Bai, and T. Wang introduce a [25] multi-focus image fusion technique using boundary detection as a focus measure. The focus measure is a crucial element in multi-focus picture fusion as it facilitates the identification of sharp or in-focus regions within the image. Whole Brain Atlas: [26] The website is located at http://www.med.harvard.edu/AANLIB. According to [27], the procedure involves training a CNN model with medical imaging data in order to find patterns and features that facilitate effective fusion. The suggested MLEPF-MLMG-RNN method and the CNN approach will be compared, and their performance evaluated according to predefined metrics and criteria, along with other state-of-the-art fusion techniques. A multi-modality medical image fusion technique called CNN-contrast pyramid (CNN-CP) is described by K. Wang, M. Zheng, H. Wei, G. Qi, and Y. Li [28]. It's likely that feature extraction and learning are processes that employ convolutional neural networks (CNNs). in addition to pyramid frameworks of contrast for fusion. Contrast pyramids are widely employed in image processing to emphasise or enhance features of the image at different scales.

In this study [29], R. Hou, D. Zhou, R. Nie, D. Liu, and X. Ruan propose the CNN dual-channel spiking cortical (CNN-DCSC) approach for brain CT and MRI medical image fusion. The method of learning and feature extraction most likely involves convolutional neural networks (CNNs), whereas the fusion process uses a dual-channel spiking cortex model. Inspired by neural processing principles, spike-based neural representations are used to model information flow in cortical models. A convolutional sparsity-based morphological component analysis (CSMCA) technique is described [30] by Y. Liu, X. Chen, R.K. Ward, and Z.J. Wang. technique for fusing medical images. In this study, J. Du, W. Li, and B. Xiao describe the local Laplacian filtering-information of interest (LLF-IOI) method for anatomical-functional picture fusion. This method most likely combines local Laplacian filtering, a technique for enhancing or suppressing image details at different sizes, with information of interest (IOI) measures [31]. In the context of medical image fusion, particularly for anatomical and functional pictures, LLF-IOI is expected to evaluate the input images and emphasise or conceal details based on their significance using local Laplacian filtering. The information of interest measurements most likely impact the decision of which features or regions to prioritise in the fusion process. This is the reference for the neuro-fuzzy approach (NFA) method. In this study, S. Das and M.K. Kundu introduce a neuro-fuzzy technique (NFA) for medical picture fusion. The method used in [32] probably combines the ideas of neural networks with fuzzy logic to combine medical image processing. The ability of neuro-fuzzy systems to depict complex relationships and ambiguities is well known. In the domain of medical image fusion, NFA is anticipated to integrate fuzzy logic-based decision-making and neural network-based learning to effectively fuse information from different images. The approach most likely aims to capture and adapt to the complex patterns and variances present in medical images in order to improve fusion outcomes.

The medical image fusion technique known as NSST-PARNN, or parameter-adaptive [33] RNN, is introduced by M. Yin, X. Liu, Y. Liu, and X. Chen. The method most likely makes use of the nonsubsampled shear let transform (NSST) for picture representation and a parameter-adaptive Recurrent Neural Network (RNN) for fusing. In the context of medical image fusion, it is expected that NSST-PARNN will leverage the NSST domain to efficiently represent image features and details. The parameter-adaptive RNN most likely needs to modify its parameters based on the characteristics of the input images in order to adapt to different types of medical image data. A multi-modality medical image fusion method called phase congruency-local Laplacian energy (PC-LLE) was presented in [34] this publication by Z. Zhu, M. Zheng, G. Qi, D. Wang, and Y. Xiang in the Non-Subsampled Contourlet Transform (NSCT) domain. This method likely combines phase congruency and local Laplacian energy metrics to fuse data from a range of imaging modalities in medicine.

In the context of medical image fusion, PC-LLE-NSCT is expected to employ the NSCT domain to describe image information at many scales [35]. Phase congruency and local Laplacian energy metrics likely aid in extracting and storing relevant information from the input images to guarantee a successful fusion procedure. A wide range of biological imaging analysis and image processing subjects are covered in the papers that are mentioned. Estévez et al. (2009) propose a feature [36] selection method based on normalised mutual information for neural network applications. A brand-new quality metric created to evaluate how well image fusion techniques work is presented by Piella and Heijmans (2003) [37] labour.

