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A Project Synopsis (20CS51I) on

"An Efficient YOLOv8 Framework for Brain Tumor Segmentation and Classification"

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Table of Contents

ABSTRACT

Brain tumor classification is crucial for prompt diagnosis and life-saving treatment. Brain tumor functionality and classification: A novel approach employing You Only Look Once (YOLO) technology for brain tumor functionality and classification. This test meets the need to accurately and correctly identify brain tumors to improve diagnosis and treatment. Brain tumors come in four main varieties.: meningioma, glioma, and pituitary tumor, but no tumors. We used pre-existing data for tumor diagnosis and tested different learning models according to tumor classification. In diagnosis, segmentation is necessary to identify regions containing tumors seen in medical images such as MRI scans. Our method offers use of YOLO's real-time product search capabilities and makes them relevant for clinical use. The method achieves 95% F1-Score, 96.2% precision, 93.6% recall, and 97.2% mAP50 in identifying and segmenting tumor regions while using a large database of MRI scans as training. This method is superior to traditional segmentation methods as it provides a fast and accurate target detection method. Therefore, its integration into a unified system via regional distribution makes it a good tool for medical use, facilitating the diagnosis process.

Keywords — Magnetic Resonance Imaging (MRI), Brain tumor, You-Only-Look-Once (YOLO), Meningioma, Glioma and Pituitary.

CHAPTER 1

INTRUDUCTION

Brain cancer is a debilitating disease that is common and causes many deaths, even in wealthy nations. One of the most significant organs in the human body is the brain. Since it aids in decision-making and regulates the operation of all the other organs. It is principally in charge of managing the many voluntary and involuntary bodily functions and serves as the central nervous systems command centre. The International Agency for Research on Cancer estimates that each year, around 97,000 people worldwide pass away from brain tumours, and another approximately 1,26,000 are diagnosed with them. The human body divides cells to create new ones, and it generally controls cell development and multiplication. New cells are quickly added to the body when an aging or damaged one dies. However, injured or aberrant cells may grow uncontrollably in situations where this orderly mechanism falters. Tumours are lumps of tissue that can be caused by these cells. For instance, primary brain cancers remain localized within the brain where they arise. In contrast secondary brain cancers begin in other body parts before spreading to the brain.

Tumours fall into two main groups, particularly malignant (cancerous) and benign (noncancerous). Among them, malignant tumours develop fast within the brain, damage the normal tissues, and it could mirror themselves in the various sections of the frame. Malignant tumours can harm the neighboring tissues and metastasize, developing new cancers in a certain body elements. Whereas the benign tumours do now not invade close by tissues and cannot metastasize. Unlike malignant tumours, benign tumours do not grow rapidly if they are appropriately removed from the organ. Benign tumours do not spread, yet they can occasionally become quite large, cause severe symptoms, or even endanger life. Benign and malignant tumours represent distinct varieties of unusual cellular growths within the frame, with sizeable variations of their conduct, effect, and treatment implications. Non-cancerous growths known as benign tumours keep growing and do not spread to other parts of the body. They typically grow slowly and feature well-defined borders. These tumours are not much harmful than malignant ones. However, they can nonetheless reason issues if they press on critical organs, nerves, or blood vessels. Treatment frequently involves surgical removal, and the diagnosis is normally favorable. Benign tumours are much less in all likelihood to recur after being eliminated. Malignant tumours are cancerous one and feature the ability to invade close by tissues and spread (metastasize) to distant elements of the frame via the bloodstream or lymphatic machine. They frequently develop really quickly and have irregular

borders. These tumours are more risky due to their aggressive nature and ability to disrupt the feature of essential organs and systems. Treatment commonly involves a aggregate of surgical operation, radiation remedy, chemotherapy, and targeted treatments. The analysis varies depending on factors which include the type, vicinity, degree, and grade of the tumour, as well as the patient's usual health. Determining whether a tumour is benign or malignant is essential for selecting the best course of therapy and projecting the patient's potential result. Human brain is crucial for controlling actions and decision-making, acting as the central hub of the nervous system. Protecting it from harm is essential and among potential threats, tumours are significant concern. There are basically four grades for brain tumours. Grade I: These tumours do not spread quickly and develop slowly. These are connected to a higher chance of enhanced order and may be surgically eliminated nearly entirely. One such tumour is a pilocytic astrocytoma. Grade II: They may migrate to surrounding tissues and advance to higher grades, these tumours also grow over time. These tumours may be detected even though treatment is taken by the patient. Grade III: The growth of these types of tumours has been faster than grade II malignancies and cloud spread to adjoining tissues. These tumours require post-operative chemo or radio therapy because surgery alone is insufficient to treat them. Grade IV: The most dangerous and likely to spread malignant tumours are in this category. They might even use blood vessels to spread their growth.

