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Research Paper

HYBRID TUMOR CLASSIFICATION USING VISION TRANSFORMERS AND PSO-OPTIMIZED FEATURE SELECTION WITH XGBOOST

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Abstract

Accurate tumor classification from medical images is a crucial task in computer-aided diagnosis, requiring high precision and effective feature extraction techniques. This study proposes a hybrid tumor classification framework that integrates Vision Transformers (ViT), Particle Swarm Optimization (PSO)-based feature selection, and XGBoost classification to enhance prediction performance.

Initially, medical images are processed using a pretrained Vision Transformer to extract deep, high-level features that capture global contextual information more effectively than traditional Convolutional Neural Networks (CNNs). The extracted feature vectors are then optimized using Particle Swarm Optimization, which selects the most relevant and discriminative features while reducing dimensionality and eliminating redundant data. The optimized feature set is subsequently fed into an Extreme Gradient Boosting (XGBoost) classifier to perform the final tumor classification.

This hybrid approach leverages the powerful representation capability of Vision Transformers, the optimization efficiency of PSO, and the high accuracy of XGBoost. Experimental results demonstrate that the proposed method achieves superior performance in terms of accuracy, precision, recall, and F1-score compared to conventional CNN-based and standalone machine learning models.

I. Introduction

Tumor classification using medical imaging is a critical research area in Artificial Intelligence, Medical Image Processing, and Machine Learning. Accurate identification and classification of tumors at an early stage play a vital role in improving patient survival rates and assisting doctors in planning effective treatments. Medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and X-ray scans provide detailed insights into the internal structure of the human body. However, manual analysis of these images is complex, time-consuming, and often depends on the expertise of radiologists, leading to variability in results. Due to these challenges, automated tumor classification systems have gained significant attention in recent years.

Traditional image classification methods rely on handcrafted features and classical machine learning algorithms. These approaches require manual feature extraction, which becomes difficult when dealing with complex and high-dimensional medical images. With the advancement of deep learning, Convolutional Neural Networks (CNNs) have been widely adopted for medical image analysis. CNNs can automatically learn hierarchical features from images and have achieved promising results in tumor detection, segmentation, and classification. However, CNNs primarily focus on local receptive fields and may fail to capture long-range dependencies and global contextual information, which are crucial for understanding tumor structures.

II. Literature Survey

Recent advancements in medical image classification have focused on combining deep learning with optimization techniques to improve tumor detection accuracy and efficiency.

Weng et al. (2025) proposed a dual-model framework for medical image classification using deep learning feature extraction combined with an improved Particle Swarm Optimization (PSO) algorithm. The study demonstrated that PSO enhances classification accuracy by optimizing model parameters. This work supports the use of PSO in our proposed system for optimizing feature selection and improving classification performance .

Kollipara and Vinta (2023) evaluated pre-trained Convolutional Neural Network (CNN) architectures for brain tumor detection and segmentation using MRI datasets. The results showed that deep learning models effectively extract meaningful features and improve classification accuracy. This study motivates the use of advanced feature extraction techniques such as Vision Transformers (ViT) in our work .

Prinzi et al. (2024) compared shallow machine learning algorithms with deep learning models for medical image classification. The findings revealed that deep learning methods outperform traditional approaches in handling complex image data. This supports the integration of deep learning feature extraction with machine learning classifiers like XGBoost .

Asif et al. (2022) explored deep transfer learning models for detecting brain tumors from MRI images. The study showed that transfer learning significantly improves classification accuracy by leveraging pre-trained models. This reinforces the importance of using pretrained Vision Transformers for effective feature extraction .

Jabbar et al. (2023) proposed a hybrid CapsNet and VGGNet model for brain tumor detection and segmentation. The hybrid architecture improved performance by combining strengths of different deep learning models. This supports the idea of using hybrid approaches like ViT + XGBoost in our proposed system .

