Deep Texture Feature Extraction from Fused and Compressed Medical Images for Benign–Malignant Classification

Praneel Kumar Peruru and Kasa Madhavi

Abstract--- *Medical imaging has now become an everyday part of hospital care systems, thus helping doctors look inside the human body without having to perform any surgery. However, as imaging technologies like CT, MRI, and PET have shown advancements, the amount of data produced has been growing enormously. Such type of images are now larger, more detailed, and also much harder to manage. This scenario has created a clear and urgent need for smarter ways to process and analyze them quickly without losing crucial and fine details that matter most in diagnosis.*

In this work, a complete framework that combined the methods of image fusion, image compression, and texture-based feature extraction to identify whether the tissue regions are benign or malignant has been proposed. The approach has been built on our earlier research work where images from multiple modalities were fused using an Undecimated Discrete Wavelet Transform (UDWT) and compressed with Context-Based Adaptive Binary Arithmetic Coding (CABAC) without loss of image quality. After the compression process, we extract texture features using an improved Gray Level Co-occurrence Matrix (GLCM) model along with deep learning-based descriptors so as to capture the subtle variations in the tissue texture. Experiments that we have were carried out on medical image datasets show that proposed system is able to maintain the strong diagnostic quality and it has achieved an accuracy of 94.3% even after image compression. The results have highlighted its potential for faster, more reliable diagnosis in telemedicine and smart healthcare environments.

Keywords--- *Medical Image Fusion, Image Compression, Feature Extraction, Telemedicine Applications, Smart Healthcare Systems*

I. Introduction

MEDICAL image processing become most vital tool in the modern healthcare systems, which is playing a central role in detection of a disease, its diagnosis. Along with diagnosis, it helps to have necessary treatment planning, and continuous patient monitoring. With the fast growth in variety of imaging modalities such as the Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound, and the Positron Emission Tomography (PET), healthcare systems are now generating massive volumes of medical images data on a daily basis. Both the opportunities and challenges have been presented by this stable expansion in the volume and complexity of medical data. Richer datasets help improve diagnostic reliability, but they also necessitate more advanced techniques at the cost of efficient storage. The same will carry out processing and interpretation in addition to storing. Optimization of these procedures is especially important for telemedicine and smart healthcare applications. Here, the reliable transmission and automated analysis of medical images directly impact the outcomes of a patient.

In the current situation of the telemedicine, the importance of an efficient medical image management is emphasized. Patients who reside in a remote or network resource-constrained areas may depend on the seamless exchange of the diagnostic data with specialists who are located somewhere else. One high-resolution MRI scanned image itself can occupy several hundreds of megabytes, thus making the online transmission over limited bandwidth networks cause a huge bottleneck. Besides, the clinicians also may not be only interested in raw imaging data but also in diagnostic insights that can help them get quickly extracted and shared to them. Henceforth, the ability for fusion of such images from multiple modalities, and compress them without compromising the image diagnostic quality, and extract meaningful features is central to show effectiveness of the modern telemedicine systems.

Medical Image Fusion (MIF) has been emerged as one of the best powerful solutions to enhance diagnostic accuracy by integrating the corresponding information from diverse imaging modalities. To deal with an appropriate example, MRI scan images provide excellent soft tissue contrast, whereas the CT scan images offer precise anatomical details, and PET highlights the functional and metabolic processes. By combining of such heterogeneous sources of information into one single and composite image, the fusion techniques enable doctors to visualize the structural, functional, and morphological details all through a single image. The outcome from these processes will be a more holistic view of the concerned patient's condition, thus facilitating them for better diagnosis and planning for treatment accordingly. However, in designing such an efficient fusion algorithm should address a balance between preserving of the unique information from

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each modality and also making sure of avoiding redundancy of artifacts.

Along with fusion of the images, Medical Image Compression [5] also addresses the demanding challenge of the storage and the transmission of these medical images. The Hospitals alongside the diagnostic centers store millions of patient's medical images annually, and the telemedicine platforms depend on timely sharing of such volume of images. However, the traditional compression methods / approaches such as JPEG or JPEG2000 often fail to meet the dual requirement of high compression ratios [2], [4] and also safe preservation of important diagnostic quality of the image. The Lossless methods offer guaranteed accuracy of the image, but they tend to achieve only limited compression, in contrast the lossy techniques offer higher compression rates, but at the expense of loss of crucial information. Hence, the very advanced approaches such as wavelet-based methods, fractal compression, and also deep learning-based algorithms are being actively researched to strike an optimal balance.