CHAPTER 2

LITERATURE SURVEY

The literature from 2021 to 2024 shows a rapid evolution in machine learning and deep learning techniques for brain tumour detection and classification using MRI data.

In 2021, researchers like Gupta et al. introduced multi-task and attention-based CNN architectures such as MAG-Net, capable of both segmentation and classification, highlighting the importance of attention mechanisms for accurate tumour localization.

By 2022, studies such as Qader et al. and Pitchai et al. improved accuracy through optimization-based CNNs and region-based networks (RCNNs). These models achieved strong results (~97% accuracy) by focusing on hyperparameter tuning and region detection, though they were computationally intensive and often limited to small datasets.

In 2023, Saeedi et al. demonstrated that simplified 2D CNNs could still perform effectively for MRI-based classification, achieving near 97% accuracy while being computationally efficient. However, such models lacked volumetric understanding of 3D brain structures.

The most recent works in 2024—including Ahmed et al. and Gasmi et al.—reflect a shift toward transformer-based architectures and ensemble learning. The Vision Transformer (ViT) + GRU hybrid model and ensemble CNN frameworks achieved over 98–99% accuracy, showing improved robustness and feature representation. These models, however, require higher computational resources and larger datasets for training.

Overall, this progression illustrates a clear trend:

- Early years (2021–2022) focused on CNN optimization and attention.
- Mid-phase (2023) emphasized efficiency and model simplification.
- Recent years (2024) highlight transformer and ensemble methods, improving performance and stability.

Despite remarkable accuracy gains, challenges remain in dataset diversity, model generalization, and clinical validation before these approaches can be adopted in real-world medical diagnosis.

Year	Author(s) & Title	Method / Model	Dataset	Key Result	Remark
2021	Gupta et al. – MAG-Net: Multi-task Attention Guided Network	CNN with attention & multi-task learning	Figshare MRI	High accuracy in both segmentation & classification	Strong multitaskdesign, limited dataset
2022	Qader et al. – DCNN with Hybrid Optimization (G-HHO)	Deep CNN + hybrid metaheuristic optimization	Augmented MRI set	~97% accuracy	Good performance but may overfit small data
2022	Pitchai et al. – RCNN for Brain Tumour Prognosis	Region-based CNN (RCNN)	Public MRI	Improved tumour region detection	Heavy computation load
2023	Saeedi et al. – MRI-based Brain Tumour Detection using CNNs	2D CNN	MRI dataset (multi-class)	Up to 96–97% accuracy	Fast & effective, but lacks 3D spatial info
2024	Ahmed et al. – Vision Transformer + GRU Hybrid Model	ViT + GRU hybrid	Standard MRI dataset	>98% classification accuracy	Introduces transformers for MRI
2024	Gasmi et al. – Ensemble Learning for Brain Tumour Classification	Ensemble of deep models	BraTS / MRI	Improved stability & accuracy (~99%)	More robust but computationally expensive

Table 2.1: Summary of tools and technologies used for An efficient YOLOv8 Framework for Brain Tumour Segmentation and Classification.

CHAPTER 3

PROBLEM STATEMENT

The problem statement for brain tumour classification and segmentation with the usage of YOLO revolves around developing an efficient and accurate machine to automatically stumble on, segment, and classify brain tumours from medical imaging information. This includes leveraging YOLO's abilities in item detection to precisely discover tumour areas within MRI scans. The segmentation factors goal to create exact mask or barriers around detected tumours, presenting vital spatial records for next evaluation. Once segmented, the system ought to classify tumours primarily based on their traits along with size, form, and texture, distinguishing among different sorts. This type step is crucial for scientific analysis and remedy making plans, enabling healthcare experts to make informed choices concerning patient care. By using YOLO, the aim is to streamline and decorate the accuracy of these approaches, in the long run enhancing patient effects thru quicker and more reliable category of brain tumours.

