I. INTRODUCTION

Brain tumors are caused by aberrant, uncontrollable cells that grow quickly. Uncontrollably dividing cells create abnormal cell formations in the brain that can harm other healthy cells and interfere with normal brain function. In children in the United States between the ages of 0 and 14, brain tumors emerged as the primary cause of cancer-related deaths in 2016[1].

Because of their complexity and possible severity, brain tumors provide a substantial medical challenge. For treatment to be effective and for patient outcomes to be improved, early and precise detection is essential. Because of its excellent resolution and contrast, magnetic resonance imaging (MRI) is the recommended imaging modality for the identification of brain tumors [2]. However, MRI scan interpretation takes a lot of time and is prone to human error, hence automated and trustworthy detection techniques must be developed[3].

Deep learning has transformed a number of industries recently, including medical imaging. Convolutional Neural Networks (CNNs) have gained traction in the medical field due to their impressive performance in image recognition tasks. The CNN-based You Only Look Once (YOLO) model family has become well-known for striking a balance between speed and accuracy in object detection tasks. Because of its real-time detection capabilities, YOLO is especially appealing for clinical applications where making decisions quickly is crucial.

Three fundamental methods are employed by YOLO: Intersection Over Union (IOU), Bounding Box Regression, and Residual Blocks[4]. Early identification and precise treatment planning are critical for the accurate diagnosis of brain tumors. Medical image analysis demands meticulous digital image processing, particularly when segmenting abnormal brain tissues from normal ones. Early detection of brain tumors significantly mitigates the impact of surgery and treatment, thus improving patient prognosis. Regardless of whether brain tumors are cancerous, they can impair brain function if they grow large enough to compress surrounding tissues, underscoring the importance of early detection.

This paper introduces YOLOv9, the latest iteration of the YOLO series, and explores its application in detecting brain tumors from MRI scans. YOLOv9 incorporates several enhancements over its predecessors, including improved backbone networks, advanced feature pyramids, and novel loss functions, making it well-suited for the intricate task of medical image analysis[5].

Our study focuses on comparing the performance of YOLOv9 on two distinct MRI datasets to evaluate its robustness and generalizability. We combine these datasets to train the model comprehensively and assess its accuracy across different data sources. The two datasets used in this study are Dataset A and Dataset B, each containing a diverse range of MRI scans with labeled brain tumors.

We aim to demonstrate that YOLOv9 can significantly improve the accuracy and efficiency of brain tumor detection by leveraging combined data from multiple sources. Our approach involves extensive preprocessing of MRI data to enhance model performance, training the model on the combined dataset, and evaluating its performance against each dataset individually and in combination. The results indicate that YOLOv9 not only achieves superior detection accuracy but also operates at a speed conducive to real-time clinical use.

The rest of this paper is organized as follows: Section 2 reviews related work in brain tumor detection and previous YOLO versions. Section 3 details the methodology, including the YOLOv9 architecture, data preprocessing steps, and dataset descriptions. Section 4 presents the experiments and results, highlighting the model's performance on individual and combined datasets. Section 5 discusses the findings, challenges, and potential improvements. Finally, Section 6 concludes the paper and outlines directions for future research.