HybridYOLOv8–CNN Framework for Automated Analysis of Temporal fMRI Brain Networks

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Abstract- *Functional Magnetic Resonance Imaging (fMRI) provides critical insights into dynamic brain activity and connectivity patterns, enabling the study of neural functions over time. Traditional clustering methods, such as Topological Data Analysis (TDA), are limited to grouping brain networks and cannot accurately detect or classify active regions or abnormalities like tumors. Manual interpretation of MRI and fMRI data is time-consuming, prone to human error, and often inconsistent across multi-site datasets. To overcome these challenges, the proposed system introduces a hybrid YOLOv8 and Convolutional Neural Network (CNN) framework for automated detection, localization, classification, and staging of brain tumors along with analysis of normal brain activity. YOLOv8 precisely detects and localizes active brain regions in MRI and fMRI-derived maps, generating bounding boxes and confidence scores. The CNN extracts deep spatial and temporal features enabling accurate classification of brain states and tumor stage determination. Experimental results demonstrate high accuracy in brain activity analysis, tumor detection, and staging. This automated method reduces dependence on manual interpretation, providing faster, more reliable, and interpretable clinical insights.*

I. INTRODUCTION

Brain tumors are among the most life-threatening conditions affecting the human nervous system. Early and accurate detection plays a crucial role in improving treatment outcomes and increasing patient survival rates. Traditional diagnostic methods such as MRI scans often require expert interpretation, which is time-consuming and subject to human error. With rapid advances in artificial intelligence and computer vision, deep learning has emerged as a powerful tool for medical image analysis.

Among various object detection algorithms, YOLOv8 stands out due to its real-time detection capability, high accuracy, and efficiency. This project leverages the YOLOv8 model alongside CNN for automated brain tumor detection and fMRI analysis. The system is trained on multi-site MRI datasets, capable of detecting tumors with high precision while reducing dependency on manual analysis. The primary objectives of this study are:

- To develop a hybrid YOLOv8 and CNN framework for automated brain tumor detection, localization, and staging.
- To extract deep spatial and temporal features for accurate classification of brain states.
- To ensure robustness across multi-site datasets with varying scanner types and temporal resolutions.

II. LITERATURE REVIEW

Brain tumor detection and fMRI analysis have been extensively studied using deep learning. The following review covers key works relevant to the proposed hybrid framework.

Deep Learning for Brain Tumor Classification

A multiscale recursive neural network framework was proposed for classification and segmentation of brain tumors in MRI, demonstrating superior segmentation accuracy using coarse and fine features. Deep transfer learning using VGG16, ResNet, and Inception models has achieved high accuracy in automating brain abnormality classification, significantly reducing training data requirements. Surveys on multigrade brain tumor classification highlight CNN, RNN, and hybrid deep architectures as effective solutions in smart healthcare systems, with data augmentation and ensemble learning addressing data imbalance challenges.

YOLOv8 and Object Detection in Medical Imaging

YOLO-based architectures have been successfully applied for real-time tumor detection in MRI, offering high precision and speed for localization tasks. YOLOv8 combined with CNN for feature extraction demonstrated improved detection accuracy and interpretability compared to conventional methods. Concatenation-based deep learning models have further enhanced tumor diagnosis by integrating low-level and high-level features for improved classification precision.

Temporal fMRI Analysis

Statistical Parametric Maps (SPM) and General Linear Models have been widely used for functional imaging analysis. Clustering approaches based on Topological Data Analysis group brain networks using temporal features, though limited to clustering without detection. Feature extraction techniques including PLA, PAA, and Fourier transforms reduce dimensionality in time series data. Event-related fMRI has demonstrated the ability to trace temporal sequences of cortical activation with 100-200 millisecond resolution, supporting mental chronometric measurements.

Gaps in Existing Literature

While existing studies provide valuable insights, key gaps remain:

1. Existing TDA methods cannot simultaneously detect, localize, and classify brain regions.
2. Most systems fail to integrate spatial localization with temporal feature extraction.
3. Limited integration of serverless and automated classification for clinical applications.

The proposed hybrid YOLOv8-CNN framework addresses these gaps comprehensively.

III. SYSTEM STUDY

Existing System

The existing system primarily relies on Topological Data Analysis (TDA) for temporal clustering of fMRI brain networks. TDA analyzes topological features of dynamic brain connectivity — loops, voids, and connected components — to group similar brain states over time. This method is robust to noise but limited to clustering; it cannot detect, localize, or classify specific brain regions or abnormalities. TDA systems are also sensitive to scanner variability and require manual interpretation, making them impractical for fast clinical diagnostics.

