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Detecting and Classifying Atypical Teratoid/Rhabdoid Tumors using YOLO-v11 and VGG-19

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***Abstract*— This research presents a snapshot deep learning method to identify atypical teratoid/rhabdoid tumors (AT/RT) in pediatric patients using MRI data. The procedure considers VGG-19 for classification and YOLOv11 for real-time tumor location. VGG-19 gave around 92% accuracy in differentiating AT / RT from healthy tissue, whereas YOLOv11 real-time detection accuracy was 92.5%, suggesting its relevance for time-sensitive clinical situations. Scaling, normalization, and data augmentation helped make the model more resilient. Transfer learning using pre-trained weights from ImageNet (VGG-19) and COCO (YOLO-v11) was utilized for more efficient training. Models were then trained for about 40 epochs using tuned hyperparameters. Precision, recall, and F1-score measures validated the performance of the model. This research demonstrated that VGG-19 is good for diagnostic classification, and YOLO-v11 works well for making real-time cancer diagnoses. This method allowed early and reliable AT/RT diagnosis in pediatric patients-to the advantage of treatment outcome. Future work will look at other rare pediatric brain tumors and multi-modal imaging.**

***Index Terms*— Atypical Teratoid /Rhabdoid Tumor (AT / RT), VGG-19, YOLO-v11, Deep Learning, Pediatric brain tumor.**

I. Introduction

Brain tumors are among the most serious and complicated medical disorders affecting the central nervous system, accounting for a considerable portion of neurological impairments and cancer-related deaths worldwide [1],[4]. There are two types of these tumors: primary, which start in the brain, and secondary, which spread to other parts of the body.[6] They frequently cause a variety of debilitating symptoms, including seizures, cognitive difficulties, eyesight loss, and, in extreme circumstances, death [10]. Despite advances in medical imaging and diagnostic technologies, reliable and early diagnosis of brain tumors remains a significant clinical issue due to tumor heterogeneity and overlap with other brain disorders [4]. One of the rarest and most aggressive types of brain tumors is called an atypical teratoid/rhabdoid tumor (AT/RT) [2]. AT/RT generally affects newborns and young children, usually under the age of three. Its fast development, high recurrence rate, and resistance to traditional therapy make early detection critical to improving patient outcomes [6]. However, because of its rarity and aggressive nature, AT/RT frequently offers diagnostic challenges, particularly in its early stages, when it can be readily confused with other less severe illnesses [8]. Magnetic resonance imaging (MRI) is the most used imaging tool for identifying brain malignancies, including AT/RT [15].
Magnetic resonance imaging offers high-resolution, noninvasive imaging that allows doctors to assess tumor size, location, and impact on surrounding tissues.

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However, correct interpretation of MRI data is mainly dependent on the skill of radiologists. Even trained specialists may face difficulty when diagnosing uncommon tumors such as AT/RT due to minor imaging findings or a lack of diagnostic experience, potentially leading to a delayed or inaccurate diagnosis [6]. AI and Deep Learning (DL) have emerged as key technologies in medical imaging. CNNs have demonstrated successful classification, segmentation, and object identification in healthcare applications.[13]. These models can learn complex patterns and features directly from imaging data, which decreases the need for manual analysis and offers more dependable diagnostic results [8].
The paper studies the use of two cutting-edge deep learning models—VGG-19 and YOLO-v11—to improve AT/RT identification and diagnosis in pediatric brain MRI images. VGG-19, a 19-layer deep CNN, is extremely successful in capturing the fine-grained characteristics required for accurate picture categorization [10]. YOLO-v11 (You Only Look Once) is an accurate object identification model which detects and localizes tumors in MRI images simultaneously, making it ideal for clinical processes that require speed and precision [19]. Various preprocessing methods, such as image resizing, normalization, and data augmentation, are used to improve the performance of the model. [1]. In addition, transfer learning from pre-trained weights on large scale datasets (ImageNet for VGG-19, and COCO for YOLO-v11) accelerates training and improves generalization, which is especially significant in the context of small and imbalanced data as in rare diseases, such as AT/RT [19].
This technique seeks to provide a robust and efficient AT/RT diagnostic system by combining classification and localization capabilities. The combination of VGG-19 and YOLO-v11 provides a viable option to help radiologists make quick and accurate judgments, ultimately leading to better treatment planning and clinical outcomes for young patients with this aggressive malignancy [2], [6].