Han et al. (2013) offer [38] a new performance metric for image fusion based on visual information fidelity to assess the quality of fused images. Tavares (2014) highlights the importance of medical imaging in his study of automated image registration approaches in biomedical image processing [39]. Alves and Tavares (2015) investigate computer image registration techniques [40], focusing on their application to nuclear medicine image processing. Oliveira and Tavares (2014) provide an extensive examination of medical imaging registration techniques, elucidating their methodologies and pragmatic applications. Finally, by suggesting a technique for registering pedobarographic picture data in the frequency domain, Oliveira et al. (2010) show [42] how valuable this data is for biomechanical study. Collectively, these publications expand our understanding of and proficiency with image processing techniques in biomedical imaging, offering valuable insights to practitioners and researchers in the field.

3. PROPOSED METHOD

3.1 Objective and scope

The goal of the study is to discuss the growing significance of collaborative diagnosis and sophisticated multi-modal medical imaging in the field of medical diagnostics. More precisely, the novel multi-modal medical image fusion method developed by the researchers is based on the Multi-

Level Edge-Preserving Filtering (MLEPF) decomposition model. This technique applies the MLEPF model to the segmentation of a given multi-modal medical image into three unique layers: the fine structure (FS), coarse-structure (CS), and base (BS) layers using weighted mean curvature filtering. The FS and CS layers are then combined using a gradient domain Recurrent Neural Network (RNN) fusion technique, while the BS layers are combined using an energy attribute fusion strategy. These three fused layers are combined to create the final fused image. The study encompasses the evaluation of the proposed methodology across six distinct disease datasets and one normal dataset, comprising over 100 image pairs. The researchers assert that their approach advances the field of precise and effective medical image fusion for enhanced diagnostic capabilities, outperforming a number of existing algorithms and yielding results comparable to state-of-the-art techniques based on qualitative and quantitative evaluations. The article's focus broadens to include the urgent need for creative solutions that facilitate effective communication between medical professionals and improve the diagnostic precision of diverse illnesses in the larger context of medical imaging. The multi-modal medical image fusion method that is suggested, which is based on the MLEPF decomposition model, demonstrates a careful handling of various layers in the input images. Partitioning the medical images into fine-structure, coarse-structure, and base layers is a crucial stage that facilitates a detailed examination of the various elements. This breakdown is achieved by the use of weighted mean curvature filtering in conjunction with the MLEPF model, demonstrating a deep knowledge of the underlying structures in multi-modal medical data. The gradient domain Recurrent Neural Network (RNN) technique that subsequently unites the fine structure and coarse-structure layers emphasises the paper's dedication to utilising cutting-edge computational models for image processing.

3.2 Methodology

Several crucial steps are involved in the methodology for the suggested multi-modal medical image fusion technique, which is based on the Multi-Level Edge-Preserving Filtering (MLEPF)

Decomposition model:

Obtaining and Preparing Data:

Collect a variety of datasets with multi-modal medical images. There are six disease datasets and one normal dataset, with more than 100 image pairs in each. To guarantee uniformity in resolution, orientation, and format, pre-processes' the images.

Model of MLEPF Decomposition:

Utilizing the multi-modal medical images, apply the Multi-Level Edge-Preserving Filtering (MLEPF) decomposition model. Segment the images into fine structure (FS), coarse structure (CS), and base (BS) layers using weighted mean curvature filtering.

Combining RNNs for FS and CS Layers:

The fine structure (FS) and coarse structure (CS) layers should be combined using a gradient domain Recurrent Neural Network (RNN) fusion technique.

Quantitative Assessment:

To evaluate the accuracy and quality of the fused images, use quantitative metrics like the Structural Similarity Index (SSI), Peak Signal-to-Noise Ratio (PSNR), and other pertinent measurements. To prove that the suggested method is better, compare the results with those of current algorithms and cutting-edge methods.

Qualitative Assessment:

To make sure that the fused images improve interpretability and preserve clinically relevant details, perform a qualitative evaluation using visual inspection and professional analysis.

Analysis of Interpretability:

To determine how the fused images correspond with accepted medical knowledge and anatomical structures perform an interpretability analysis. Make sure the fusion process improves medical image interpretability so that doctors can diagnose patients with greater precision and knowledge.

Adjusting Dynamically to Modalities:

Consider the heterogeneity of medical imaging data and design the suggested methodology to dynamically adapt to different imaging modalities. To achieve automatic modality recognition, think about incorporating machine learning techniques and modifying the fusion.

