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A Review of Recent Machine Learning Approaches for Brain Tumour Detection and Classification

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Abstract: Brain tumours are a significant health concern, and timely and accurate diagnosis is crucial for patient care. Magnetic Resonance Imaging (MRI) is a widely used non-invasive diagnostic tool for brain tumour detection. However, there are challenges in accurately classifying brain tumours from MRI images, including: Image Variability in MRI images can vary in terms of resolution, contrast, and acquisition parameters, making it challenging to develop a consistent classification method.

There have been too many methods developed in recent years to diagnose brain tumour. Heterogeneity of Brain tumours come in various types (e.g., glioblastoma, meningioma) and grades (low-grade, high-grade), each requiring different treatment strategies. Accurate classification must account for this heterogeneity. From this study it has been found that identifying and extracting relevant features from MRI images that can discriminate between different tumour types and healthy brain tissue is a complex task. Limited Training Data for the availability of labelled MRI data for brain tumour classification is often limited, and collecting large datasets can be time-consuming and costly. Interpretability, ability to interpret the decisions made by machine learning models in the context of brain tumour classification is crucial for medical professionals to trust and use these tools.Therefore, there is a need to develop a robust and accurate machine learning system that can effectively classify brain tumours from MRI images by addressing the challenges of image variability, heterogeneity, feature selection, limited data, and providing interpretable results.

Keywords: Brain tumour detection, machine learning, MRI, Heterogeneity.

I. INTRODUCTION

The brain is the most vital and complex organ of the human body, responsible for regulating all bodily functions. However, abnormal and undesirable changes within the brain can lead to the development of tumours. A brain tumour is defined as the uncontrolled growth and abnormal proliferation of cells in brain tissue (Gupta et al., 2022). In recent years, the incidence of brain tumours has been steadily increasing, making it a major health concern.

Medical imaging and scanning techniques, particularly due to their high-resolution capabilities, have become essential tools for detecting and diagnosing brain tumours (Demir et al., 2023; Kumar et al., 2022). To date, more than 120 different types of brain tumours have been identified. According to a report by the American Cancer Society, approximately 18,600 adults and 3,460 children are affected by brain tumours each year. In 2021 alone, around 15 deaths were recorded due to brain tumours and other central nervous system-related conditions. Furthermore, statistics from the National Cancer Institute revealed that in 2019, there were 23,820 reported cases in the United States. By 2021, this number was projected to rise to 24,530 cases, comprising 13,840 men and 10,690 women.

According to global cancer statistics, approximately 308,102 brain tumour cases are projected in Asia, while worldwide estimates from the World Health Organization (WHO) indicate that nearly 9.6 million individuals are affected (Shah et al., 2022). Despite advances in diagnostic and therapeutic technologies, brain tumour survival rates remain critically low. The rising mortality rate has motivated extensive research into tumour detection and treatment (Chattopadhyay&Maitra, 2022).Currently, clinical management involves treatment options such as surgery, radiotherapy, and chemotherapy, which are selected depending on the tumour's type, size, and morphology. In routine medical practice, various MRI sequences are employed to determine tumour location, structure, and stage (Mehnatkesh et al., 2023; Nanda et al., 2023; Dhiravidachelvi et al., 2023; Sankareswaran& Krishnan, 2022). A crucial step in tumour classification is feature extraction, which involves identifying tumour characteristics such as position, texture,

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and shape. Traditionally, radiologists perform manual diagnosis using MRI images (Maqsood et al., 2022; Nazir et al., 2021). However, recent studies demonstrate that deep learning-based approaches outperform traditional methods for brain tumour classification (Arif et al., 2022; Shah et al., 2022; Sankareswaran et al., 2023; Kalpana et al., 2023).

