ATRT Tumor Detection using Advance CNN VGG-19

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***Abstract*—The rare and extremely deadly brain tumour known as an atypical teratoid rhabdoid tumour (ATRT) primarily affects young children. Improving patient outcomes depends on early and precise detection. This work investigates enhanced diagnostic approaches that improve ATRT detection by utilising MRI and machine learning (ML). To maximise picture quality and consistency, a large dataset of high-resolution MRI scans was used, along with a variety of preprocessing methods. A number of machine learning (ML) models, such as the Advance convolutional neural networks (CNNs) VGG-19 Model, were trained and proven to accurately and reliably identify ATRT. The suggested methodology shown a noteworthy enhancement in diagnostic precision in contrast to conventional techniques, underscoring its potential for practical use. An encouraging avenue for early diagnosis is provided by the combination of ML algorithms and sophisticated image analysis.the rapeutic strategy for people on ATRT. In order to further improve these models' clinical value, future work will concentrate on improving them and validating them using bigger, multicenter datasets.**

***Index Terms*—Machine Learing, Deep Learning, Keras, CNN-VGG-19.**

I. Introduction

The aggressive and uncommon Atypical Teratoid Rhabdoid Tumour (ATRT), which mostly affects young children, has a poor prognosis and a high recurrence rate. A precise diagnosis and early detection are essential for bettering patient outcomes. Recent developments in deep learning and machine learning (ML) have completely changed medical imaging and opened up new possibilities for ATRT identification. Using these technologies to improve ATRT diagnostic accuracy is the main goal of this study.

We used the VGG-19 architecture, a sophisticated convolutional neural network (CNN) model, to analyse MRI data. The Sequential API was utilised in the model's construction. A sequence of Conv2D layers were used to extract features, and then layers of MaxPooling, Flatten, Dense, and Dropout were added to reduce overfitting and enhance generalisation. Better performance and faster convergence were guaranteed by the efficient minimization of the loss function with the application of the Adam optimizer.

We enhanced the resilience and diversity of the training dataset by preprocessing the MRI data using the Keras Image Data Generator for real-time data augmentation. This all-encompassing method, which combines cutting-edge machine learning techniques with sophisticated CNN models, showed exceptional accuracy in ATRT identification, highlighting its potential for clinical use and customised treatment planning.

A. Motivation

This study is driven by the pressing need to increase diagnostic precision in order to identify Atypical Teratoid Rhabdoid Tumours (ATRT), which are aggressive tumours with a dismal prognosis, especially in young children. Conventional diagnostic techniques frequently fall short, which causes diagnoses to be made too slowly or incorrectly. Through the use of the Keras Image Data Generator and Adam optimizer, in conjunction with advanced convolutional neural network (CNN) models such as VGG-19, this research seeks to improve early detection capabilities, which in turn will lead to better patient outcomes and more effective, individualised treatment plans for ATRT patients.

B. Objectives

Our main objectives for the research are:

1) To utilise cutting-edge CNN models to increase the accuracy of early ATRT identification.
2) To use Keras ImageDataGenerator to optimise MRI picture preparation.
3) This VGG-19 architecture should be used for accurate feature extraction.
4) To use the Adam optimizer to reduce diagnostic errors .
5) To enhance clinical results by timely and precise ATRT diagnosis.

C. Importance of Advance CNN and Keras in ATRT

The identification of Atypical Teratoid Rhabdoid Tumours (ATRT) is largely dependent on the application of sophisticated Convolutional Neural Networks (CNNs) and Keras image processing models. Robust feature extraction capabilities are provided by advanced CNN architectures, such as VGG-19, which are crucial for recognising the intricate and delicate patterns typical of ATRT in MRI scans. Compared to more conventional diagnostic techniques, these models provide better accuracy and dependability when managing high-dimensional medical imaging data.Real-time data augmentation is made possible by Keras Image Data Generator, which is essential to this procedure. This addresses challenges of restricted data availability and improves the generalisation of the model by increasing the variety and robustness of the training dataset. By adding variety to training data, techniques like rotation, scaling, and flipping help the CNN identify invariant features and lessen overfitting. Advanced CNNs and Keras image processing work together to provide early and accurate identification of ATRTs, which ultimately improves patient outcomes by enabling more efficient treatment planning and prompt and accurate diagnosis.