Disadvantages of Existing System

- Limited Functionality: Only performs clustering; cannot detect, localize, or classify tumors.
- Lack of Spatial–Temporal Feature Learning: Fails to capture fine-grained spatial and temporal patterns.
- Manual Interpretation Required: Results are sensitive to threshold selection and require expert analysis.

Proposed System

The proposed system introduces a hybrid YOLOv8 and CNN framework for automated detection, localization, classification, and staging of brain tumors as well as temporal brain activity analysis. YOLOv8 accurately detects and localizes active and abnormal regions in brain scans, generating bounding boxes with confidence scores. The

CNN extracts deep spatial and temporal features to classify brain states, determine tumor stages, and capture dynamic functional connectivity patterns. Multi-site and multi-modal datasets ensure robustness against scanner variability.

Advantages of Proposed System

- Automated Detection and Classification: Detects tumors and active brain regions without manual intervention.
- Improved Spatial–Temporal Accuracy: CNN captures both spatial and temporal patterns of brain activity.
- Faster and Scalable Analysis: Reduces analysis time and handles large multi-site datasets.
- Robust Across Multi-Site Data: Effective despite scanner variability and differing temporal sampling rates.

IV. ARCHITECTURE DESIGN

The proposed architecture is a multi-module deep learning pipeline engineered for automated brain tumor detection and temporal fMRI network analysis. It integrates YOLOv8 for object detection with CNN for deep feature learning, forming a comprehensive and scalable neuroimaging framework.

Data Acquisition Module

High-quality MRI and fMRI datasets are gathered from multiple sources including hospitals, research labs, and public databases. The data includes healthy subjects and patients with brain tumors of various stages. Multi-site data ensures variability in scanner types, resolution, and temporal sampling rates, enabling the model to learn generalized patterns of brain activity and tumor characteristics.

Data Preprocessing Module

Acquired MRI and fMRI data undergo extensive preprocessing including noise removal, slice-timing correction, motion artifact correction, and intensity normalization. Images are resampled to uniform resolution to maintain consistency across scanners. Temporal fMRI sequences are aligned to correct for head motion, and irrelevant background data is removed to focus on areas of interest.

Feature Extraction using YOLOv8

YOLOv8 is applied to detect and localize active brain regions and tumor areas in preprocessed MRI and fMRI scans. The model divides brain images into grids and predicts bounding boxes, confidence scores, and class probabilities for each region. Detected Regions of Interest (ROIs) corresponding to neural activity or abnormal growth are annotated and visualized for clinical interpretation, significantly speeding up identification compared to manual detection.

Deep Feature Learning using CNN

The CNN processes YOLOv8-detected regions to extract deep spatial and temporal features from brain scans. Convolutional layers capture local spatial patterns while pooling layers reduce dimensionality. Temporal sequences from fMRI are processed to capture dynamic changes in connectivity. Dropout and regularization techniques prevent overfitting, forming the core learning capability that translates raw scan data into meaningful feature representations.

Classification and Tumor Staging Module

CNN-extracted features are used to classify brain activity states and determine tumor stages. Multi-class classification differentiates between normal brain regions, active functional areas, and tumor types. The system identifies tumor severity based on learned features, providing class labels, confidence scores, and bounding boxes for interpretable clinical outputs that support treatment planning and early detection.

Performance Evaluation Module

System performance is evaluated using accuracy, precision, recall, F1-score, and mean average precision (mAP) for YOLOv8 detection. Comparisons are made with traditional TDA-based clustering and manual interpretations. Cross-validation and multi-site testing ensure robustness, and efficiency metrics such as processing time per scan assess practicality for real-world clinical deployment.

V. SYSTEM SPECIFICATION

Hardware Requirements

- CPU type : Intel Pentium 4
- Clock speed : 3.0 GHz
- RAM size : 512 MB
- Hard disk capacity : 40 GB
- Monitor type : 15 Inch color monitor
- Keyboard type : Internet keyboard

Software Requirements

- Operating System : Windows OS
- Language : Python
- Back End : MySQL
- IDE : VS Code

VI. IMPLEMENTATION DETAILS

The deployment of the proposed hybrid YOLOv8-CNN framework followed a systematic approach, ensuring each module was configured to meet requirements of accuracy, robustness, and clinical applicability.

Dataset Preparation

- Multi-site MRI and fMRI datasets were collected, labeled, and preprocessed for training and validation.
- Data augmentation including rotation, flipping, and contrast adjustment increased dataset diversity.
- Train/validation/test split of 70/15/15 ensured fair and unbiased evaluation.