CHAPTER 4

OBJECTIVES

The proposed work “An efficient YOLOv8 Framework for Brain Tumour Segmentation and Classification” has the following objectives.

- Collect the MR images of brain tumour which contain four different tumour types such as meningioma, glioma, pituitary, and no tumour.
- Pre process collected brain tumour samples.
- To accurately identify and outline the boundaries of brain tumours in the MR images.
- To accurately classify the segmented regions into different categories such as Glioma, Meningioma Pituitary and No tumour.

CHAPTER 5

SYSTEM REQUIREMENTS SPECIFICATION

To develop a system for the accurately segmenting and classifying Brain tumour MRI images using YOLO (You Only Look Once) technique, we need to specify requirements across various categories: hardware, software, data, and performance. Here's a detailed System Requirement Specification (SRS) for such a project:

5.1 HARDWARE REQUIREMENTS

The minimum hardware requirements required to develop the above model are as follows:

- **GPU:** A high-performance Graphics Processing Unit (GPU) is essential for training the deep learning models like YOLOv8. NVIDIA GPUs, particularly those with Tensor Cores such as NVIDIA RTX 30 series or the A100, are recommended for their better performance in handling large-scale computations.
- **CPU:** A multi-core CPU, such as an Intel Core i7 or AMD Ryzen 7, is recommended to handle data preprocessing and other CPU-bound tasks efficiently.
- **RAM:** At least 16GB of RAM is recommended for smooth operation, with 32GB or more preferred for handling large datasets and complex models.
- **Storage:** A solid-state drive (SSD) with at least 512GB of storage is recommended for faster data read/write speeds. Additional storage may be required for large datasets.

5.2 SOFTWARE REQUIREMENTS

The minimum software requirements required to develop the above model are as follows:

- **Operating System:**

A 64-bit operating system such as Ubuntu (preferred for better compatibility with deep learning frameworks) or Windows 10/11.

- **Deep Learning frameworks and Libraries:**
    - **Python:** The main programming language for building deep learning models. Python 3.6 or higher is recommended.
    - **PyTorch:** YOLOv8 is often implemented using PyTorch, a popular deep learning framework. Install the latest version compatible with your GPU.
    - **YOLOv8:** The specific implementation of YOLOv8 can be obtained from open source repositories. Ensure compatibility with chosen deep learning framework.

- **Additional Libraries and Tools:**
  - **NumPy:** For numerical computations.
  - **Pandas:** For data manipulation and analysis.
  - **OpenCV:** For image processing tasks.
  - **Matplotlib:** For data visualization.
  - **Scikit-learn:** For additional machine learning utilities and metrics.
- **Integrated Development Environment (IDE):**
  - **Jupter Notebook/Colab Notebook:** For interactive development and experimentation.
  - **VS Code:** For more extensive coding and project management.

CHAPTER 6

PROPOSED METHODOLOGY

Deep learning frameworks provide considerable promise for future innovations especially in the field of medical image classification. YOLOv8 efficiently segments and categorizes Magnetic Resonance Imaging (MRI) images of brain tumours into four varieties: meningioma, glioma, pituitary, and no tumour. The Figure 6.1 illustrates the general architecture diagram used to categorize the various types of brain cancers. We start with slices of brain cancers that were magnetically resonance (MR) imaged and then processed through several steps. The gathered samples of brain cancer MRI images will be annotated using Roboflow. When the brain tumour samples are annotated their region and additional characteristics such as size shape and others will be taken into account. Meningioma, glioma, pituitary, and no tumour will all be labeled. Each tumours segmentation mask (for evaluation) and bounding boxes should be annotated. Before beginning the training process each of these steps is essential for getting the dataset samples ready.