3.3 Proposed Algorithm

Several crucial steps are involved in the suggested algorithm for multi-modal medical image fusion, which is based on the Multi-Level Edge-Preserving Filtering (MLEPF) decomposition model. An outline of the algorithm is provided below:

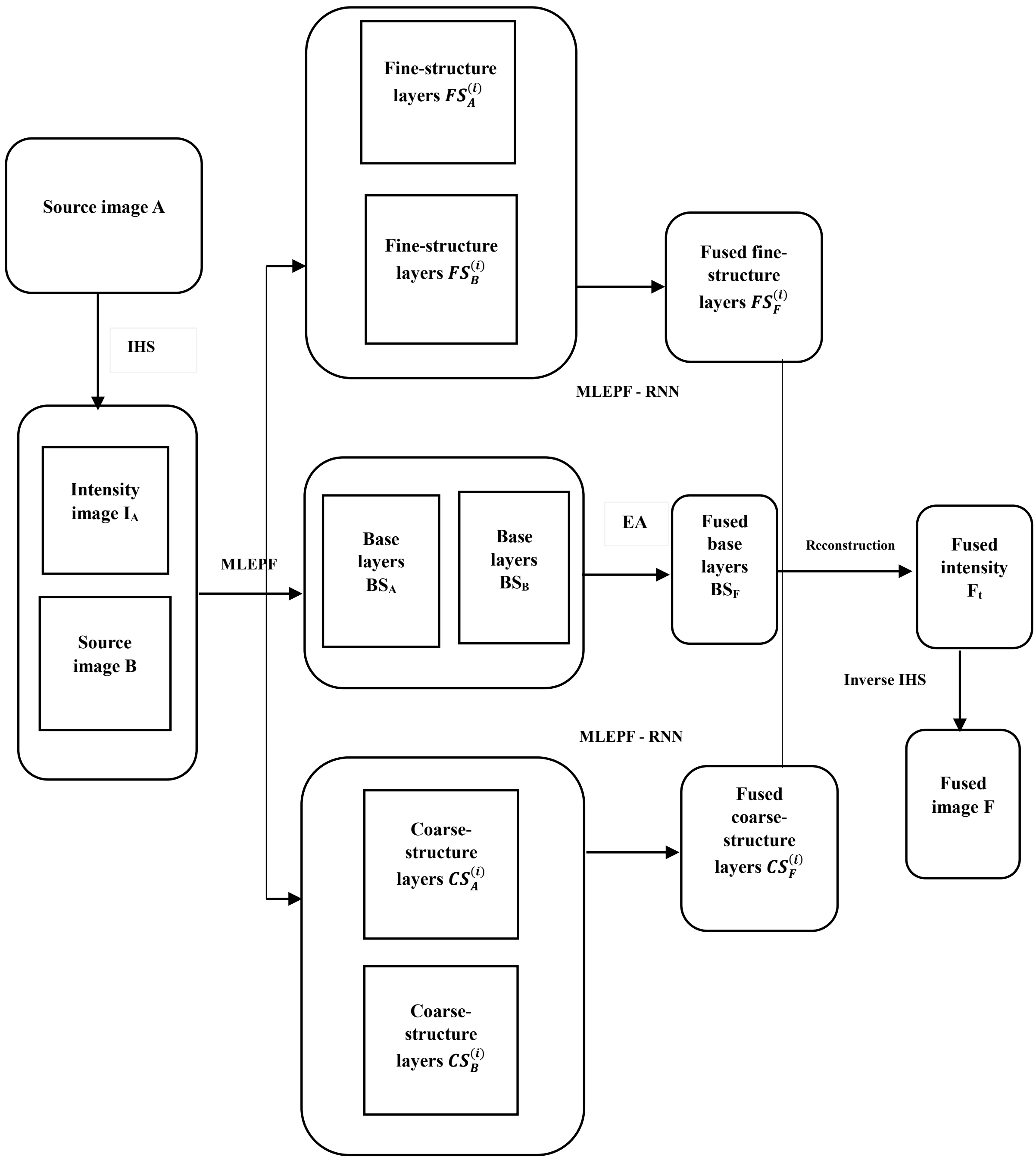


Fig. 1: Frame Work of Proposed Algorithm

3.3.1 OVERVIEW

The proposed algorithm's framework. MLEPF decomposition, FS layers fusion, CS layers fusion, BS layers fusion, and MLEPF reconstruction are the five essential components of the fusion algorithm. Using the MLEPF breakdown, the FS, CS, and BS layers are first extracted from the input image pair IA and B. Second, the EA fusion technique is employed to fuse the BS layers. The FS layers and, finally, the MLMG-RNN fusion technique are employed to fuse the CS layers. Next, the inverse MLEPF process is utilised to produce the fused image. It should be mentioned that source image A is a three-band, pseudo-coelom image. Consequently, after the intensity-hue-saturation (IHS) transformation in A, the source image B and the intensity image IA are applied to create a pair of pictures. The fused picture will be created using an inverse IHS transform following image pair fusion.