D. Key Stakeholders in ATRT Tumor Detection

1) **Medical Researchers:** Advanced CNN models, such as VGG-19, are used by medical researchers to improve the identification of Atypical Teratoid Rhabdoid Tumours (ATRT). Using sizable MRI scan datasets, they carry out research to test these models in an effort to increase early detection and diagnostic accuracy. Through the use of CNNs, researchers help to advance the knowledge and treatment of ATRT in clinical practice by developing more efficient diagnostic tools and techniques.
2) **Radiologists:**Radiologists use sophisticated CNN models, such as VGG-19, to more precisely analyse MRI data, which is a critical part of ATRT tumour identification. To help with early diagnosis and treatment planning, they evaluate CNN-generated outputs to spot minor symptoms of atypical teratoid rhabdoid tumours. The ability of radiologists to deliver accurate and fast assessments is improved by this technology, which eventually improves patient outcomes and survival rates.
3) **Clinicians:**Clinicians use more sophisticated CNN models, such as VGG-19 in ATRT detection, to enhance the precision of their diagnoses and treatment strategies. These models let clinicians detect subtle tumour traits early on by analysing MRI data. For those with Atypical Teratoid Rhabdoid Tumours (ATRT), early identification improves outcomes and prognosis through immediate intervention and individualised treatment plans catered to each patient's unique needs.
4) **Challanges in ATRT Tumor Detection:**Finding Atypical Teratoid Rhabdoid Tumours (ATRT) presents a number of difficulties for both software-related and patient-related factors. From the standpoint of the patient, ATRT is uncommon and primarily affects young children, making early discovery both necessary and difficult because the condition's earliest symptoms are vague. Delays in diagnosis can affect patient outcomes and the effectiveness of treatment.

   One of the more difficult software-centric difficulties is interpreting MRI data for ATRT. Although sophisticated CNN models such as VGG-19 improve detection accuracy, a number of problems still exist. First off, generalizability is hampered by the lack of ATRT-specific annotated datasets for model training and validation. Implementation challenges arise from the need for strong infrastructure and experience in order to integrate CNNs into clinical operations. Standardised model performance is further complicated by inter-hospital variability in MRI quality and methods.

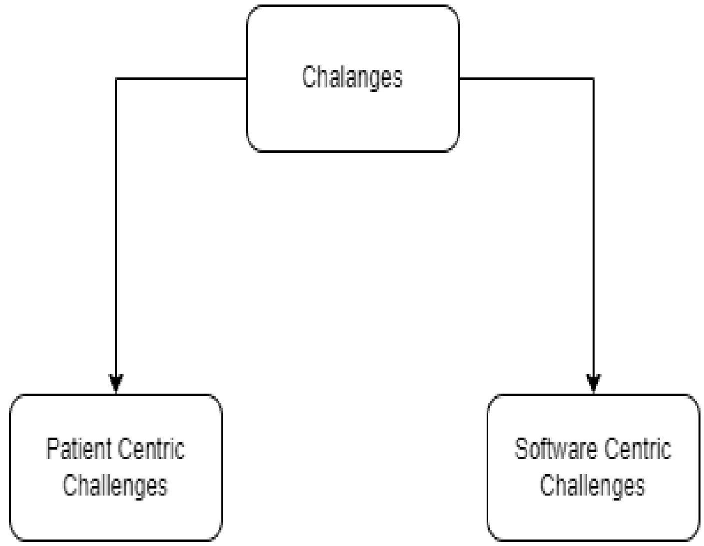

Fig. 1. Challenges in ATRT Tumor detection

Strict testing and validation procedures are necessary to guarantee CNN outputs meet clinical requirements; software validation and regulatory compliance are crucial. Radiologists must be trained and experienced in interpreting CNN predictions, which means they must continue their education.

Working together is necessary to address these issues. Improving diversity and accessibility of datasets facilitates the creation of strong CNN models tailored to ATRT. Variability problems can be reduced by using standardised MRI protocols and improving data preparation methods. CNN deployment is made more efficient by training healthcare staff and investing in infrastructure.