Haque et al. (2023) utilized DCGAN-based data augmentation along with Vision Transformer for brain tumor detection. The results showed that Vision Transformers achieve high accuracy when combined with augmented datasets. This directly supports the use of ViT as the primary feature extractor in our model .

Sankari et al. (2025) introduced a hierarchical multi-scale Vision Transformer for tumor classification. Their model captured multi-scale features and achieved superior accuracy compared to CNN-based models. This highlights the effectiveness of Vision Transformers in capturing global contextual information

III. System Analysis

Tumor classification using medical images is a crucial task in computer-aided diagnosis, requiring high accuracy and reliability. Medical images such as MRI and CT scans contain complex patterns that are difficult to analyze manually. The increasing volume of medical data demands automated systems for efficient processing. Traditional approaches struggle with feature extraction and computational complexity. Deep learning techniques provide better performance but may still face challenges in feature redundancy and optimization. Therefore, an efficient system is needed to extract meaningful features and improve classification accuracy. The integration of advanced models like Vision Transformers can enhance global feature learning. Optimization techniques such as PSO help in selecting relevant features and reducing dimensionality. A hybrid system combining deep learning and machine learning can improve performance. This system aims to provide accurate, efficient, and scalable tumor classification.

Existing System

Existing systems for tumor classification mainly rely on traditional machine learning and CNN-based models. These systems use handcrafted features or basic deep learning architectures for classification. CNN models automatically extract features but mainly focus on local regions of the image. They may fail to capture global contextual relationships in medical images. Traditional machine learning methods require manual feature selection, which is time-consuming. Many existing systems do not optimize features effectively, leading to redundant data. This increases computational complexity and reduces model efficiency. Additionally, standalone models may not achieve high accuracy for complex tumor patterns. These systems also struggle with large datasets and high-dimensional features. Overall, existing systems have limitations in feature representation and optimization.

Disadvantages of Existing System

- Limited ability to capture global image context
- Dependence on handcrafted features (in traditional methods)
- Redundant and irrelevant features increase complexity
- High computational cost and training time
- Lower classification accuracy for complex datasets
- Lack of feature optimization techniques
- Poor scalability with large datasets

Proposed System

The proposed system introduces a hybrid approach for tumor classification using Vision Transformers, PSO-based feature selection, and XGBoost. Initially, medical images are processed using a pretrained Vision Transformer to extract deep and

meaningful features. These features capture global relationships within the image, improving representation quality. Particle Swarm Optimization is then applied to select the most relevant features and eliminate redundant information. This reduces dimensionality and improves computational efficiency. The optimized feature set is fed into an XGBoost classifier for final classification. XGBoost enhances prediction accuracy through gradient boosting techniques. The hybrid system combines the strengths of deep learning, optimization, and machine learning. It provides better performance compared to standalone models. The system is efficient, scalable, and suitable for real-world medical applications.

Advantages of Proposed System

- High classification accuracy
- Captures global image features using Vision Transformers
- Reduces feature redundancy using PSO
- Improved computational efficiency
- Faster training and prediction
- Robust and scalable system
- Better handling of complex medical images