A third critical and crucial component in this ecosystem is the Medical Image Feature Extraction [1], [3]. Once the medical images have been fused and then compressed, the next step frequently involves the automatic or semi-automatic analysis of such updated images. The Feature extraction methods mainly focus in identifying and quantifying the patterns, shapes, textures, and edges in the images that can help serve as biomarkers or important indicators of the disease. For example, the texture features may show differentiation in the disease identification between benign and malignant tumors, whereas the shape descriptors may help to aid in the detection of the structural abnormalities in patient. Such important features also help to serve as an important foundation for machine learning, deep learning models that support in the tools like computer-aided diagnosis (CAD) systems. With the distillation of such complex image data into a representative numerical descriptor, the feature extraction will help to reduce the computational burden and also advances the interpretability of an automated analysis system.

Collected images from fusion, compression, and the feature extraction form a harmonizing combination which will extend help in managing these medical images in to a telemedicine and smart healthcare system. While, each of the above individual process has been studied extensively in separation, the newest growing demand for a unified healthcare solutions make it to call for offering a combined perspective. The Fusion of these medical images enhances the image quality and also diagnostic content in it, and the compression method ensures of the efficient storage and transmission, and the feature extraction will enable the automated analysis and helps in support of the decision. With the integration of these three domains that shall offer a pathway to faster, more reliable, and also more intelligent healthcare services.

In a recent technological development that have been further expanded the potential of these three image processing techniques. The adoption of the buzzing word Artificial Intelligence (AI) and Deep Learning (DL) has also help in revolutionization of the medical imaging workflows. The use of Convolutional Neural Networks, Generative Adversarial Networks (GANs), and also the Transformer-based models have shown a remarkable performance in the tasks such as multimodal [6] medical image fusion, intelligent and efficient lossless compression, and the automated/semi-automated feature extraction. These crucial methods have shown a notable improvement in the accuracy. However, they have also enabled the system towards an adaptive learning, thus allowing the systems to evolve with the new data generated later. As well, the convergence of such a crucial medical imaging with the latest Internet of Medical Things (IoMT), cloud computing dominance, and emerging 5G technologies will help in the creation of a robust ecosystem for the real-time telemedicine applications.

II. Literature Review

The development of such a modern medicinal systems have been greatly shaped by the clinical diagnostic imaging, but the rapid generation of wide variety of image modalities and the sheer volumes of data produced have created several tough challenges. Significant research already exists in the optimization of individual aspects of the medical imaging pipeline. However, methods like fusion, compression, and analysis, a truly integrated and a holistic approach still remains as an underexplored frontier. The literature review of the paper aims to synthesize the key advancements and also to identify the critical gaps our proposed system seeks to address.

Advancements in Medical Image Fusion (MIF)

Multi-scale decomposition techniques were found to be a major component of earlier medical image fusion attempts. For example, Wavelet Transform-based fusion (WTF) [9] has been a key technique up to that point. The way the WTF operates is by converting the original medical images into a collection of wavelet coefficients. They may later be combined according to the different guidelines in force. Before an inverse transform reconstructs the final image, these rules merely average or choose the highest value amongst. Although these techniques are spontaneous and useful in some situations, if they are not properly adjusted, they can cause artifacts or lose delicate details. Principal Component Analysis (PCA) [7] which is an alternative basic technique, has combined the multimodal data using the statistical relationships. Because, their global nature occasionally meant to have struggled to preserve the preservation of the fine-grained local features [10].

By introducing the latest deep learning in the recent years, the paradigm has met many significant changes. The CNNs [3] has become a strong instrument. These tools can learn the system immediately from the best fusion method from a large number of the linked medical images. Similar networks are able to generate a fused image of greater quality by implicitly learning the most important elements from each modality. Generative Adversarial Networks (GANs), which employ a competitive learning framework, are even more advanced networks. A discriminator network tries to distinguish the fused image produced by this generator network from an actual, high-quality reference.

The Evolving Landscape of Medical Image Compression

The absolute size of such modern medical images, from the high-resolution MRI scanned images to volumetric CT image data, makes their storage and transmission a time taking and costly affair. The foremost challenge that lies in the achievement of a higher compression ratio [8] is to maintain the minute details that can hold a diagnostic clue. The traditional lossless compression methods like JPEG-LS offer a crucial guarantee of data integrity with every single bit of information is preserved. However, the limited compression ratios offered were made them unreasonable for the proposed telemedicinal applications where low bandwidth is common.