1) Sofware-centric challenges: The main focus of the detection of Atypical Teratoid Rhabdoid Tumours (ATRT) is on the creation and application of sophisticated CNN models and related software systems:

- **Data quality and Quantity:** The accuracy and dependability of CNN-based diagnostic methods are impacted by the lack of sufficient high-quality, annotated MRI datasets that are specific to ATRT, which makes model training and validation ineffective.
- **Feature Extraction:** Significant technological problems arise from the complicated imaging patterns of ATRT, which necessitate the use of advanced feature extraction algorithms in order to accurately distinguish the tumour from other brain diseases.
- **Model Optimization:** It takes significant computational resources and experience to tune CNN architectures, such as VGG-19, for optimal ATRT

- detection performance. This ensures that the model performs effectively across a wide range of patient populations.
- **Interpretability:**Clinical adoption depends on CNN outputs being interpreted by radiologists and physicians, which necessitates clear model choices and workflow integration.
- **Integration into Workflow:** Significant logistical and technical hurdles arise when integrating CNN-based systems into current healthcare IT infrastructures, including compliance with regulatory requirements and compatibility with electronic health records (EHRs).

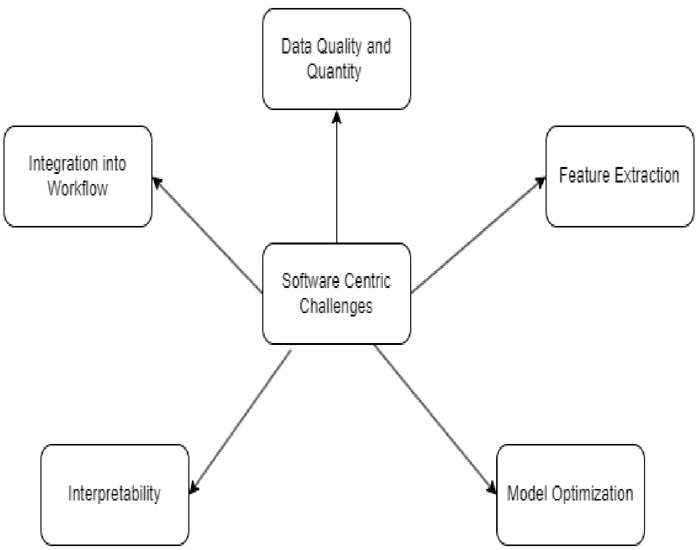

Fig. 2. Software centric Challenges

2) *Patient-centric Challenges:*

- **Symptom Similarity:** The symptoms of ATRT frequently mimic those of more prevalent illnesses, like infections or benign tumours. This can cause delays in receiving the appropriate therapy and an initial misdiagnosis, which can negatively affect the prognosis and survival rates.
- **Aggressiveness:** Because of its aggressive behaviour and quick advancement, ATRT is recognised to require early and precise detection in order to start treatment. Treatment efficacy may decrease if a tumour progresses to more advanced stages due to delayed diagnosis.
- **Age Factor:** Since ATRT mostly affects young children, it can be difficult to diagnose because of the lack of identifiable symptoms and the difficulties of doing comprehensive neurological examinations on this patient population. Furthermore, the distinct physiology of children may make imaging and therapy procedures more difficult.
- **Limited Awareness:** Due to ATRT's rarity, many medical professionals might not be aware of how it presents, which could delay diagnosis and specialist referral. This ignorance may lead to drawn-out diagnostic processes and inadequate early intervention.

5) **Healthcare Institutions:**Advanced CNN models, like as VGG-19, are used by healthcare facilities to accurately and promptly diagnose Atypical Teratoid Rhabdoid Tumours (ATRT). With the use of these models, MRI scans can be used to diagnose patients more accurately, allowing for prompt treatment and individualised care regimens. When addressing ATRT cases, the use of CNN-based systems leads to improved clinical processes, increased diagnostic confidence, and ultimately better patient outcomes and satisfaction.