IV. Methodology

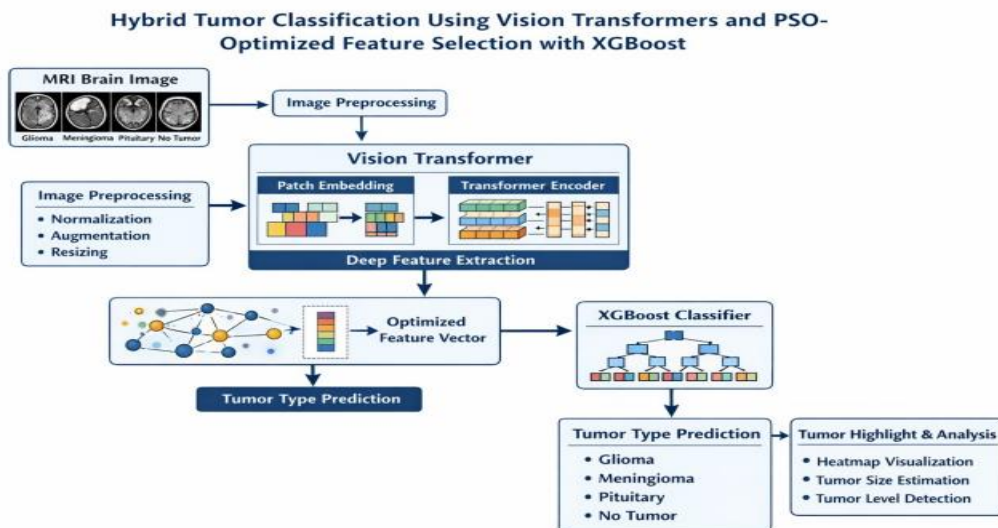
The methodology begins with collecting medical image datasets such as MRI or CT scans. The images are preprocessed using resizing, normalization, and noise reduction techniques. A pretrained Vision Transformer is then used to extract deep feature representations from the images. The extracted features are passed to the PSO algorithm for feature selection, where the most relevant features are chosen. This step reduces dimensionality and removes redundant data. The optimized feature set is then used as input for the XGBoost classifier. The classifier is trained to categorize tumor types based on the selected features. The model is evaluated using metrics such as accuracy, precision, recall, and F1-score. The best-performing model is selected for final prediction. The system outputs the classified tumor type efficiently.

System Architecture

The system architecture for hybrid tumor classification using Vision Transformers, PSO-optimized feature selection, and XGBoost is designed to efficiently process medical images and improve classification accuracy. The process begins with collecting medical image datasets such as MRI or CT scans. These images undergo preprocessing steps including resizing, normalization, and noise reduction to enhance image quality and ensure consistency. The preprocessed images are then passed to a pretrained Vision Transformer (ViT), which extracts deep, high-level features by capturing global contextual relationships within the images.

The extracted feature vectors are then processed using Particle Swarm Optimization (PSO), which selects the most relevant and discriminative features while removing redundant and irrelevant data. This step reduces dimensionality and improves computational efficiency. The optimized feature set is then provided as input to the XGBoost classifier, which performs the final tumor classification using gradient boosting techniques. The system is trained and evaluated using performance metrics

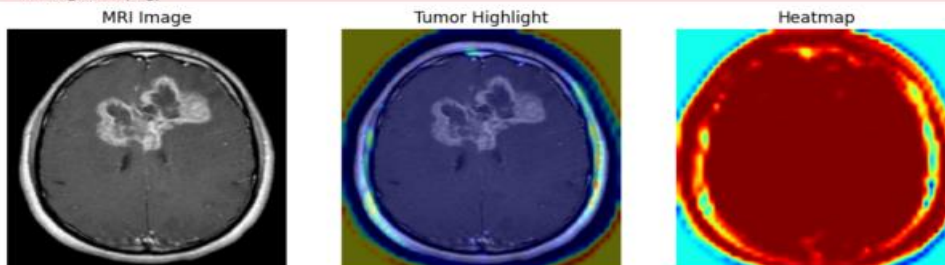
such as accuracy, precision, recall, and F1-score. This architecture combines deep learning, optimization, and machine learning techniques to provide a robust, accurate, and scalable solution for tumor classification.