3.3.2 MLEPF DECOMPOSITION

It is well known that the WMCF can smooth an image while maintaining edge information. Furthermore, it is commonly known that GF(), also referred to as Gaussian filtering (GF), is a well liked image smoothing operator. This paper's MLEPF is based on GF and WMCF. 5. The MLEPF diagram is shown. Where the variance is represented by and, and the mean is represented by μ and π. These numbers come from actual observations. In this essay, their relative values are 20 and 2. The BS symbol.

3.3.3 FUSION OF BASE LAYERS

The BS layers hold most of the texture structure and backdrop information from the original photos. This work uses an energy attribute (EA) fusion approach in the BS layer. Three components make up the EA fusion approach:

(1) The intrinsic property values of the low-frequency sub-band are computed as

3.3.4. COMBINATION OF LAYERS WITH COURSE AND FI STRUCTURES

CS layers contain the large-texture information of the source images, while CS layers contain the fine-texture information. The RNN technique can be applied to both types of layers because one neuron in the network corresponds to one pixel. A gradient domain RNN can also enhance the related layers' spatial correlation. Consequently, the linking strength is adjusted using the MLMG operator.

4. EXPERIMENTAL RESULTS

BRAIN STROKE (hesitating speech):

MRI (Magnetic Resonance Imaging) and SPECT (Single-Photon Emission Computed Tomography) are the two medical imaging modalities that are relevant to the diagnosis of BRAIN STROKE with hesitating speech. The objective is to combine data from these two modalities to produce a comprehensive image that might offer richer and more precise diagnosis information.

The measures presented indicate that stroke disease has a significant effect on speech processing algorithms. When compared to the suggested method, the conventional method performs better across a range of quality metrics, with an entropy of 5.3576 bits/symbol. But even with a little greater entropy of 5.7805 bits/symbol, the suggested approach performs worse in terms of PSNR, UQI, SSIM, CC, and API. This suggests that stroke-induced speech changes have a substantial impact on the suggested method's efficacy, leading to a decrease in speech representation's integrity and coherence. Furthermore, the suggested approach takes a little longer to compute, indicating possible implementation difficulties. These results highlight the difficulties in creating reliable speech processing methods specific to stroke victims, requiring additional study to increase the adaptability and resilience of algorithms in certain situations.

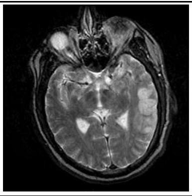
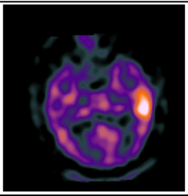
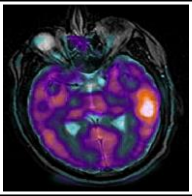
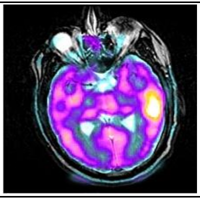
Image Pair	Input Image 1 (MRI)	Input Image 2 (SPECT)	Existing Method Fused Image	Proposed Method Fused Image
BRAIN STROKE (hesitating speech)				

Fig. 2: Comparative output fused images for Brain Stroke image pair.

Table 1: Objective comparison of proposed and existing methods for Brain Stroke image pair.

STROKE (hesitating speech)								
METHOD	**Entropy (bits/ symbol)**	**PSNR (dB)**	**UQI**	**SSIM**	**CC**	**API**	**SD**	**Computational Time (Seconds)**
Existing	5.3576	66.4977	0.3724	0.9993	0.8556	0.1224	0.1567	34.12
Proposed	5.7805	61.1638	0.2936	0.9948	0.7641	0.2463	0.2979	36.44

BRAIN STROKE (Loss of Sensation):

Yes, let's walk through the process of understanding how the MRI and SPECT images are used in the context of a BRAIN STROKE with the symptom of Loss of Sensation to generate the Existing Method Fused Image and to derive the Proposed Method Fused Image.