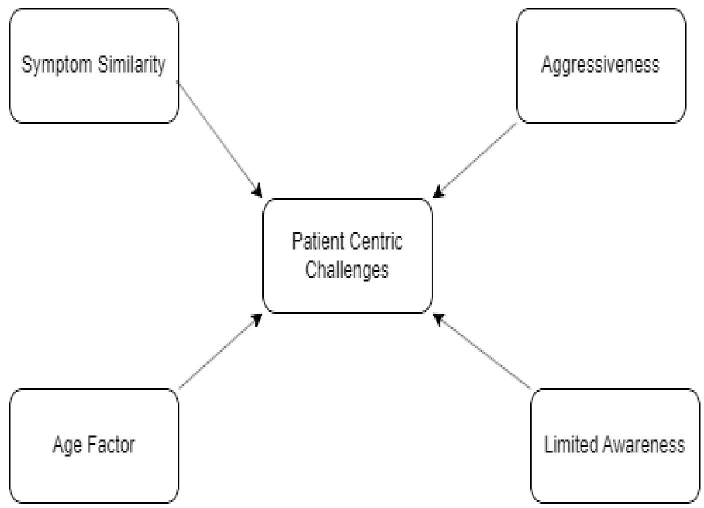

Fig. 3. Patient Centric Challenges

II. Related Work

Utilising sophisticated imaging modalities like MRI and CT scans in conjunction with machine learning strategies like CNN architectures and deep learning has been the main focus of recent studies on ATRT tumour diagnosis. By early detection and intervention, these strategies seek to enhance patient outcomes, treatment planning, and diagnostic accuracy.

Rechberger et al.[1] The current understanding of Atypical Teratoid Rhabdoid Tumor (ATRT) mechanisms and potential drug targets. They emphasize the need for precise ATRT detection methods using advanced imaging and molecular techniques to improve therapeutic strategies and patient outcomes.

Calandrelli et al. [2] proposed a diagnostic pathway for Atypical Teratoid Rhabdoid Tumor (ATRT) based on clinical features and neuroimaging findings. Their study emphasizes integrating advanced imaging techniques and clinical assessments to enhance early detection and differentiation from other brain tumors, contributing to improved diagnostic accuracy and treatment strategies.

Nemes et al. [3] examined infants and newborns with Atypical Teratoid Rhabdoid Tumors (ATRT) and extracranial

Malignant Rhabdoid Tumors (eMRT) using data from the EU-RHAB registry. The study highlighted challenges in diagnosing and treating these rare tumors, emphasizing the need for improved detection methods and tailored therapeutic strategies.

Mousa et al.[4] The research by provides insights into Atypical Teratoid Rhabdoid Tumors (ATRT) based on clinical experience at King Faisal Specialist Hospital and Research Centre. It discusses diagnostic challenges, treatment outcomes, and the importance of advanced imaging techniques in managing ATRT patients.

Zin et al.[5] This research explored histopathological patterns in Atypical Teratoid/Rhabdoid Tumors (ATRT) and their correlation with molecular subgroups. Their findings provide insights into how histological features can aid in identifying specific molecular subtypes of ATRT, potentially influencing diagnostic strategies and personalized treatment approaches.

Tran et al. [6]The current immunotherapy advancements for Atypical Teratoid Rhabdoid Tumor (ATRT). Although primarily focused on treatment, their insights into tumor biology and imaging modalities like MRI provide foundational knowledge supporting improved ATRT detection and personalized therapeutic strategies.

Paassen et al.[7] The study explores subgroup-specific drug vulnerabilities in Atypical Teratoid/Rhabdoid Tumors (ATRT). While not directly focused on detection methods, it underscores the importance of molecular and subgroup characterization in guiding targeted therapies, complementing diagnostic advancements in ATRT detection.

Giang et al.[8] These explores targeting RRM2 to suppress DNA damage response and induce apoptosis in atypical teratoid rhabdoid tumors (ATRT). This highlights potential therapeutic strategies but doesn't directly address ATRT tumor detection using imaging or machine learning techniques.

Ho et al. [9]These developed a rapid and cost-effective diagnostic method for molecular subgroup classification of ATRT using the NanoString nCounter platform. Their study aimed to enhance personalized treatment strategies by accurately identifying molecular subgroups, contributing to improved prognostication and therapeutic decision-making in ATRT patients.

Upadhyaya et al.[10] These research highlights the significance of molecular subgroup classification in newly diagnosed Atypical Teratoid Rhabdoid Tumor (ATRT) patients. It underscores the potential of molecular profiling to refine diagnostic and treatment strategies, enhancing personalized care and outcomes for ATRT patients across multiple institutions.