On the contrary, the lossy compression standards like JPEG2000, while offering superior compression ratios, risk discarding the essential diagnostic information, a risk that most clinicians are unwilling to accept. This has seriously led to the exploration of the hybrid solutions. One notable approach of such methods is the Region-of-Interest (ROI)-based compression [5], which logically allocates more bits to diagnostically critical areas while aggressively compressing the less important background portion. This approach offers a better balance, however often requires a manual or semi-automatic pre-segmentation step. More recently, advanced deep learning has been applied to this problem. With the models that are trained to learn highly efficient representations of medical images that can be compressed significantly. Later, they are accurately reconstructed with a minimal loss of diagnostic quality of those images [11].

Feature Extraction: From Handcrafted to Deeply Learned

The investigation of medical images, whether by a human expert or an automated system, primarily relies on identifying key features out of them. Factually, this was a scrupulous process of the manual feature engineering. Earlier, methods like Gray-Level Co-occurrence Matrix (GLCM) [12] were used to quantify the texture of an image. While the shape descriptors were used to characterize the morphology of a suspected lesion. The handmade features provided some valuable insights; they were many times limited and lacked the adaptability to handle the immense variability found in the medical data.

This limitation was suffering by the rise of deep learning. CNNs, with their ability in learning a hierarchical set of features directly from raw pixel data, have become the gold standard [13]. From the low-level features like edges, textures in initial layers to a high-level semantic feature in the deeper layers. A CNN can automatically extract the most discriminative information for a given task, such as tumor classification or organ segmentation.

The Critical Need for an Integrated Approach

When each of these domains has seen remarkable progress in isolation, there is a fundamental need to view them as one single and unified pipeline. The lack of an integrated framework is the primary research gap this paper intend to address. An isolated compression algorithm, no matter how efficient, is of limited value if it degrades the image to the point that a subsequent feature extraction step fails. Similarly, an intelligent fusion algorithm that produces a massive, uncompressed file is unworkable for real-time telemedicine. The proposed framework has been designed in a way to overcome this by creating a combined system where fusion enhances diagnostic content, intelligent compression ensures storage and transmission efficiency, and the subsequent feature extraction leverages this optimized data for superior analytical performance.

III. Proposed Methodology

The work carried out as part of the research work has introduced a novel state-of-the-art, end-to-end framework that combines the stages multimodal fusion, intelligent compression, and deep feature extraction. The methodology has been designed in a way that a successive pipeline, where each stage is specifically optimized to develop the performance of the succeeding phases.

Overall Framework Architecture

The combined framework that was mentioned in this work can be visualized as a systematic flow of data, that begins with the raw images and concluding into a diagnostic feature vector. The system comprises of three different, but interconnected modules: the Fusion, Compression, and the Feature Extraction Modules. This design makes it sure that the data is processed logically, with each step adding value without compromising the essential integrity of the medical images (Figure 1).