II. Literature Review

Deep learning plays an enormous role in medical imaging in improving the brain tumour detection and classification. YOLOv8 and VGG-19, for object detection and image classification, respectively, have become the two popular CNN architectures on account of their efficiency.
YOLOv8 (You Only Look Once version 8) is one of the recently introduced models in YOLO series which is well known for its high speed and precise real-time detection capabilities. In the medical field, YOLOv8 has been widely used for medical image analysis. for brain tumour segmentation and localization. Yao et al. [5] proposed an improved YOLOv8 model for medical images that can detect tumour lesions at a high accuracy. Similarly, Vineela et al. [15] used YOLOv8 to detect brain tumours and established its effectiveness in detecting the tumour limits in various MRI types. Suhas et al. [4] further developed this idea of fusing YOLOv8 with segmentation-based networks like U-Net and Mask R-CNN by forming an ensemble system, where both detection accuracy and localization memory were enhanced. This demonstrates YOLOv8 can locate tumour locations with low latency which is crucial for clinical workflows.
Conversely, VGG-19, a deep CNN with 19 weight layers, performs exceptionally well on classification tasks because of its uniform and straightforward architecture. It has been successfully applied to medical imaging feature extraction, especially tumor type differentiation. In their comparison of YOLOv8 with VGG-19, Varshini et al. [7] discovered that although YOLOv8 was better at localization, VGG-19 was better at classification, particularly when used in conjunction with transfer learning approaches. Thus, VGG-19 appears to be more appropriate for tasks involving tumor grading and classification.
Interestingly, research has also investigated the complimentary integration of VGG-19 and YOLOv8, utilizing VGG-19's classification capabilities and YOLOv8's localization strength to create reliable, hybrid diagnostic systems [7]. This collaboration provides a viable path for improving automated brain tumor analysis systems' precision, speed, and interpretability.
These advancements highlight how integrating cutting-edge detection and classification models can help enable trustworthy, AI-driven clinical decision-making in neuro-oncology.

III. Problem Statement

Children under the age of three are susceptible to the uncommon and extremely aggressive juvenile brain cancer known as atypical teratoid/rhabdoid tumor (AT/RT). It is often difficult to diagnose because its early symptoms mimic those of benign illnesses. Low survival rates and rapid development can result from misdiagnosis or delayed detection. Even while MRI is still the most reliable non-invasive method of imaging brain tumors, effective interpretation necessitates a high level of skill, especially for uncommon tumors like AT/RT. Due to radiologists' inexperience with diagnosis and subtle imaging findings, manual diagnosis is prone to inaccuracy.

An automated, hybrid AI-based system that can do both is therefore desperately needed MRI image classification for AT/RT detection, Real-time tumor localization to support emergency care or surgical planning In order to close the gap in dual-purpose detection systems for uncommon pediatric brain tumors, this study uses deep learning to provide high diagnostic accuracy and quick response.

IV. METHODOLOGY

The proposed approach aims to provide a comprehensive AI-based system for the early detection and localization of atypical teratoid/rhabdoid tumors (AT/RT) in pediatric brain MRI brain images. AT/RT is a highly aggressive and uncommon central nervous systemtumour of infancy, which typically occurs in newborns and young children. Due to its aggressive course and poor prognosis, Unlike other leptomeningeal dissemination from solid cancer, it is critical for an accurate and early diagnosis to get better treatment outcomes. This method combines the optimal properties of two advanced deep learning models: VGG-19, a deep convolutional neural network for classification task, and YOLOv11, which is a real-time object detection system for identifying tumour positions in the image plane. The methodology consists of seven major stages: data collecting, preprocessing, model selection, model training, assessment, visualization, and integration into a single diagnostic framework.

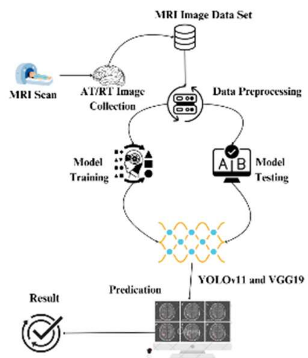

Figure 1. System Architecture

A. Dataset Collection

A brain MRI dataset was downloaded from Kaggle, featuring labeled scans that show either the presence or absence of brain tumors. From this collection, only pediatric cases were kept, paying special attention to unique AT/RT images because that tumor is rare and aggressive in children. Training, validation, and testing groups were created; approximately 70% of the final data went to training, 20% to validation, and 10% to testing.