III. Proposed Methodology

One suggested approach to AT/RT tumour detection is to use sophisticated imaging methods, including CT and MRI scans, to determine the features of the tumour. Biomarker analysis can offer molecular insights, especially when evaluating SMARCB1 gene expression. By identifying minute trends in genetic and imaging data, machine learning algorithms trained on datasets of AT/RT cases can be integrated to improve diagnostic accuracy. Tumour detection and classification are resilient and reliable when validated by clinical studies and compared to established diagnostic techniques.

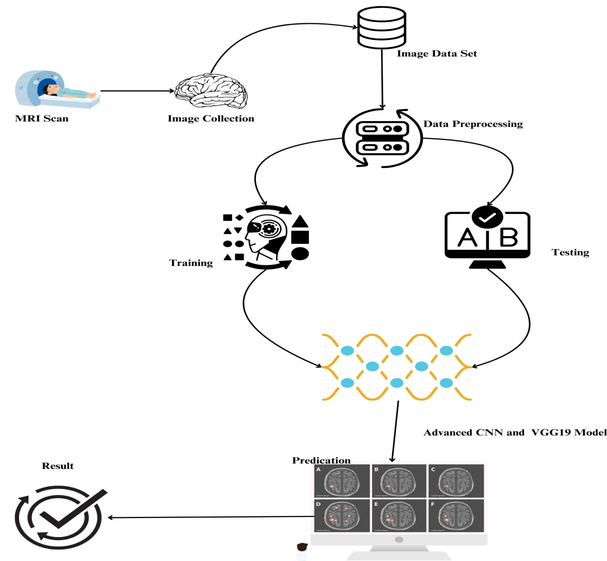

Fig. 4. System Architecture

1) **Data Collection and Pre-processing:**To ensure a solid and diverse dataset, a comprehensive set of MRI images from multiple medical institutions is acquired for ATRT tumour detection data gathering. It is essential to pre-process these photos in order to improve uniformity and quality. To enhance image clarity, methods like noise reduction, intensity standardisation, and normalisation are used. In addition, rotations, translations, and flips are performed on the data using the Keras ImageDataGenerator. This augmentation makes the dataset more variable, which enhances the model's performance and generalisation during training and, in the end, results in more accurate ATRT identification.
2) **Model Development:**Important steps in the suggested ATRT tumour detection methodology include CNN model training and optimisation. To ensure diversity and representation, the training dataset includes a carefully selected set of MRI scans from different medical institutes, containing both ATRT-positive and negative instances. To improve dataset variability and model generalisation, these images go through extensive preparation procedures like as normalisation and augmentation using the Keras ImageDataGenerator. The model's parameters are iteratively optimised through the use of the Adam optimizer, which minimises the binary cross-entropy loss function during training. A different dataset is used for validation in order to adjust hyperparameters and avoid overfitting. The goal of this procedure is to create a reliable CNN model that can reliably identify ATRT tumours from other brain diseases, enabling early detection and enhancing clinical decision-making for healthcare providers.