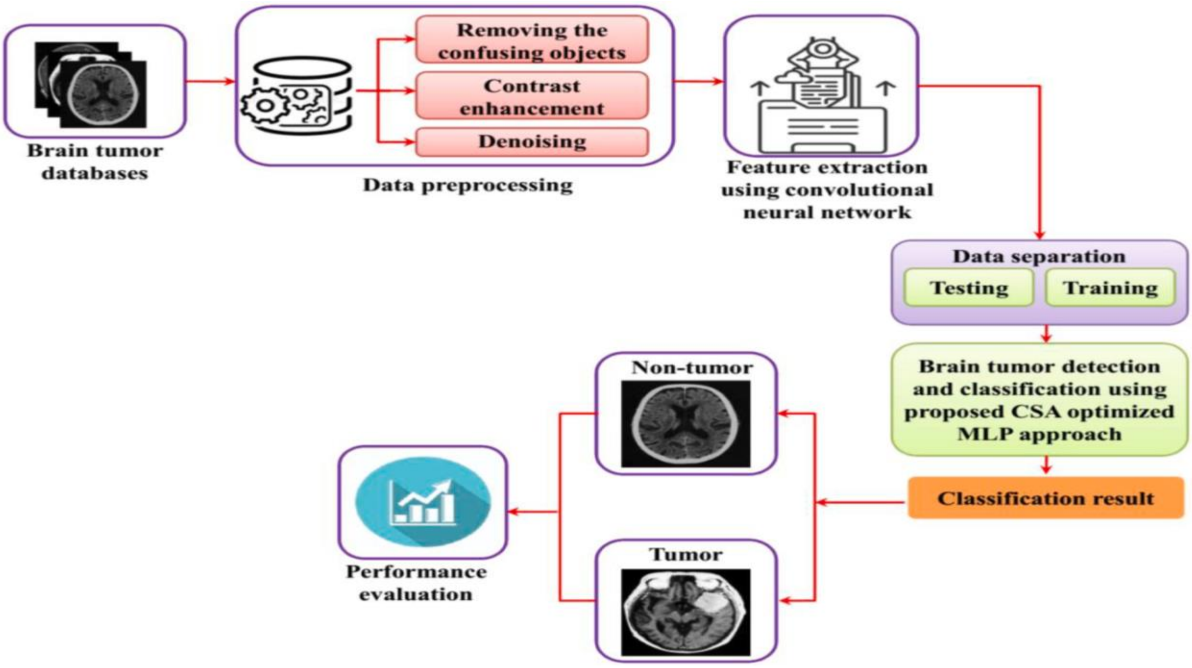

Figure 1: Overall architecture of the CSA-MLP method.

Machine Learning (ML) and Artificial Intelligence (AI) techniques have proven effective in analyzing complex data and distinguishing subtle patterns that may not be easily detectable by humans. These approaches have been applied across multiple domains, including medical imaging, where they can significantly improve the accuracy of brain tumour detection. In particular, ML and AI extract features directly from original MRI scans during training, which enhances image quality and enables more reliable classification (Masood et al., 2021; Nawaz et al., 2022). Such computational intelligence methods assist clinicians in identifying and categorizing tumours with greater precision.

In this study, we propose a novel Crossover Smell Agent Optimized Multilayer Perceptron (CSA-MLP) model for brain tumour detection using MRI images. This method is designed to aid clinicians by enabling early and accurate diagnosis of tumours. Early-stage identification is often difficult, as tumours are usually detected only after reaching an advanced stage (MuthuvelArumugam et al., 2024). While several established methods such as KNNRF-DT, CNN, RF, TL, YOLOv3, AKNN, WHHO, and DCNN have been developed, they face significant limitations, including:Increased processing time for accurate classification, inability to handle large datasets effectively, difficulty in accurately locating tumour regions, failure to reliably determine tumour size, sensitivity to noise in MRI images, leading to degraded classification performance.

These limitations often result in reduced accuracy and robustness. To address these challenges, the proposed CSA-MLP framework integrates the Multilayer perceptron with the Crossover Smell Agent (CSA) optimization technique, enabling effective hyper parameter tuning and improved learning performance. The contributions of this work are as follows:

Development of an automated CSA-MLP method to accurately distinguish between tumour and non-tumour MRI images.Enhanced prediction performance of the MLP classifier by fine-tuning hyper parameters (e.g., learning rate, number of layers, neurons per layer) using the CSA algorithm.Integration of a crossover strategywith the CSA optimizer to obtain optimal hyper parameter values, improves detection robustness, reduce noise, and enhance image quality.This proposed approach demonstrates the potential to overcome current limitations, offering a more reliable and efficient solution for brain tumour detection and classification.