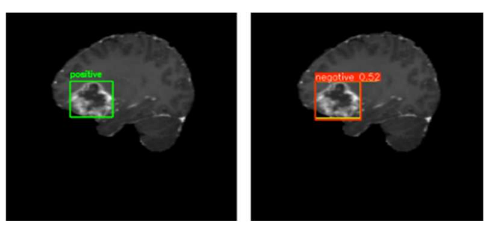

Figure 2. Dataset Sample

B. Data Preprocessing

As Figure 3 shows the method for MRI image preprocessing, which includes scaling, normalization, and data augmentation to improve model performance. The images were resized to 224×224 for VGG-19 and 640×640 for YOLOv11 to meet model input requirements. Normalization further normalized the pixel value to [0, 1], which facilitates the training of the model. Data augmentation methods including horizontal and vertical flipping, ±15° rotation, scale shift, crop, and brightness and contrast adjustments were applied to enhance dataset diversity and prevent overfitting. These procedures contributed to the generalization and the robustness of the models, which is important for identification of rare and complex tumours like AT/RT in the paediatric brain MRI.

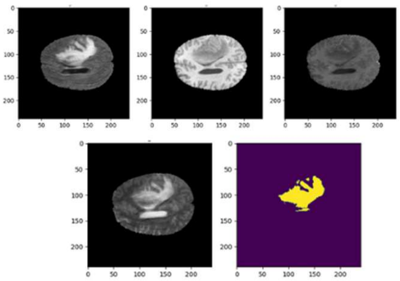

Figure 3. MRI Image Preprocessing using VGG-19

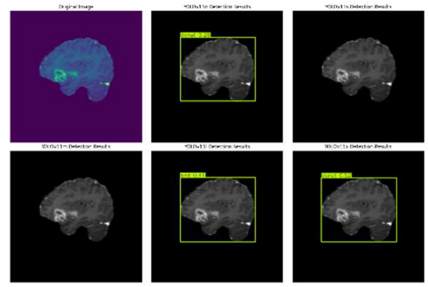

Figure 4. MRI Image Preprocessing using YOLOv11

C. Model Selection

VGG-19: VGG-19 is a Convolutional Neural Network with 19 layers. Experts have trained it on the ImageNet dataset and then tweaked it to work with our MRI dataset. This network helps doctors spot tumours by telling the difference between images with tumours and those without.

YOLOv11: A real-time object detection model. The COCO dataset trains it, and it adapts to spot and pinpoint tumour areas in MRI scans.

D. Training Configuration

We carefully designed our training approach for both deep learning models in this study. For the VGG-19 model, we fine-tuned it using the Adam optimizer with a modest learning rate of 0.0001 over 40 epochs, processing 32 samples at a time. We chose the Binary Cross Entropy loss function since it works particularly well for our yes/no classification needs.

The YOLO-v11 model required a different approach. We trained it with the same Adam optimizer but used a more aggressive learning rate of 0.001 and a smaller batch size of 16, while still maintaining the same 40-epoch training duration. For this model, we implemented a more complex loss function that balances two critical factors: accurately identifying objects and precisely locating them within images. This combined approach significantly improved the model's ability to detect objects in real-time.

E. Evaluatiom Metrics

The performance was quantified using the following measures:

- Accuracy: The percentage of total predictions our model got right, giving us a quick snapshot of overall performance.
- Precision: How often our model is correct when it predicts something is positive, showing its reliability for positive classifications.
- Recall: Our model's ability to find all the actual positive cases, revealing how comprehensive its detection capabilities are.
- F1-Score: A balanced measure combining precision and recall into one metric, particularly useful when these two metrics trade off against each other.
- Confusion Matrix: A visual tool that maps predictions against actual outcomes, helping us identify specific strengths and weaknesses in our classification approach.
- Learning Curves: Visual tracking of how our model's performance evolves during training, helping us spot problems like overfitting or determine when to stop training.