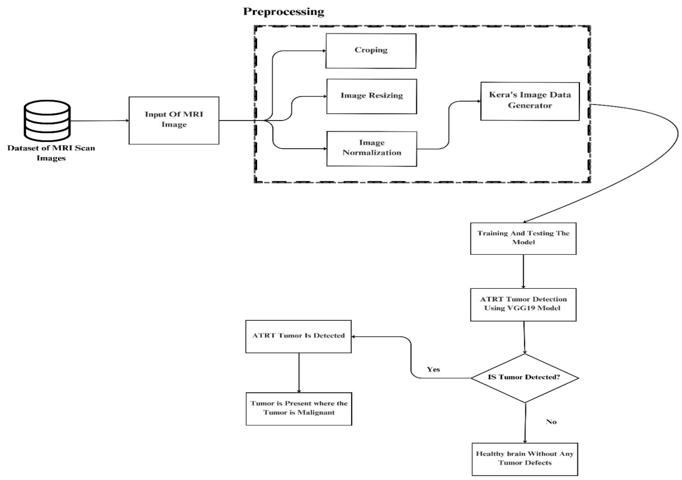

Fig. 5. Data Collection and Processing

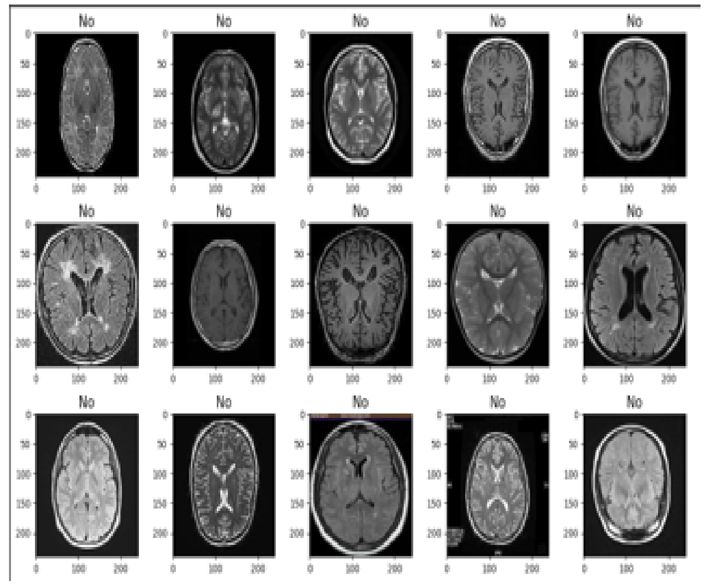

Fig. 6. Data-Set Images with No-Tumor

3) **Training and Optimizing Dataset:**Preparing the dataset is a critical stage in training and optimising a model for Atypical Teratoid Rhabdoid Tumour (ATRT) detection. It is imperative to have a varied and representative dataset that includes high-resolution MRI images of both ATRT-positive and -negative individuals. Data quality and variability are guaranteed via preprocessing methods including normalisation, noise removal, and augmentation using the Keras ImageDataGenerator. Then, to train the model on one subset and test its performance on another, the dataset is divided into training and validation sets, usually using an 80-20 ratio. During training, the Adam optimizer is used to effectively minimise the loss function of the model and improve its generalisation to new data.
4) **Interpret-ability and Integration:**The ATRT detection model will be integrated into a Django-based web application for easy interpretability and smooth incorporation into clinical processes. With this framework, database integration and backend management are made simple, guaranteeing scalability and real-time updates. To develop a user-friendly interface, JavaScript (JS) and CSS will be used in the frontend design process. The decisions made by the model will be visualised and explained through the use of techniques like Grad-CAM and LIME. During ATRT diagnosis and treatment planning, our method guarantees that radiologists and clinicians may simply interpret and rely on the model outputs.
5) **User Devices:** Computational technology and user devices such as MRI scanners are essential for ATRT tumour detection. High-resolution pictures produced by MRI scanners are utilised for diagnosis; these images are processed by powerful computing equipment utilising sophisticated CNN models to improve detection accuracy.

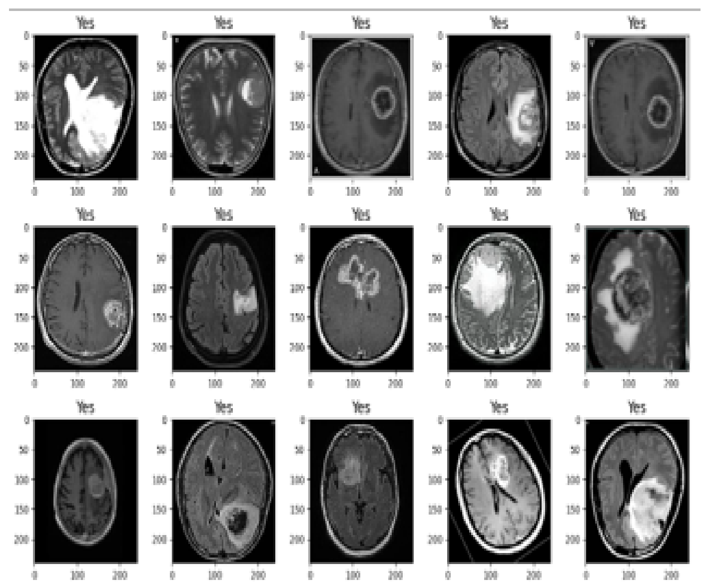

Fig. 7. Data-Set Images with Tumor

IV. Results and Discussions

The deep layer structure of the VGG-19 architecture, which consists of 16 convolutional layers and 3 fully linked layers, is what made it appealing for the extraction of intricate features from MRI scans and other medical pictures. VGG-19, which has a homogeneous architecture and narrow receptive fields, is particularly good at collecting fine details and complex patterns. A dataset of MRI images, both ATRT and non-ATRT, that had been preprocessed using normalisation and augmentation methods to improve robustness and variability was used to train the model. The ability of the model to generalise across many patients and imaging situations is enhanced by this method, which is important for precise diagnosis and treatment planning in clinical settings. Furthermore, VGG-19 can learn hierarchical representations thanks to its deep network topology, which is crucial for identifying minute variations in medical images.