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II. MACHINE LEARNING

Brain tumours are abnormal cell proliferations in the brain, classified as either benign or malignant (cancerous). Timely and precise diagnosis plays a vital role in planning treatment and improving patient outcomes. Traditional diagnostic approaches rely on manual examination of MRI and CT scans, which are often labour-intensive, subjective, and prone to errors. Machine learning (ML) techniques provide a way to enhance automation, accuracy, and consistency in such tasks. In particular, deep learning (DL) is actively applied for brain tumour detection and classification from MRI data. Researchers have proposed various methods to improve diagnostic accuracy. Transformer-based models have been utilized for multimodal brain tumour segmentation (Wang et al., 2021), while the Hyperdense Inception 3D U-Net has shown strong performance in tumour segmentation (Qamar et al., 2020). Other studies have applied algorithms such as Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), and ensemble methods for classifying tumour subtypes including gliomas, meningiomas, and pituitary tumours (Liu et al., 2021; Akram et al., 2022; Zhou et al., 2020; Ahmad et al., 2025).

Over the past decade, ML-based research in brain tumour analysis has made significant advancements. Using primarily MRI data, these methods have enabled faster, more reliable, and automated detection, segmentation, classification, and prognosis. Key contributions include: Higher Diagnostic Accuracy DL models such as CNNs and Transformers often achieve accuracy rates above 90% on benchmark datasets, outperforming conventional diagnostic approaches. Improved Tumour Segmentation: Architectures like U-Net, 3D CNNs, and TransBTS provide more accurate delineation of tumour boundaries while reducing the burden on radiologists. Personalized Prognosis and Treatment: By combining imaging data with genomic and clinical information, ML models can predict survival rates, recurrence risks, and treatment responses, supporting personalized medicine.

III. RELATED WORKS

Ari et al. (2018) outlined a three-stage framework comprising tumour region extraction through image processing, tumour classification using Extreme Learning Machine with Local Receptive Fields (ELM-LRF), and pre-processing. Initially, unwanted noise was removed using local smoothing and nonlocal means techniques. In the second stage, ELM-LRF was employed to classify cranial MR images as benign or malignant, and tumours were further categorized into three stages.

Similarly, Abdalla et al. (2018) discussed the methodologies used for brain tumour identification with Artificial Neural Networks (ANN) in conjunction with MRI data. Their approach, incorporated into a Computer-Aided Detection (CAD) system, began with enhancement and post-processing of MRI scans to prepare them for analysis. This was followed by segmentation using a thresholding method based on the mean gray level. Zaw et al. (2019) proposed a method aimed at detecting brain tissues affected by high-grade tumours, specifically glioblastomamultiforme (GBM), which is known for its rapid growth and tendency to spread. Their technique applied Naïve Bayes classification to accurately delineate tumour regions containing malignant tissues.

In another study, Manjunath et al. (2019) described a tumour grading approach where feature extraction was utilized to align the tumour with its relevant class. The complexity of this work lies in combining symbolic data extraction with Convolutional Neural Networks (CNNs). The effectiveness of the method was validated using CNN and Back Propagation Neural Network (BPNN) classifiers. The proposed optimization-based brain tumour diagnosis model using MRI images involves several sequential phases. The method was evaluated on the publicly available REMBRANDT dataset, which includes images of meningiomas, gliomas, pituitary tumours, as well as normal (non-tumour) cases. The dataset was divided into training and testing subsets for performance assessment.

In the pre-processing stage, Region of Interest (ROI) extraction, RGB-to-grayscale conversion, and Modified Anisotropic Diffusion Filtering (MADF) were applied to enhance image quality. For tumour segmentation, the En-DeNet framework was employed, while the YOLO NAS deep learning model was utilized for tumour feature extraction and classification. The system classified MRI images into four categories: (1) Non-cancerous meningioma, (2) Pituitary tumour, (3) Glioma, and (4) No tumour. Following classification, misclassified or "sick" images were removed from the dataset to refine accuracy. The stepwise stages of the proposed segmentation and classification framework are illustrated in Figure 2.