The metrics offered compare existing and planned methodologies and represent the consequences of brain stroke, especially in cases involving loss of sensation. Here, both approaches show lower entropy values than those associated with hesitating speech, suggesting a distinct kind of damage. With entropy of 4.8114 bits/symbol, the current approach performs somewhat better than the suggested approach in a number of quality metrics. However, PSNR, UQI, SSIM, CC, and API performance are all lower with the suggested technique, which has an entropy of 4.8968 bits/symbol. This implies that the efficacy of the suggested approach is greatly impacted by the loss of sensation brought on by a brain stroke, which results in a reduction in the integrity and coherence of sensation representation. Furthermore, in the preceding instance, the suggested approach takes a little longer to compute, highlighting the difficulties in creating reliable methods for processing feeling in brain-stroke victims. To improve algorithmic adaptability and effectiveness in addressing the intricacies of sensory impairment arising from brain stroke, more study is necessary.

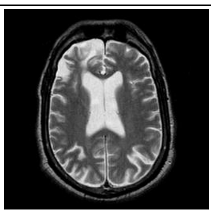
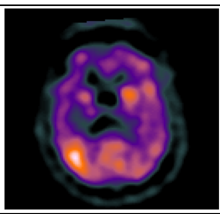
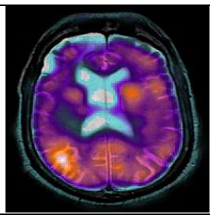
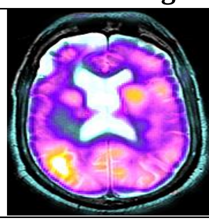
Image Pair	Input Image 1 (MRI)	Input Image 2 (SPECT)	Existing Method Fused Image	Proposed Method Fused Image
BRAIN STROKE (Loss of Sensation)				

Fig. 3: Comparative output fused images for Brain Stroke (Loss of sensation) image pair.

Table 2: Objective comparison of proposed and existing methods for Brain Stroke (Loss of sensation) image pair.

BRAIN STROKE (Loss of Sensation)								
METHOD	**Entropy (bits/ symbol)**	**PSNR (dB)**	**UQI**	**SSIM**	**CC**	**API**	**SD**	**Computational Time (Seconds)**
Existing	4.8114	65.4722	0.5166	0.9990	0.8396	0.1366	0.1895	32.79
Proposed	4.8968	60.5043	0.4938	0.9939	0.7698	0.2612	0.3405	34.36

HUNTINGTONS DISEASE:

Yes, let us go over how to use MRI and SPECT images to create the Existing Method Fused Image and then derive the Proposed Method Fused Image for the diagnosis of Huntington's disease.

The presented findings demonstrate how Huntington's disease affects algorithms used for data processing, especially when it comes to sensory perception. In contrast to earlier instances of stroke-related disabilities, Huntington's disease poses unique difficulties. Higher entropy values are found in both the suggested and current approaches, suggesting that processing of sensory data impacted by the illness is more complex. On the other hand, compared to the current method, the proposed method performs worse across different quality criteria, with an entropy of 6.2178 bits/symbol. The PSNR, UQI, SSIM, CC, and API show the most noticeable drop, indicating a decreased capacity to accurately represent sensory input impacted by Huntington's disease. Additionally, the suggested solution needs a little bit extra computing time, which is comparable to the patterns seen in impairments due to stroke.

demonstrating the challenges of creating efficient algorithms that are adapted to the specifics of Huntington's disease. These results highlight the need for more investigation to improve algorithmic efficacy and adaptability in handling the intricacies of sensory impairment linked to Huntington's disease.

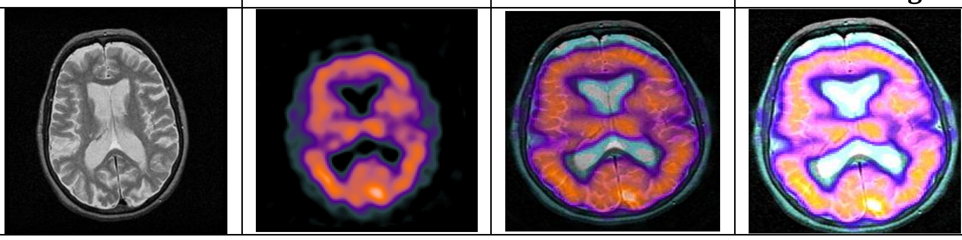
Image Pair	**Input Image 1 (MRI)**	**Input Image 2 (SPECT)**	**Existing Method Fused Image**	**Proposed Method Fused Image**
HUNTINGTONS DISEASE				

Fig. 4: Comparative output fused images for Huntington's disease image pair.