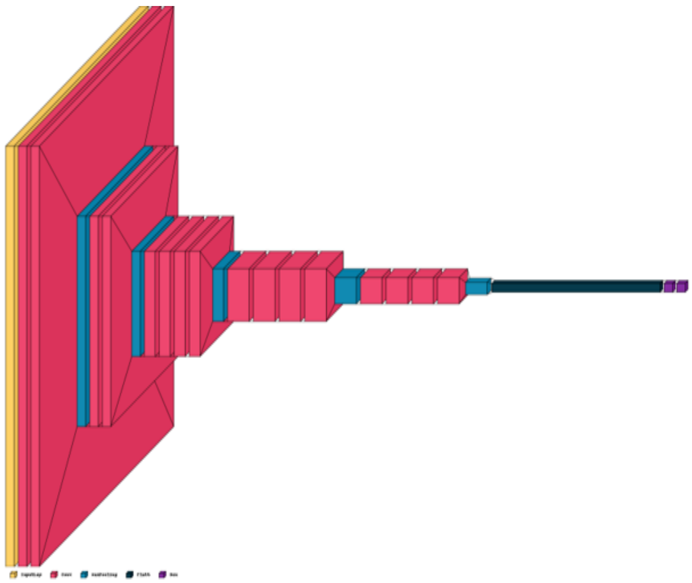

Fig. 8. VGG19 Result Accuracy

The deep layer structure of the VGG-19 architecture—which consists of three fully connected layers and sixteen convolutional layers—was chosen because it can effectively extract complicated characteristics from medical pictures, such as MRI scans. VGG-19 is renowned for catching fine details and complex patterns because to its homogeneous architecture and narrow receptive fields. In order to improve variability and robustness, normalisation and augmentation techniques were applied to a dataset of MRI images, both ATRT and non-ATRT, before the model was trained. By using this method, the model's generalisation capabilities across various patient types and imaging conditions are enhanced, which is important for precise diagnosis and treatment planning in clinical settings. Furthermore, the deep network structure of VGG-19 allows it to learn hierarchical representations, which are critical for differentiating minute details in medical images.

Further evaluation of the model's stability was conducted using measures including validation accuracy trends and loss curves. Throughout training, the loss function fell gradually, suggesting that the Adam optimizer was doing a good job at optimising. After a predetermined number of epochs, validation accuracy peaked, suggesting that the model did not overfit to the training set but instead continued to perform consistently on various dataset subsets.

The resulting model was tested on an independent test set consisting of unseen MRI scans to assess real-world performance. At 89 percent, the test accuracy—a crucial criterion for evaluating clinical applicability—showed that the model was robust in its capacity to identify ATRT tumours from fresh patient data. The usefulness of the VGG-19 design and the preprocessing methods used in this work are reaffirmed by the high test accuracy.

The VGG-19 model's performance was evaluated against baseline models and less complex CNN architectures. The VGG-19 model demonstrated consistently better accuracy and stability in the results, highlighting the significance of model depth and complexity in capturing the complex features characteristic of ATRT tumours in MRI images.

TABLE I
COMPARISON BETWEEN CNN AND VGG 19

Model	CNN	VGG-19
Training Accuracy	0.85	0.92
Validation Accuracy	0.78	0.89
Stable	NO	YES
Test Accuracy	0.75	0.87
Layers Models	CONV2D DENSE DROPOUT MAXPOOLING2D	CONV2D DENSE DROPOUT FLATTEN MAXPOOLING2D

The hierarchical feature learning capabilities of the CNN architecture are responsible for its effectiveness. Max-pooling layers lower dimensionality and retrieve important information from MRI images, while convolutional layers are skilled at collecting the spatial hierarchies of features. These features are included for classification via fully connected layers at the end of the network, with dropout layers helping with regularisation to avoid overfitting.