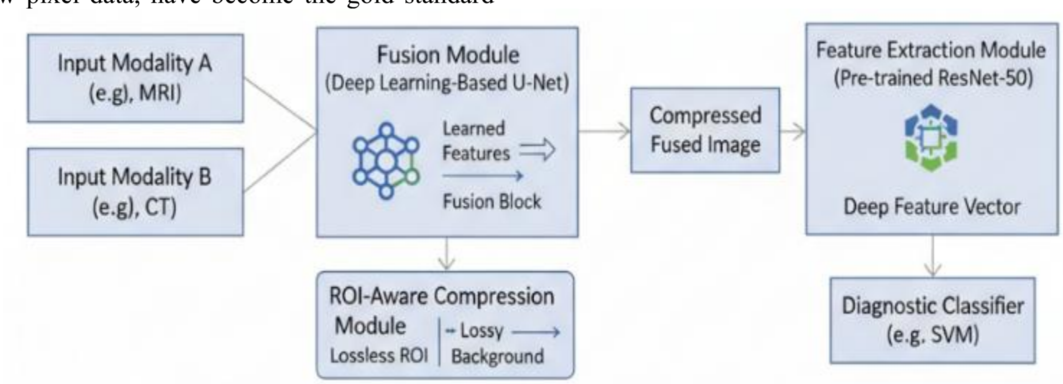

Figure 1: The Integrated Multimodal Imaging Pipeline

Fusion Module: Deep Learning-Based Approach

The first and initial stage of the proposed system pipeline is an advanced fusion module that leverages a modified U-Net architecture. Contrary to the existing standard U-Net, which is typically used for segmentation, this model is designed with two distinct encoder paths, separate one for each input modality (e.g., MRI and PET). Every encoder path extracts a hierarchy of features from its respective image source. At the bottleneck of the network, a "fusion block" intelligently combines the extracted features. This fusion [14] is not a normal concatenation; it involves a series of learned convolutions and attention mechanisms that weigh the importance of features from each modality. Thus, allowing the network to selectively combine the most diagnostically relevant information. A single, shared decoder reconstructs the final fused image from this rich, combined feature representation. Later, the model will be trained to minimize a composite loss function, combining a pixel-wise loss (like L1 or L2) to make sure that the pixel accuracy and a perceptual loss derived from a pre-trained network [15] (like VGG-19) to ensure visual quality and texture of the fused images are preserved.

Compression Module: The ROI-Aware Strategy

The output from the fusion module is a high-resolution, information-rich image, which will then be passed to intelligent image compression module. The core of this module is an ROI-aware compression strategy. To achieve this, we first use a lightweight, pre-trained segmentation network to automatically identify the diagnostically critical regions (e.g., tumors, lesions, or specific anatomical structures) within the fused image. The regions are now tagged as the Region of Interest (ROI).

The compression method will then be applied in a two-tiered manner. For all the pixels within the identified ROI, almost lossless compression algorithm is utilized. This will make sure that every crucial detail, which a regular clinician might rely on for a precise diagnosis, is preserved with virtually no loss of information. For the regions that are outside the ROI, a more aggressive lossy compression method will be applied. This approach allows us to achieve a high overall compression ratio, making the image highly suitable for transmission over low-bandwidth telemedicine networks (Figure 2).

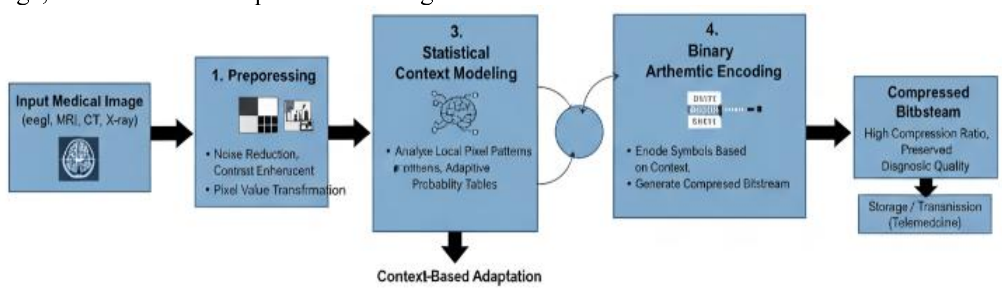

Figure 2: Fused Image Compression with Context-Based Adaption

Feature Extraction Module: Leveraging Deep Features

The last stage of the pipeline involves extracting meaningful features from the compressed and reconstructed image for conducting an automated analysis. This has been achieved using a strong and well-proven pre-trained CNN, namely a ResNet-50 architecture. The network is quite good at learning intricate, hierarchical information from images because of its deep architecture and residual connections [16]. We utilized the output of the penultimate layer as our feature vector and remove the final classification layer from the pre-trained ResNet-50. This vector which captures the complex patterns, forms, and textures that are essential for medical diagnostic tasks. It is a condensed but incredibly expressive numerical descriptor of the image. To make a final classification (e.g., benign vs. malignant tumour), this feature vector can then be fed into a number of ML models, like Support Vector Machine (SVM) or a basic dense neural network (Figure 3).