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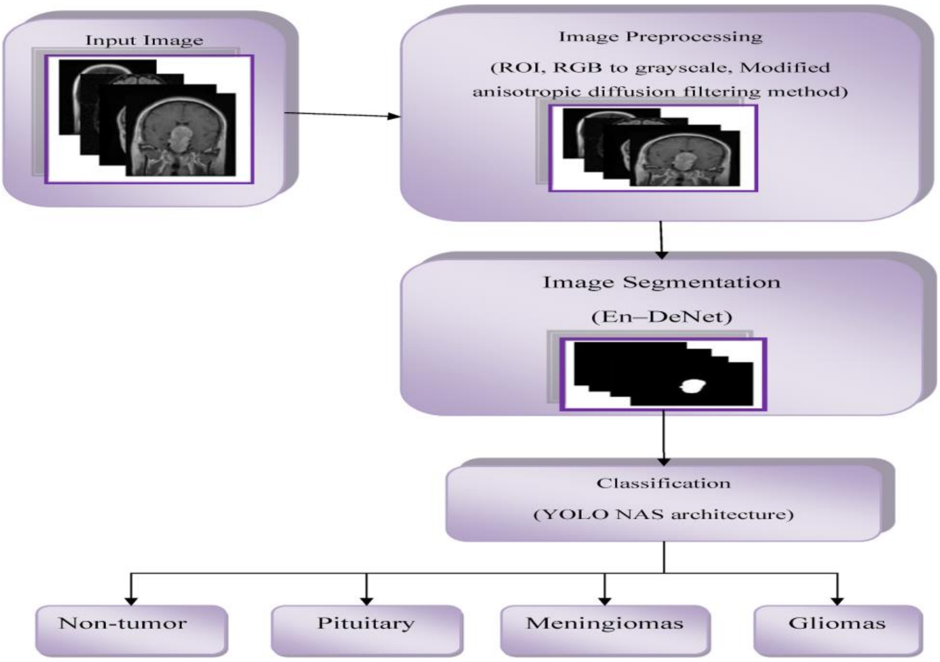

Figure 2: Brain tumour classification using the proposed YOLO NAS framework (M.S. Mithun et al.,2024)

This study introduces a novel framework termed Dual Vision Transformer - DSUNET, which integrates advanced transformer - based architectures with a newly designed DSUNET model. The proposed system is designed to achieve high-precision brain tumour segmentation without reliance on external inputs. By employing a dual vision strategy, the model effectively captures comprehensive tumour characteristics across different imaging modalities.