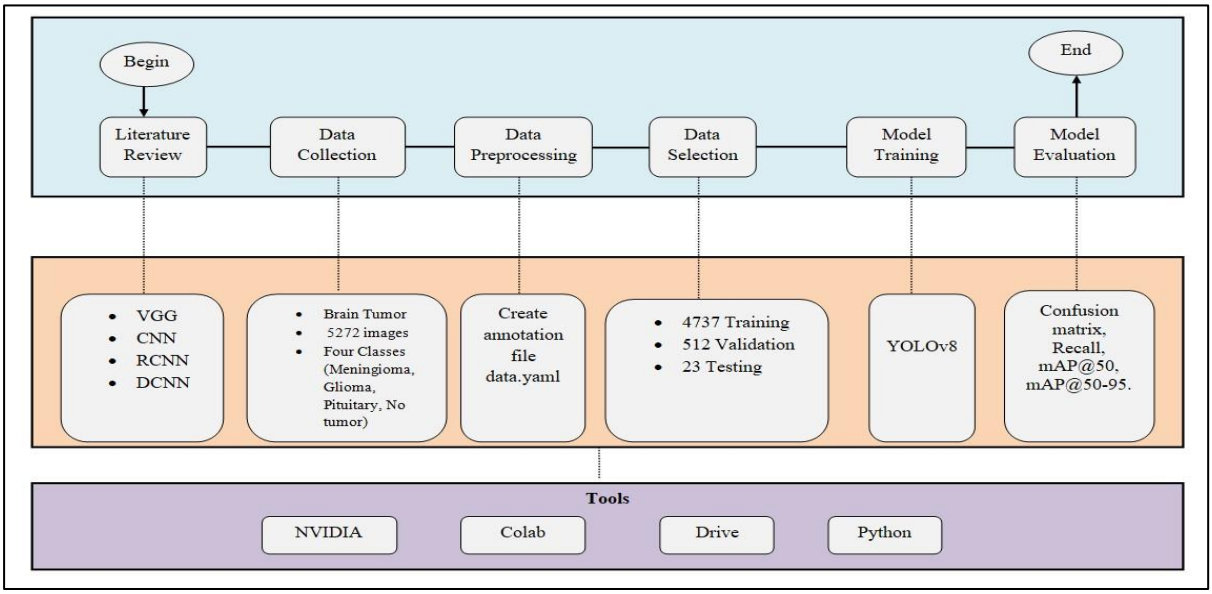

Figure 6.1: YOLO-based Brain Tumour Segmentation and Classification Flow block diagram.

This flowchart illustrates the workflow of a brain tumour detection project using deep learning (YOLOv8). Here's a brief explanation of each stage

1. Literature Review

- Researchers review existing work on brain tumour detection using models like **VGG, CNN, RCNN, DCNN** to understand current techniques and gaps.

2. Data Collection

- A **Brain Tumour dataset** is collected with **5272 MRI images** divided into **four classes**:
    - Meningioma
    - Glioma
    - Pituitary
    - No tumour

3. Data Preprocessing

- Data is prepared for training by creating **annotation files** (data.yaml) that describe image paths and class labels.

4. Data Selection

- Dataset is split into:
    - **4737 images** for training
    - **512 images** for validation
    - **23 images** for testing

5. Model Training

- The **YOLOv8 (You Only Look Once version 8)** model is trained on the dataset to detect and classify brain tumours efficiently.

6. Model Evaluation

- Model performance is assessed using:
    - **Confusion Matrix**
    - **Recall**
    - **mAP@50**, **mAP@50–95** (mean Average Precision at IoU thresholds)

Tools Used

- **NVIDIA** – for GPU acceleration
- **Google Colab** – for training in the cloud
- **Google Drive** – for data storage
- **Python** – for implementation

The figure 6.2 shows the end-to-end deep learning workflow for brain tumour detection using

YOLOv8 — from data collection to model evaluation — leveraging Python and cloud-based tools for efficient training and analysis.