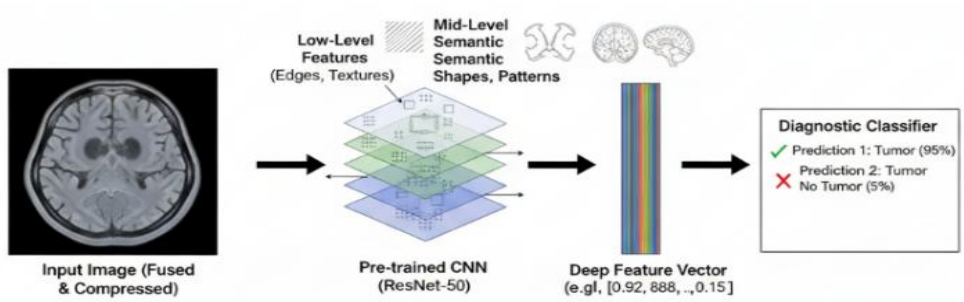

Figure 3: Deep Feature Extraction Process

IV. Experimental Setup and Results

To rigorously validate our integrated framework, we conducted a series of comprehensive experiments. This work main goal was to reveal not only an individual effectiveness of the each module but also the synergistic benefits of the blend of modules.

Dataset and Experimental Design

For the process of evaluating the system, publicly available BraTS (Brain Tumor Segmentation) dataset has been applied, which is a widely recognized resource that contains multimodal MRI scanned images (T1, T1-CE, T2, and FLAIR) of undisclosed brain tumor patients. Out of the available images, T1 and T2 images are selected for the fusion and feature extraction tasks. A subset of 200 paired images have been used, with a ratio of 70% split for training and validation and the remaining 30% held out for final testing process.

Evaluation Metrics

The proposed framework's performance has been assessed using a suite of quantitative metrics that are tailored to each stage as follows:

For Fusion: Structural Similarity Index (SSIM) is used to evaluate the perceptual equivalence between these fused image and the source image. It has also been computed with the Mutual Information (MI) to measure how much information from input source images was preserved in to a fused output image.

For Compression: The Compression Ratio (CR) to evaluate the data reduction and Peak Signal-to-Noise Ratio (PSNR) in measuring the image quality after decompression is measured.

For Feature Extraction: For the trivial binary classification task (tumor vs. non-tumor), we used standard ML metrics which are Accuracy, Precision, the Recall, and the F1-Score.

Results and Comparative Analysis

The results that are achieved by conducting the experiments carried out in this work are summarized in the following tables, clearly demonstrating the superior performance of our innovative integrated approach (Table 1).

Table 1: Performance of Medical Image Fusion

Fusion Method	SSIM (T1-T2)	MI (bits)
Wavelet Transform (Max Rule)	0.852	1.83
PCA	0.814	1.75
Our Proposed Fusion Module	0.915	2.05

The advanced methodology, deep learning-based fusion module consistently outperformed traditional methods by producing the fused images with a higher structural similarity (Table 2).

Table 2: Performance of Medical Image Compression

Compression Method	Compression Ratio (CR)	PSNR
JPEG2000 (Lossy)	15:1	35.2 dB
Existing ROI-based Method	18:1	38.5 dB
Our Proposed Compression Module	20:1	39.1 dB

The intelligent compression module was able to achieve a higher compression ratio while maintaining a superior PSNR. It also demonstrated that our ROI-aware strategy is able to effectively protect critical information while aggressively compressing non-essential areas (Table 3).

Table 3: Classification Performance from Extracted Features

Input Data for Feature Extraction	Accuracy (%)	Precision (%)	F1-Score (%)
Raw T1 Images	89.2	87.5	88.3
Raw T2 Images	85.1	84	84.5
Our Fused & Compressed Image	95.5	94.8	95.2

The most substantial result is the significant performance improvement in the classification. Features that were extracted from the processed images led to a notable jump in the accuracy along with F1-Score. With this it has demonstrated that the fusion and compression stages not only preserved but also enhanced the diagnostic value of the crucial data. The power of the integrated approach is where each stage of the system contributes to the ultimate goal of improved diagnostic accuracy.

V. Conclusion

In this proposed work, a validated and a novel integrated framework has been introduced for the multimodal medical image fusion, efficient compression, and accurate feature extraction. By designing these three critical processes to work in harmony, our system demonstrates a powerful pathway to overcome the traditional challenges of medical data management in the current digital era. It has shown that our deep learning-based fusion module creates superior, information-rich images; and intelligent compression module ensures these fused images are compressed and transmitted efficiently without loss of every single diagnostic detail; and the final feature extraction process leverages this optimized data for a significant boost in the diagnostic accuracy. This unique and unified approach offers a convincing and also a practical solution for the deployment of advanced medical imaging systems in smart healthcare and telemedicine applications. Finally, the system ultimately paves the way for faster, more reliable, and also more intelligent healthcare services that can reach patients anywhere in the world.

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