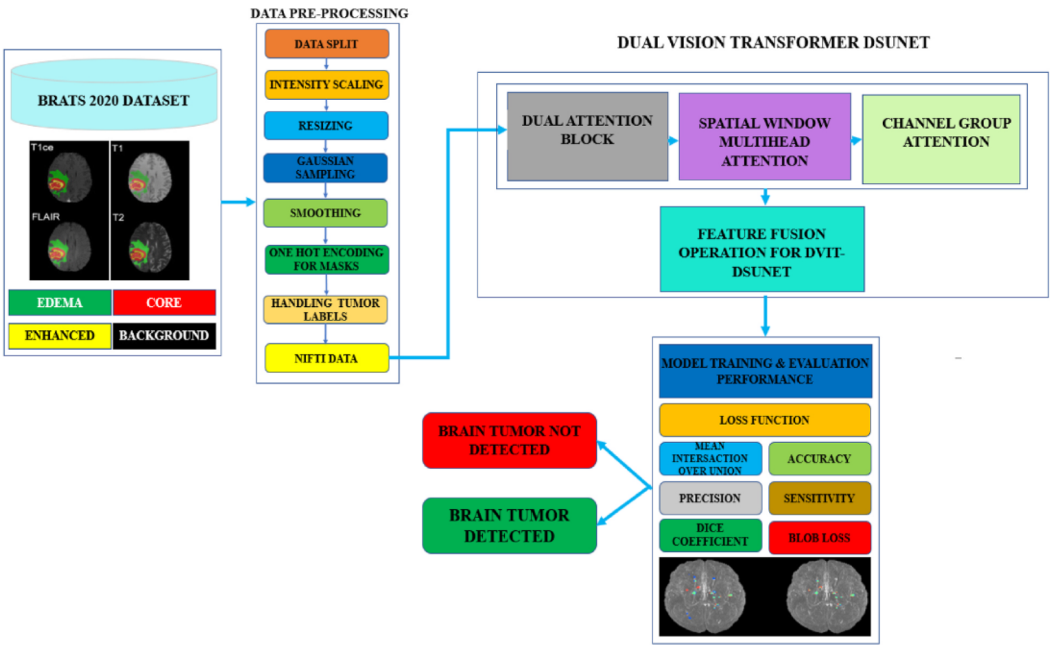

Figure 3: Framework for the dual vision Transformer - DSUNET with feature fusion for brain tumour segmentation (Mohammed Zakariah et al., 2024).

The study introduces a novel advancement in feature fusion techniques, enabling the integration of information from multiple imaging modalities. By combining diverse data sources, the proposed approach substantially improves the accuracy and reliability of brain tumour segmentation, leading to a more precise characterization of tumour features. Evaluation results using the Dice Coefficient demonstrate that the Dual Vision Transformer-DSUNET model achieves superior segmentation performance compared to existing methods. The consistently high Dice scores highlight the model’s capability to accurately delineate tumour regions, which is crucial for effective diagnosis and treatment

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planning. Furthermore, the study enhances segmentation quality by incorporating multimodal data into the diagnostic and therapeutic workflow for brain tumour patients. The improved segmentation functionality allows for clearer visualization of tumour morphology and growth patterns, thereby supporting clinicians in making more informed decisions and formulating personalized treatment strategies. This research underscores the potential of dual vision transformers combined with feature fusion to advance computational imaging methods. By addressing the limitations of current brain tumour segmentation techniques, the proposed strategy sets a foundation for future improvements in medical image analysis. For segmentation, the dataset consisting of 3,064 MRI images was utilized, with ground truth annotations obtained directly from the repository. The ground truth masks were extracted using coordinate information provided in MATLAB structures.The same dataset was also used for classification, where class labels were included in the MATLAB structure. Based on this information, the 3,064 scans were categorized into three classes: meningioma (708 images), glioma (1,426 images), and pituitary tumours (930 images).

The proposed architecture comprises two main components: an encoder and a decoder. In the encoder stage, Bayesian Optimization (BO) was applied to fine-tune the hyperparameters of the backbone network, ResNet18. After training, hierarchical features were extracted, and the Atrous Spatial Pyramid Pooling (ASPP) module was employed to capture multi-scale contextual information using varying dilation rates. The features generated by the ASPP module were then fused, with skip connections and image pooling further enhancing feature integration. At this stage, the down-sampled representation retained finer contextual details, improving the overall segmentation process.