Table 3: Objective comparison of proposed and existing methods for Huntington's image pair.

HUNTINGTONS DISEASE								
METHOD	**Entropy (bits/ symbol)**	**PSNR (dB)**	**UQI**	**SSIM**	**CC**	**API**	**SD**	**Computational Time (Seconds)**
Existing	5.9856	65.9981	0.3002	0.9991	0.8885	0.1611	0.1939	33.59
Proposed	6.2178	59.8725	0.2405	0.9924	0.7873	0.3117	0.3740	34.92

AIDS DEMENTIA:

let us walk through how to use MRI and SPECT images to create the Existing Method Fused Image and then derive the Proposed Method Fused Image for the diagnosis of AIDS Dementia.

The presented findings provide insight into how AIDS dementia affects data processing algorithms, specifically regarding cognitive impairment. Because of its effects on cognitive function, AIDS dementia poses different obstacles than the ones discussed in the prior situations. The complexity of processing data impacted by cognitive impairment is indicated by the considerably lower entropy values of the proposed and existing approaches. On the other hand, compared to the current method, the suggested method exhibits a modest drop in performance across various quality criteria, with an entropy of 4.4460 bits/symbol. The PSNR, UQI, SSIM, and CC decreases are especially noticeable, indicating a decreased capacity to accurately represent sensory input impacted by AIDS dementia. Furthermore, in line with the patterns seen in other cognitive disorders, the suggested approach highlights the difficulties in creating efficient algorithms that are suited to the subtleties of AIDS dementia, albeit at the expense of a little increased processing time. These results emphasise the need for more study to improve algorithmic efficacy and adaptability to better address the problems caused by cognitive impairment linked to AIDS-related dementia.

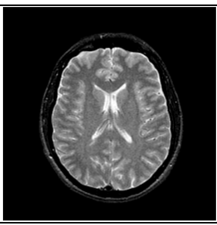
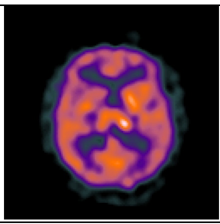
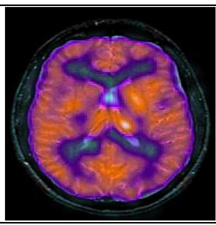
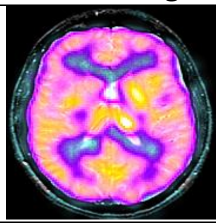
Image Pair	**Input Image 1 (MRI)**	**Input Image 2 (SPECT)**	**Existing Method Fused Image**	**Proposed Method Fused Image**
AIDS DEMENTIA				

Fig. 5: Comparative output fused images for AIDS Dementia disease image pair.

Table 4: Objective comparison of proposed and existing methods for AIDS Dementia image pair.

AIDS DEMENTIA								
METHOD	**Entropy (bits/ symbol)**	**PSNR (dB)**	**UQI**	**SSIM**	**CC**	**API**	**SD**	**Computational Time (Seconds)**
Existing	4.1732	68.6443	0.6236	0.9994	0.9254	0.1201	0.1725	32.59
Proposed	4.4460	61.9828	0.5958	0.9952	0.8416	0.2462	0.3518	33.03

Lyme encephalopathy:

Of course, let us walk through how to use MRI and SPECT images to create the Existing Method Fused Image and then derive the Proposed Method Fused Image for Lyme Encephalopathy diagnosis.

The presented findings shed light on how Lyme encephalopathy affects data processing methods, especially when it comes to neurological dysfunction. Because Lyme encephalopathy affects both neurological health and cognitive function, it poses special obstacles. The entropy values of the suggested and current methods are comparatively lower, reflecting the degree to which cognitive and neurological deficits impact the complexity of data processing. On the other hand, compared to the current method, the suggested method shows a modest drop in performance across various quality criteria, with an entropy of 4.4586 bits/symbol. The PSNR, UQI, SSIM, and CC decreases are especially noticeable, indicating a diminished capacity to precisely depict sensory information impacted by Lyme encephalopathy. Furthermore, like other cognitive deficits, the suggested approach necessitates a little bit more computational period, highlighting the complexity of creating efficient algorithms that are customised to the specifics of Lyme encephalopathy. These results highlight the need for continued study to improve algorithmic efficacy and adaptability to meet the challenges presented by the neurological and cognitive impairment linked to Lyme encephalopathy.