F. Integration and Use Case

The suggested system incorporates both VGG-19 and YOLOv11 models, resulting in a balanced and efficient method to AT/RT identification. VGG-19 is best suited for diagnostic purposes, as it provides high accuracy in determining the presence or absence of AT/RT, allowing radiologists to make informed clinical decisions. In contrast, YOLOv11 excels in real-time applications such as surgical navigation or emergency diagnostics, where rapid tumor localization is crucial. By combining these models, a dependable and fast diagnostic framework has been created, allowing for both precise classification and real-time detection. This hybrid strategy improves the early and precise detection of AT/RT in pediatric patients, resulting in timely and successful treatment planning.

To improve their performance on the pediatric brain MRI dataset, the VGG-19 and YOLO-v11 models each had their own training setup. We fine-tuned our VGG-19 model using the Adam optimizer with a conservative learning rate of 0.0001. The model trained for 40 epochs, processing 32 samples at a time, and we employed

Binary Cross Entropy as our loss function since we were dealing with binary classification problems, for our YOLO-v11 model, we took a slightly different approach. While we still used the Adam optimizer, we increased the learning rate to 0.001 and reduced the batch size to 16, maintaining the same 40-epoch training duration. This model required a more complex composite loss function that simultaneously handled three critical aspects: classifying objects correctly, accurately placing bounding boxes around them, and determining the likelihood that an object exists in each region.

V. Result and Discussions

The performance evaluation of the proposed brain tumor detection models, YOLOv11 and VGG-19, produced very positive findings. Both models performed well in detecting Atypical Teratoid/Rhabdoid Tumors (AT/RT) in pediatric brain MRI data. VGG-19 performed well in picture classification tests, with good precision and recall, which is critical for diagnostic accuracy. Meanwhile, YOLOv11 demonstrated efficacy in real-time tumor localization, providing rapid and accurate detection appropriate for clinical applications requiring speedy decision-making. These findings show the possibility of in corporating deep learning models into automated diagnostic systems to aid in the early diagnosis and treatment planning of aggressive pediatric brain tumors.

A. Evaluation of YOLOv11

Figures 5 and 6 illustrate the training progress of the YOLO-v11 model. The accuracy curves show steady improvement across epochs, indicating effective learning and reliable tumor detection. The training and validation loss curves for box, class, and DFL losses consistently decline. This shows good convergence and minimal overfitting. These trends confirm that the model is strong in localizing AT/RT tumors from pediatric MRI scans in real time.

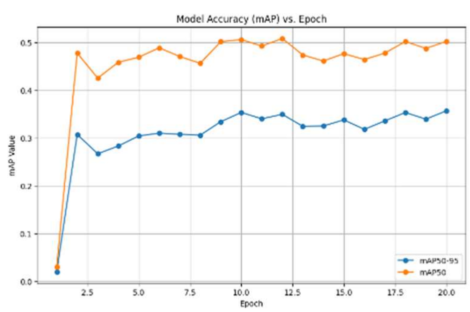

Figure 5. Training & Validation accuracy

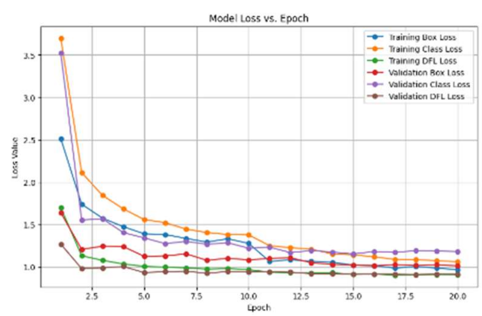

Figure 6. Loss in Training & Validation accuracy

B. Evaluation of VGG-19

The loss and accuracy curves for the VGG-19 model for 20 epochs using a batch size of 32 are shown in Figures 3 and 4. From the loss curves, at the early stages, the training and validation loss dropped quickly in the early epoch prior progressively converging, showing efficient learning and stabilization. While training accuracy is initially great, it progressively decreases and stabilizes. Validation accuracy fluctuates and remains quite low, which might indicate underfitting or instability during training. Despite this, the model shows adequate learning behavior and no symptoms of severe overfitting, as the difference between training and validation losses is modest.