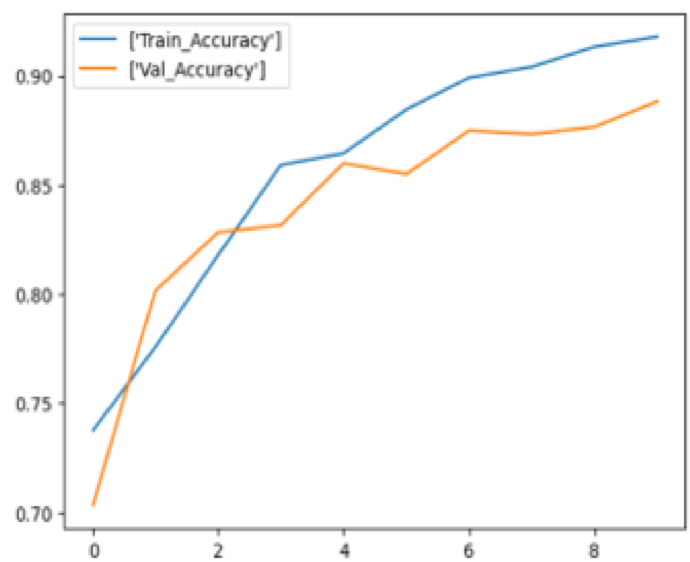

Fig. 9. Model Accuracy

When convolutional neural networks (CNNs) are used for ATRT tumour detection, the term "model loss" describes the degree to which the model's predictions match the real labels during training. Binary cross-entropy loss is commonly utilised in binary classification tasks such as differentiating between MRI scans that are ATRT-positive and negative.To reduce this loss, the model's weights and biases are iteratively adjusted during training. A smaller loss shows that the model performed better in differentiating between ATRT and non-ATRT images, with predictions being closer to the real labels.It is crucial to track and evaluate the loss curve during training in order to evaluate the convergence and stability of the model's performance. Elevated initial loss values could indicate that the model is having difficulty deriving significant patterns from the data, but declining loss throughout epochs is an indication of better adaptation and learning. In the end, reducing model loss helps to increase ATRT tumour detection utilising CNNs' accuracy and dependability.

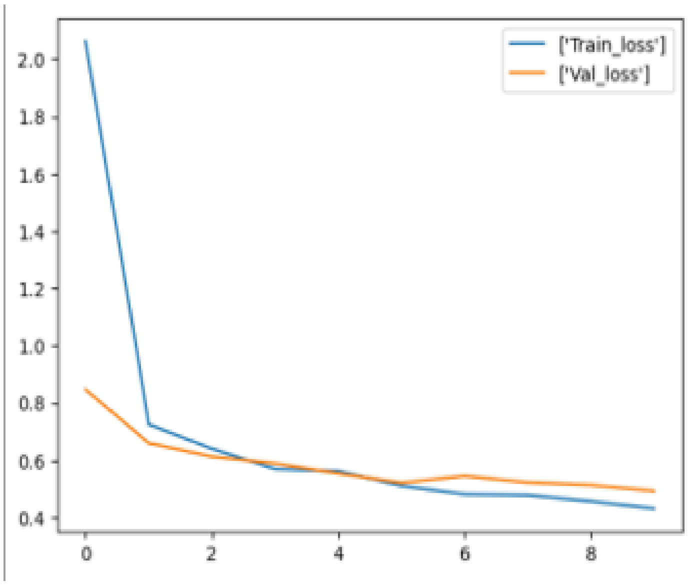

Fig. 10. Model Loss

The VGG-19 model's great accuracy in ATRT identification has important clinical ramifications. Timely treatment treatments can potentially improve patient outcomes and survival rates if ATRT is diagnosed accurately and early. Such sophisticated CNN models might be included into clinical workflows to give radiologists and other healthcare professionals useful decision support tools that would help with more accurate diagnosis and individualised treatment planning.

Notwithstanding the encouraging outcomes, there are a few drawbacks. The generalisation of the model may be impacted by the fact that the dataset utilised may not accurately reflect all ATRT case variants. To improve the robustness and application of the model across a range of patient demographics and imaging situations, future research efforts could concentrate on obtaining larger and more diverse datasets. In addition, investigating ensemble learning strategies and fine-tuning hyperparameters may enable the model to outperform existing benchmarks.

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