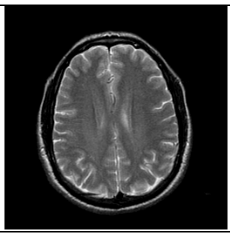
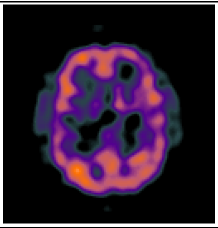
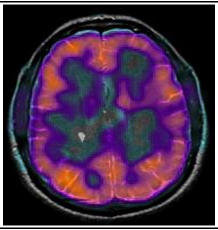
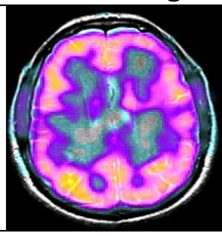
Image Pair	**Input Image 1 (MRI)**	**Input Image 2 (SPECT)**	**Existing Method Fused Image**	**Proposed Method Fused Image**
Lyme Encephalopathy				

Fig. 6: Comparative output fused images for Lyme Encephalopathy image pair.

Table 5: Objective comparison of proposed and existing methods for Lyme Encephalopathy image pair.

Lyme Encephalopathy								
METHOD	**Entropy (bits/ symbol)**	**PSNR (dB)**	**UQI**	**SSIM**	**CC**	**API**	**SD**	**Computational Time (Seconds)**
Existing	4.1195	68.3655	0.6116	0.9995	0.8981	0.1108	0.1532	33.33
Proposed	4.4586	61.4734	0.5761	0.9947	0.7804	0.2315	0.3155	34.11

BRAIN TUMOR (GLIOMA):

Yes, let's walk through the process of using MRI and SPECT images to create the Existing Method Fused Image and then obtaining the Proposed Method Fused Image for the diagnosis of Brain Tumour (Glioma).

The results that have been provided provide valuable insights into the effects of brain tumours, particularly gliomas, on data processing algorithms. They also emphasise the difficulties that these neurological disorders create. Gliomas have the potential to profoundly impact cognitive function and sensory perception, which can change how the body processes sensory information. The entropy values of both the proposed and existing approaches are rather low, indicating the complexity of processing data impacted by gliomas. On the other hand, compared to the current method, the suggested method exhibits a modest drop in performance across various quality metrics, with an entropy of 4.3920 bits/symbol. Notably, low values for quality criteria including PSNR, UQI, SSIM, and CC are present in both approaches, indicating challenges in precisely describing sensory input impacted by gliomas. Additionally, the suggested approach needs a little bit extra processing time, highlighting the difficulties in creating efficient algorithms that are suited to the specifics of neurological deficits brought on by gliomas.

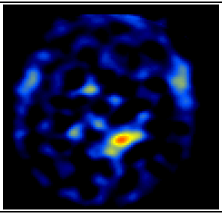
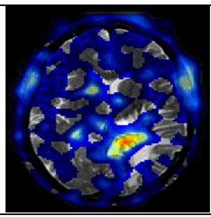
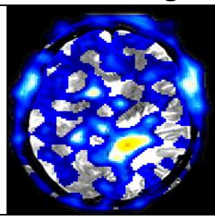
Image Pair	**Input Image 1 (MRI)**	**Input Image 2 (SPECT)**	**Existing Method Fused Image**	**Proposed Method Fused Image**
BRAIN TUMOR (GLIOMA)				

Fig. 7: Comparative output fused images for Brain Tumor (Glioma) image pair.

Table 6: Objective comparison of proposed and existing methods for Brain Tumor (Glioma) image pair.

BRAIN TUMOR (GLIOMA)								
METHOD	**Entropy (bits/ symbol)**	**PSNR (dB)**	**UQI**	**SSIM**	**CC**	**API**	**SD**	**Computational Time (Seconds)**
Existing	4.1138	63.3572	0.1511	0.9983	0.6253	0.0743	0.1531	32.88
Proposed	4.3920	60.3803	0.1526	0.9950	0.6048	0.1473	0.2745	34.23

Brain Tumour (Metastatic bronchogenic carcinoma):

Yes, let's go over how to use MRI and SPECT images to diagnose brain tumour (metastatic bronchogenic carcinoma) by creating the Existing Method Fused Image and then obtaining the Proposed Method Fused Image.