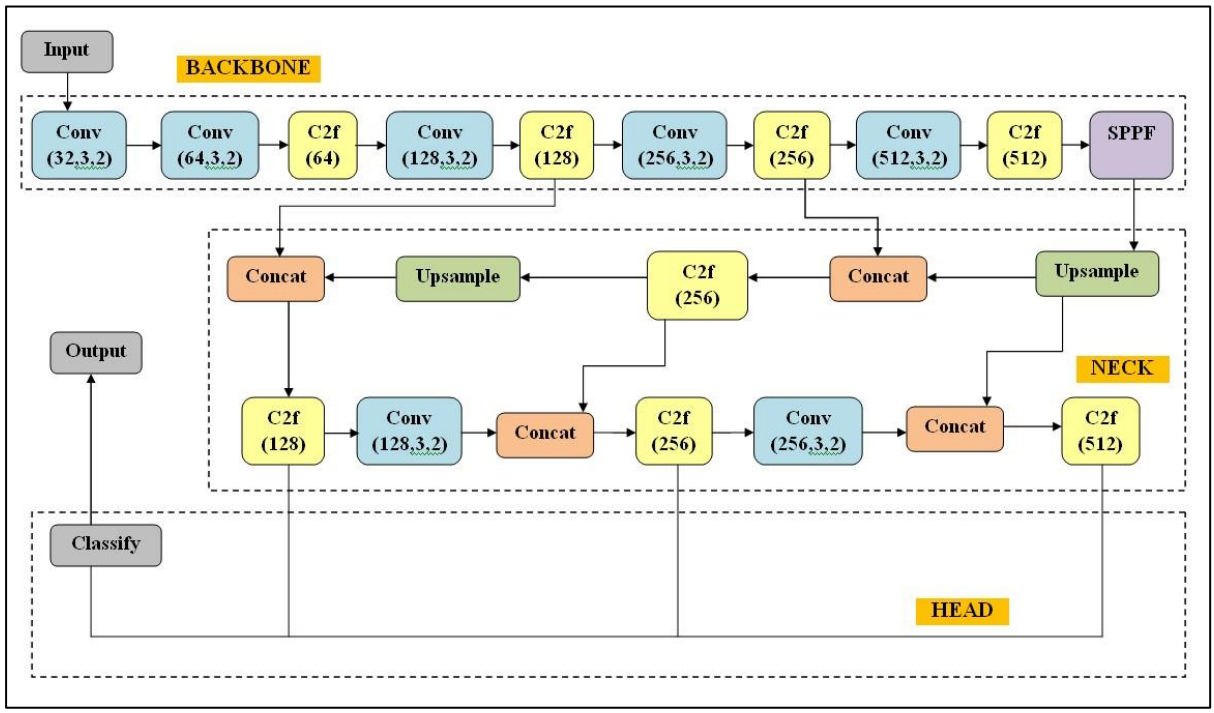

Figure 6.2: YOLOv8 Architecture for segmentation and classification of brain tumour.

This diagram represents the YOLOv8 (You Only Look Once version 8)architecture, which is a deep learning model used for object detection and classification (like detecting brain tumours in MRI images).

Let's break it down into its three main parts — Backbone, Neck, and Head

1. Backbone

The **Backbone** extracts important features from the input image.

It captures edges, textures, and shapes using several layers:

- **Conv (Convolution Layers)**:
  Extract basic features by applying filters to the image.
  Example: Conv(32,3,2) → 32 filters, 3×3 kernel size, stride 2.
- **C2f Modules**:
  These are **feature extraction blocks** that improve learning efficiency and help detect small details.
  Example: C2f(64) means the module outputs 64 feature maps.
- **SPPF (Spatial Pyramid Pooling – Fast)**:
  Collects features at multiple scales to help detect objects of different sizes.

Purpose: To transform the input image into a high-level feature map with rich information.

2. Neck

The **Neck** connects the Backbone and the Head.
It **combines and refines features** from different layers of the Backbone using operations like:

- **Upsample**: Increases the resolution of feature maps to combine information from deeper and shallower layers.
- **Concat (Concatenation)**: Merges features from different layers to strengthen spatial and contextual understanding.
- **C2f and Conv layers**: Further process and refine these combined features.

Purpose: To mix features of different resolutions for better object localization and detection accuracy.

3. Head

The **Head** performs the final **classification and object detection**.

- It takes the processed features and predicts:
    - **Bounding boxes** (where the object is)
    - **Class labels** (what the object is)
    - **Confidence scores**

Purpose: To produce the final detection results — the location and category of each detected object.

CONCLUSION

The proposed work introduces a YOLOv8-based method for segmenting and classifying brain tumours region in MRI scans. The outcomes suggest that the approach of separating and categorizing tumours yields accurate and efficient results. By enhancing the model's performance, YOLOv8 improves its capability to manage various tumour types and imaging conditions. Its real-time brain tumour detection, coupled with high accuracy, positions YOLO as a valuable asset in the medical image analysis. The model has shown impressive precision and recall rates in identifying and classifying different brain tumour types, including meningioma, glioma, no tumour, and pituitary tumours. Its ability to accurately segment tumours from MRI images is essential for precise localization, which is vital for treatment planning and monitoring. The use of mAP@0.5 and mAP@0.5:0.95 metrics demonstrates that the model performs reliably across different Intersection over Union (IoU) thresholds, highlighting its robustness in various clinical situations.

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