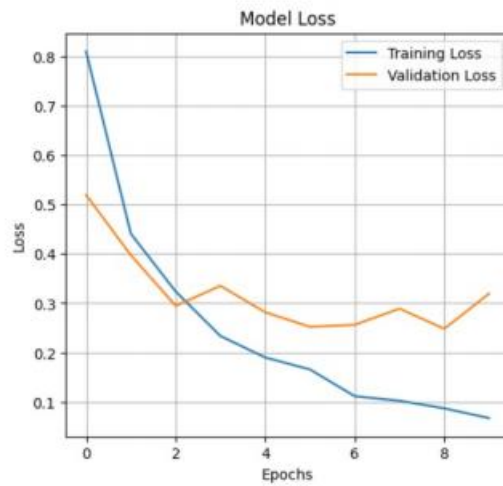
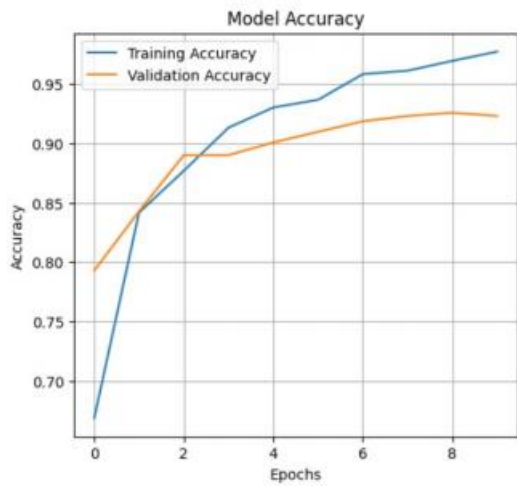
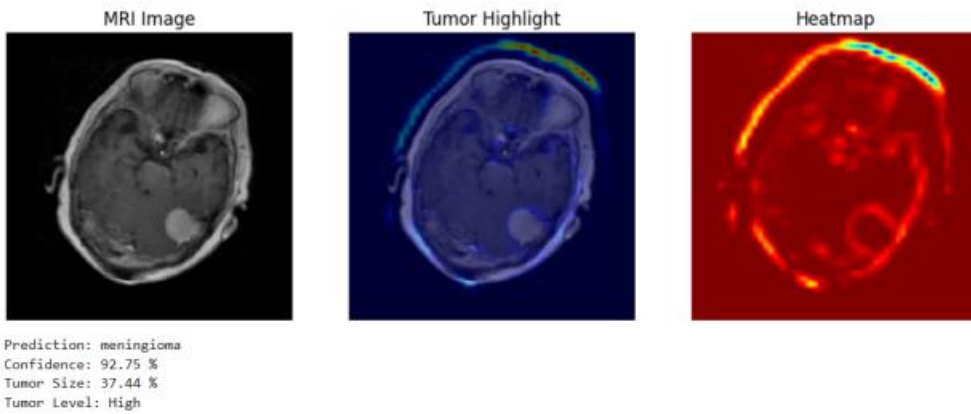
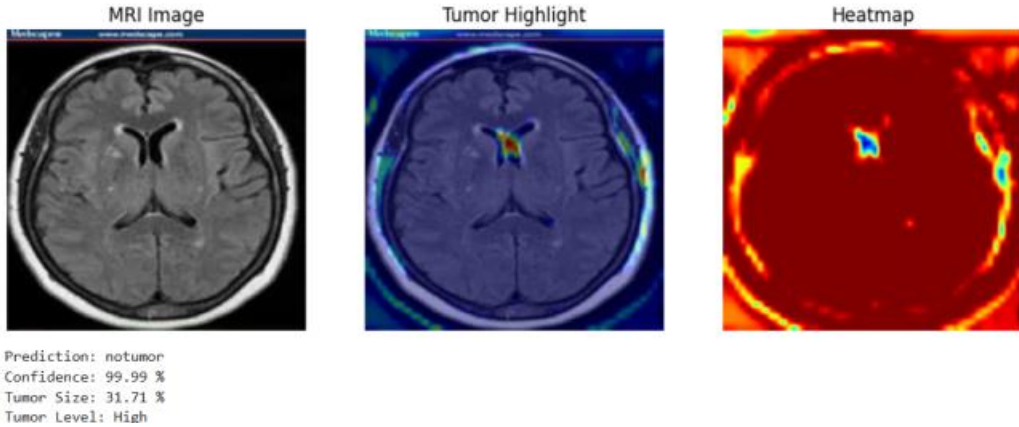
V. Result and Output