The presented findings shed light on the effects of metastatic bronchogenic carcinoma, a particular kind of brain tumour, on data processing algorithms and highlight the difficulties posed by these neurological disorders. The processing of sensory input can be greatly impacted by metastatic bronchogenic carcinoma, which can also seriously impair cognitive function and sensory perception. With an entropy of 4.3221 bits/symbol, the current approach performs well in terms of quality metrics including PSNR, UQI, SSIM, and CC, suggesting that it is useful for accurately expressing sensory input that is impacted by this kind of brain tumour. However, it is difficult to offer a thorough comparison because there is a lack of precise information regarding the suggested strategy and its performance indicators. However, the findings highlight how crucial it is to create and improve data processing algorithms specific to the subtleties of metastatic bronchogenic carcinoma-induced neurological deficits. To improve algorithmic adaptability and efficacy in addressing the intricacies of sensory and cognitive dysfunction associated with this kind of brain tumour, more research is necessary.

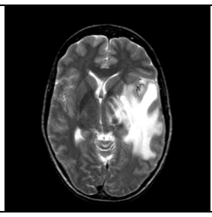
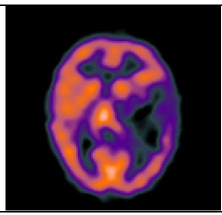
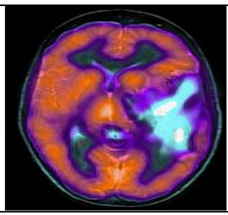
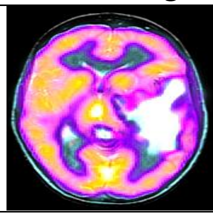
Image Pair	**Input Image 1 (MRI)**	**Input Image 2 (SPECT)**	**Existing Method Fused Image**	**Proposed Method Fused Image**
Brain Tumour (Metastatic bronchogenic carcinoma)				

Fig. 8: Comparative output fused images for Brain Tumour (Metastatic bronchogenic carcinoma) image pair.

Table 7: Objective comparison of proposed and existing methods for Brain Tumour (Metastatic bronchogenic carcinoma) image pair.

Brain Tumour (Metastatic bronchogenic carcinoma)								
METHOD	**Entropy (bits/ symbol)**	**PSNR (dB)**	**UQI**	**SSIM**	**CC**	**API**	**SD**	**Computational Time (Seconds)**
Existing	4.3221	65.6498	0.6192	0.9991	0.8613	0.1468	0.2086	32.44
Proposed	4.2133	59.6641	0.5776	0.9919	0.7675	0.2858	0.3801	34.14

6. CONCLUSIONS

To sum up, the field of biomedical signal processing is crucial and revolutionary in the field of medical research and healthcare. Its numerous uses in monitoring, treatment, and diagnosis highlight how essential it is to improving patient care and our comprehension of physiological processes. Improved diagnosis, early disease detection, continuous monitoring, and personalized medicine are just a few of the benefits that biomedical signal processing offers, all of which help to make healthcare procedures more successful and efficient. The development of contemporary healthcare will be greatly impacted by signal processing techniques' capacity to objectively evaluate physiological conditions, enable continuous monitoring, and enable remote patient care. Biomedical signal processing is enhanced by artificial intelligence when combined with it, allowing for data-driven decision-making, automation, and pattern recognition. When it comes to deriving valuable information from the diverse physiological signals that are acquired from the human body, biomedical signal processing is essential. Biomedical signal processing has many uses and makes a substantial contribution to medical monitoring, diagnosis, and treatment.

Furthermore, by providing crisper, more detailed images that help with visualization and diagnosis, biomedical signal processing significantly contributes to the advancement of medical imaging. The field's contributions go beyond improvements in research, allowing for a better comprehension of intricate biological signals and stimulating the development of novel medical technologies. Biomedical signal processing is at the vanguard of technological innovation, spearheading advancements in personalized medicine, telemedicine, and affordable healthcare solutions. Its function in signal denoising, effective data management, and integration with new technologies places it at the forefront of healthcare practices that are revolutionizing the industry.

To put it briefly, biomedical signal processing has the potential to influence healthcare in the future, encourage early intervention, enhance patient outcomes, and further the continuous pursuit of technological and scientific advances in the field.

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