Enhancing Image Processing Efficiency for MRI Data: Comparative Analysis of Threading and Parallel Processing

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***Abstract*—By using threading and parallel processing approaches, this work aims to improve the effectiveness of MRI-based image processing for brain tumor identification. These consist of shared memory, Message Passing Interface (MPI), and GPU programming. Our method optimizes computational speed while preserving model correctness by focusing on crucial processing steps including preprocessing, normalization, and training. We evaluate improvements in processing time, computational efficiency, and resource consumption by comparing model performance with and without threading in a methodical manner. We show through this comparative research that threading and parallel processing techniques greatly minimize bottlenecks, improving the suitability of MRI operations for clinical real-time applications. This study addresses the scalability and computational issues in brain tumor diagnostics by providing a thorough methodology for incorporating threading into image processing pipelines.**

***Keywords*—MRI, Threading, Parallel Processing, Deep Learning, Image Processing, Preprocessing, GPU Programming, Computational Efficiency**

I. Introduction

Brain tumors contribute to high rates of morbidity and mortality, making them a major worldwide health concern. The improvement of patient outcomes depends on early and precise detection. Because it can provide precise structural and functional images, magnetic resonance imaging (MRI) is still a key diagnostic tool for brain tumors. However, scalability and real-time applications are significantly hampered by the computational requirements of processing high-resolution MRI data [1]–[3].

There are several steps in MRI workflows, such as preprocessing, normalization, and deep learning model training for tumor classification. Preprocessing alone takes up around 30–40% of the processing time, making these steps computationally demanding. Additionally, depending on the architecture's complexity, training deep learning models on sizable MRI datasets frequently takes hours or even days [4], [5]. The requirements of large-scale or real-time implementations are frequently too great for conventional procedures, particularly in settings with limited resources.

A solution is offered by threading and parallel processing algorithms, which divide up computational jobs among several processors or cores. Concurrent task execution is made possible via GPU programming, shared memory, and MPI, which greatly cuts down on processing time and enhances resource usage. Research has shown that using threading and parallelization approaches can reduce training time by up to 70% and preprocessing time by 40% [6]–[8]. However, most of the research that is currently available concentrates on particular tasks, like training or inference, without assessing how they affect entire MRI workflows.

The purpose of this work is to close this gap by methodically contrasting the performance of models that use parallel processing and threading with those that do not. In order to offer practical insights into streamlining MRI operations for real-time clinical applications, we assess criteria including computing speed, resource efficiency, parallel processing, performance, and accuracy [9]–[11].

II. Literature Review

Evolution of Deep Learning Architectures for MRI Tumor Detection

MRI-based tumor detection procedures have become much more accurate and efficient with the incorporation of deep learning models. Using CNNs for feature extraction and SVMs for reliable classification, hybrid architectures such as CNN-SVM models have shown 96.5% accuracy [4]. By identifying intricate spatial and structural patterns in MRI data, sophisticated designs like DenseNet169 and ResNet152 have raised accuracy levels to above 97.8% [7], [12].

YOLOv5 and YOLOv7, two real-time detection frameworks, have made significant progress in the field with mean average precision (mAP) ratings of 98.2% and 97.3%, respectively. With processing rates as low as 10 milliseconds per image, these models are very efficient for multiclass tumor classification applications [6], [8], [13]. These developments demonstrate how well deep learning works for tumor diagnosis while emphasizing the necessity of computationally efficient methods to manage massive MRI datasets [3].

Bottlenecks in Conventional MRI Workflows

Despite advances in deep learning, MRI workflows continue to encounter significant bottlenecks:

1) **Preprocessing Overheads:** Up to 40% of the processing time is spent on the extensive preprocessing required for high-resolution MRI images, which includes noise reduction and normalization [1], [2].
2) **Training Complexity:** Scalability and real-time application are constrained by the training complexity of models such as DenseNet and ResNet, which often necessitate high-performance hardware [9], [14].
3) **Data Imbalance:** Model performance tends to be skewed, with sensitivity to minority classes being reduced when rare tumor types account for less than 10% of most datasets [5], [15].

In order to overcome these difficulties, threading and parallel processing techniques allow computationally demanding activities to be completed concurrently. Training speed increases of up to 70% have been demonstrated in studies that use GPU acceleration for CNN procedures like convolution and pooling [6], [16]. Execution times have been lowered by 30–50% when multi-threading techniques are used for preprocessing activities like data augmentation and normalization [17]–[19]. Through the effective use of MPI for distributed training, workloads can be split among several processors, further increasing scalability [10], [13].

The combined effect of threading and parallel processing approaches on complete MRI operations is still poorly understood, despite its potential in certain jobs. Previous research frequently concentrates on discrete phases, like inference optimization, without taking pretreatment and normalization into account. Moreover, there is a large gap in the practical applicability of these strategies due to the inadequate investigation of their scalability in resource-constrained contexts [11], [20].

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