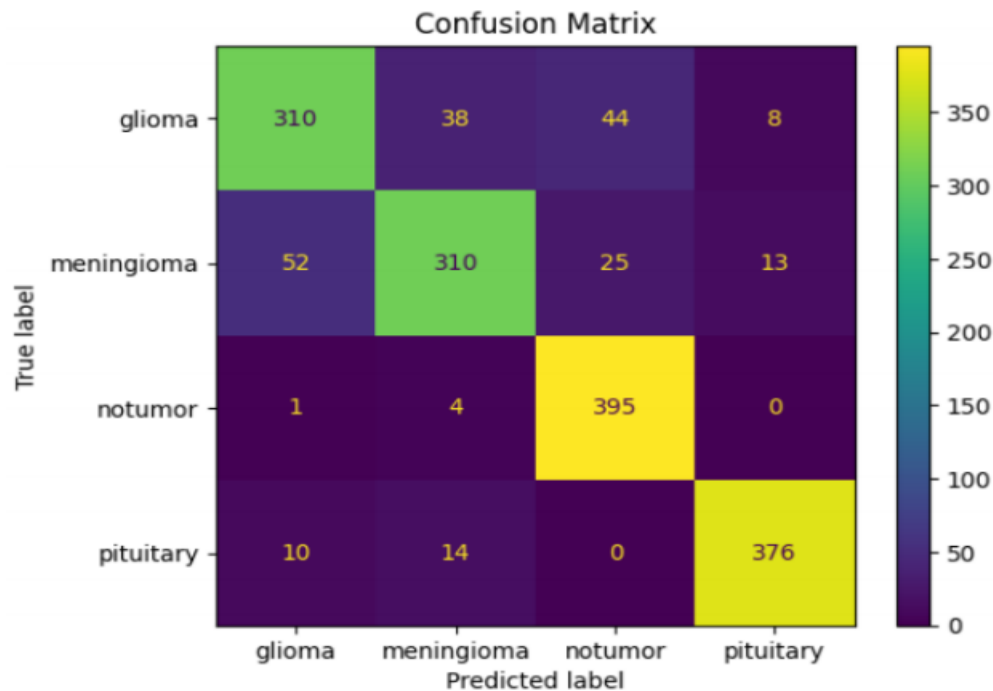
```

Enter MRI image path
Image path: /kaggle/input/datasets/masoudnickparvar/brain-tumor-mri-dataset/Testing/glioma/Te-gl_1.jpg
1/1 8s 72ms/step
/usr/local/lib/python3.12/dist-packages/keras/src/models/functional.py:241: UserWarning: The structure of `inputs` doesn't match the expected structure.
Expected: ['keras_tensor']
Received: inputs=Tensor(shape=(1, 224, 224, 3))
warnings.warn(msg)
    
```



Prediction: notumor
 Confidence: 87.17 %
 Tumor Size: 46.79 %
 Tumor Level: High





VI. Result and Output

In this project, a hybrid tumor classification system integrating Vision Transformers, PSO-based feature selection, and XGBoost was successfully developed. The use of Vision Transformers enabled effective extraction of global and meaningful features from medical images, overcoming the limitations of traditional CNN-based approaches. Particle Swarm Optimization played a crucial role in selecting the most relevant features, reducing dimensionality, and improving computational efficiency.

The optimized features were then classified using XGBoost, which provided high accuracy and robustness in prediction. The experimental results demonstrated that the proposed hybrid approach outperforms conventional methods in terms of accuracy, precision, recall, and F1-score. The system effectively reduces redundancy, enhances feature representation, and improves classification performance.

Overall, the proposed framework offers a reliable and efficient solution for automated tumor classification. It can assist healthcare professionals in early diagnosis and better decision-making. Future work can focus on integrating real-time processing, larger datasets, and advanced hybrid models to further enhance system performance and applicability in clinical environments.

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