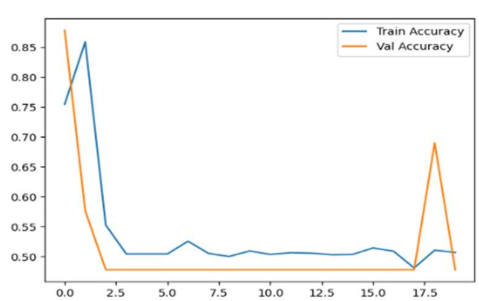

Figure 7. Training & Validation accuracy

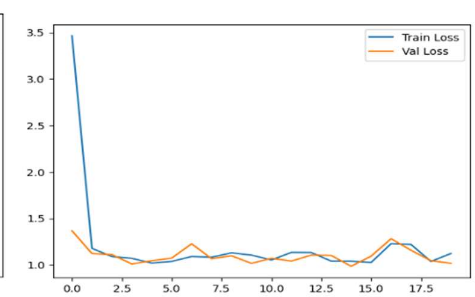

Figure 8. Loss in Training & Validation accuracy

C. Performance Validation and Insights

Figure 9 depicts the output findings of the two deep learning models—VGG-19 and YOLO-v11—used to detect Atypical Teratoid/Rhabdoid Tumors (AT/RT) in pediatric brain MRI data. A thorough examination of their performance metrics indicates that both models are quite competent, but VGG-19 performs marginally better across important assessment criteria.

TABLE I. PERFORMANCE METRICS OF DIFFERENT SECURITY DETECTION ALGORITHMS

Detection Model	YOLOv11	VGG 19
Accuracy	0.92	0.92
Precision	0.95	0.98
Recall	0.90	0.91
F1-score	0.92	0.94

VGG-19 is now more effective at accurately identifying tumor areas while reducing negative results due to its increased precision and recall. Because the accuracy of the diagnosis has a significant influence on treatment choices, this is particularly crucial in clinical settings. In addition, the model attains higher F1 score, which indicates a compromise on recall and precision. It's ideal for applications where high reliability and diagnostic dependability of performance are essential.

$$Accuracy = \frac{TP+T}{TP+FP \quad TN+} \qquad (1)$$

$$Precision = \frac{TP}{TP+F} \qquad (2)$$

$$Recall = \frac{TP}{TP+F} \qquad (3)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (4)$$

For real-time object detection and localization, YOLO-v11 works well but it comes to classification metrics, it is quite underperforming. Its quickness and capacity to interpret pictures fast make it excellent for circumstances requiring instant decision-making, such as surgical help or rapid screening scenarios.

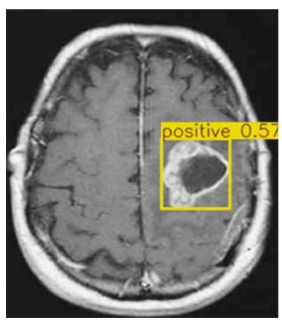

Figure 9. Training & Validation accuracy

In conclusion, both models have useful capabilities: VGG-19 is best suited for jobs demanding high classification accuracy and comprehensive picture analysis, whereas YOLO-v11 is ideal for real-time tumor location. Together, they provide a solid foundation for improving the early and reliable identification of AT/RT in children.

VI. CONCLUSION AND FUTURE SCOPE

This study successfully developed a system for the diagnosis of brain cancers using the deep learning models YOLO-v11 and VGG-19. The findings show that both models are capable of accurately detecting brain cancers from MRI data, but VGG-19 performs better across a range of metrics. In clinical settings, where reducing false negatives is crucial, VGG-19's high precision and recall rates in particular demonstrate its potential usefulness. These model’s robustness and dependability in medical diagnostics are further supported by their exceptional accuracy and F1 scores. Future studies could employ more complicated data augmentation methods may be examined in future works to improve the model performance and to increase the diversity of training datasets.

Enhancing detection robustness and accuracy may also be possible by investigating the incorporation of extra deep learning models and architecture. Adding more and more varied samples to the dataset may also aid in the creation of more generalized models, this would ultimately help develop a more accurate & reliable brain tumor detection system. These developments would guarantee that AI-based diagnostic systems continue to evolve, offering major advantages in brain tumor early detection and treatment planning.

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