Model Training

- YOLOv8 was fine-tuned on annotated MRI datasets using transfer learning from pre-trained weights.
- CNN was trained on YOLOv8-detected ROIs using Adam optimizer with learning rate scheduling.
- Early stopping and dropout regularization were applied to prevent overfitting.

Integration and Pipeline

- YOLOv8 output bounding boxes are fed directly as input to the CNN for deep feature extraction.
- A unified end-to-end pipeline processes MRI/fMRI scans from raw input to classification output.
- Batch processing enables efficient analysis of large multi-site datasets in clinical settings.

Deployment Strategy

- The system was implemented in Python using PyTorch and Ultralytics YOLOv8 libraries.
- VS Code IDE was used for development with MySQL backend for dataset and result management.
- The framework supports both single-image inference and batch processing for scalability.

VII. RESULTS AND EVALUATION

The proposed hybrid YOLOv8-CNN framework was evaluated through experiments assessing its accuracy, robustness, and efficiency for brain tumor detection and temporal fMRI network analysis.

Detection Accuracy

YOLOv8 achieved high mean average precision (mAP) for detecting brain tumor regions across diverse MRI datasets. Bounding boxes accurately localized tumor regions with minimal false positives. The model demonstrated robust performance across different scanner types and MRI modalities, confirming strong generalizability.

Classification Performance

The CNN classifier achieved high accuracy for multi-class brain tumor staging and brain state classification. Precision, recall, and F1-score metrics confirmed reliable differentiation between normal, active, and abnormal brain regions. The hybrid model consistently outperformed traditional TDA-based clustering in all evaluation metrics.

Key Performance Metrics

- Detection mAP: Superior localization accuracy compared to baseline TDA methods.
- Classification Accuracy: High performance across all tumor stage categories.
- Processing Time: Near real-time inference suitable for clinical deployment.
- Robustness: Consistent accuracy maintained across multi-site and multi- scanner datasets.

Cost and Efficiency Analysis

The hybrid framework significantly reduced processing time compared to manual analysis. Automated end-to-end inference eliminated the need for manual ROI selection, reducing radiologist workload. The scalable architecture enables processing of large datasets without proportional increases in computational cost.

VIII. DISCUSSION AND FUTURE ENHANCEMENTS

The evaluation confirms that the proposed hybrid YOLOv8-CNN framework effectively addresses limitations of existing TDA-based systems. By combining spatial localization with temporal feature extraction, the system delivers accurate, interpretable, and clinically actionable results.

Strengths of the Framework

- Automated end-to-end pipeline from MRI/fMRI acquisition to tumor staging.
- High accuracy and robustness across multi-site and multi-scanner datasets.
- Interpretable outputs including bounding boxes, class labels, and confidence scores.
- Scalable architecture suitable for large-scale neuroimaging research.

Limitations

- Requires large annotated datasets for optimal training performance.
- Current implementation focuses on 2D MRI; 3D volumetric analysis not yet fully integrated.
- Computational resources may constrain real-time deployment on edge devices.

Proposed Enhancements

To address current limitations, the following enhancements are proposed:

- Integration of 3D-CNNs or Vision Transformers for improved volumetric and temporal feature learning.
- Incorporation of multi-modal data including CT scans and PET imaging for holistic assessment.
- Predictive modeling for tumor progression and patient outcome forecasting.
- Real-time deployment using model quantization and edge computing platforms.
- Explainability tools such as Grad-CAM for transparent clinical interpretability.
- Federated learning to improve generalizability without sharing sensitive patient data across sites.

IX. CONCLUSION

The proposed hybrid YOLOv8 and CNN framework provides an efficient and automated solution for analyzing brain activity and detecting brain tumors from MRI and fMRI data. It overcomes the limitations of traditional TDA-based clustering by providing precise localization, classification, and staging of brain abnormalities. YOLOv8 effectively detects active and abnormal brain regions, while CNN extracts deep spatial and temporal features for accurate classification.

The system demonstrates high accuracy, robustness, and interpretability across multi- site datasets. It reduces dependency on manual interpretation, saving time for radiologists and minimizing human errors. Tumor detection and staging are integrated into the framework, supporting early diagnosis and treatment planning.

In conclusion, this approach represents a significant advancement in automated neuroimaging analysis and clinical decision support. Future work will focus on extending the system to real-time monitoring, 3D-CNN integration, multi-modal imaging, and federated learning for broad clinical applicability.

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