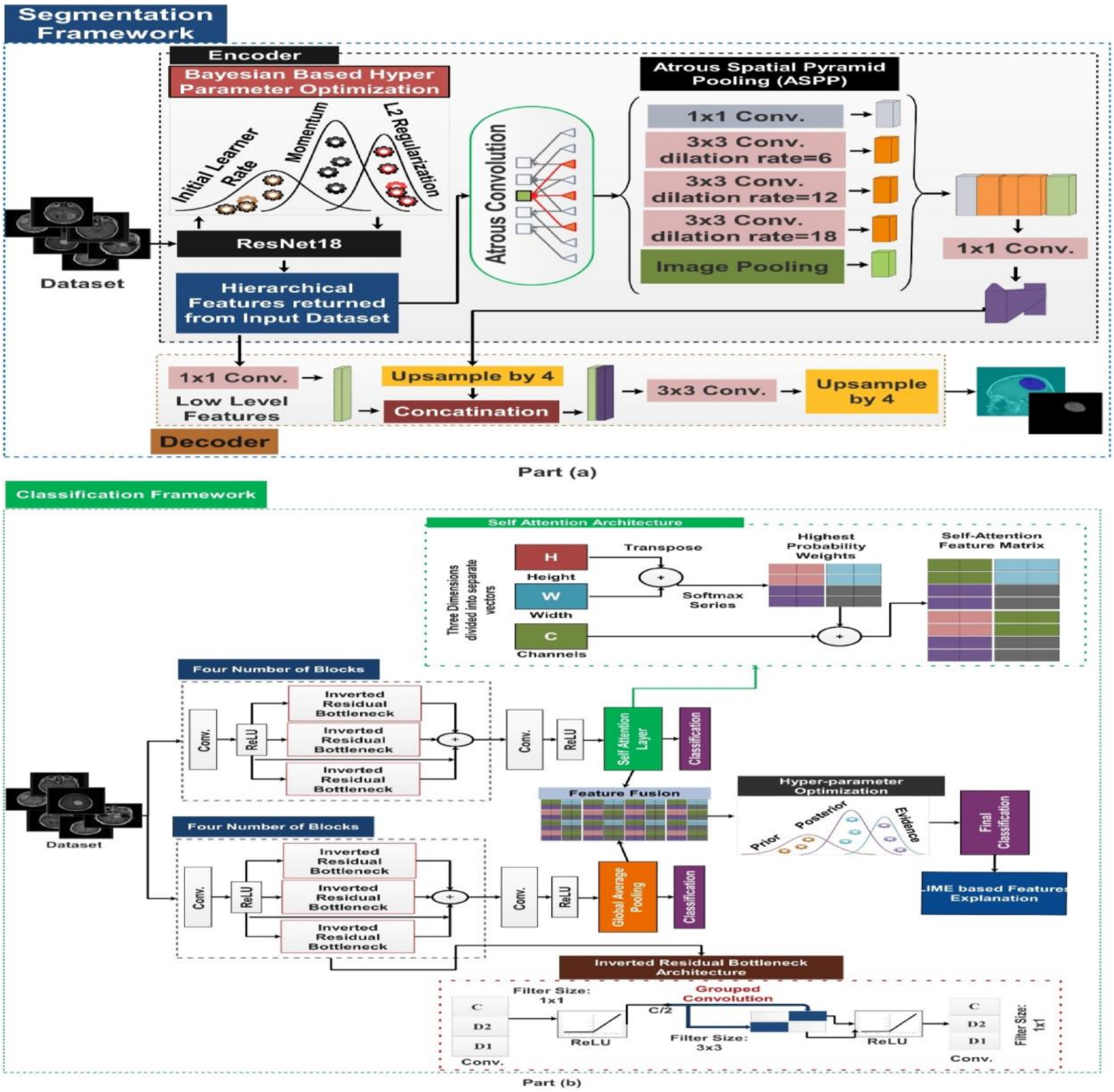

Figure 4: Proposed framework of brain tumour segmentation and classification (Muhammad Sami Ullah et al., 2024)

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In the decoder stage, up-sampling operations are applied to restore the down-sampled feature maps obtained from the encoder. Deconvolution layers are employed for this purpose, ultimately producing semantically segmented output images. The subsequent section provides a detailed description of the proposed optimized DeepLabv3+ framework.The dataset is processed through the DeepLabv3+ architecture, where ResNet18, pre-trained on large-scale datasets, is utilized as the backbone for hierarchical feature extraction. ResNet18 was selected due to its balance of moderate depth, efficiency, and the inclusion of skip connections, which help mitigate the vanishing gradient problem during training. Since the effectiveness of feature extraction largely depends on the training process, Bayesian Optimization (BO) was applied to fine-tune key hyperparameters of ResNet18, including the initial learning rate, momentum, and L2 regularization. The features extracted from the backbone are then passed to the Atrous Spatial Pyramid Pooling (ASPP) module, which employs atrous convolutions with multiple dilation rates. This enables the network to capture contextual information at both local and global scales. By leveraging parallel atrous convolutional branches with varying receptive fields, the ASPP module enhances the model’s capacity to extract fine-grained and broad contextual features.

For tumour classification, the study proposes a hybrid model integrating Attention-Augmented CNN, Random Forest, and U-Net. This framework combines the strengths of deep learning and traditional machine learning to improve both segmentation and classification accuracy. MRI brain images of different tumour types undergo pre-processing steps such as denoising and contrast enhancement to improve image quality. Feature extraction methods, including texture and shape analysis, are then applied to identify patterns indicative of specific tumour types. Figure 6 illustrates the block diagram of this advanced segmentation and classification framework, which integrates state-of-the-art methods to enhance the precision and efficiency of brain tumour analysis.

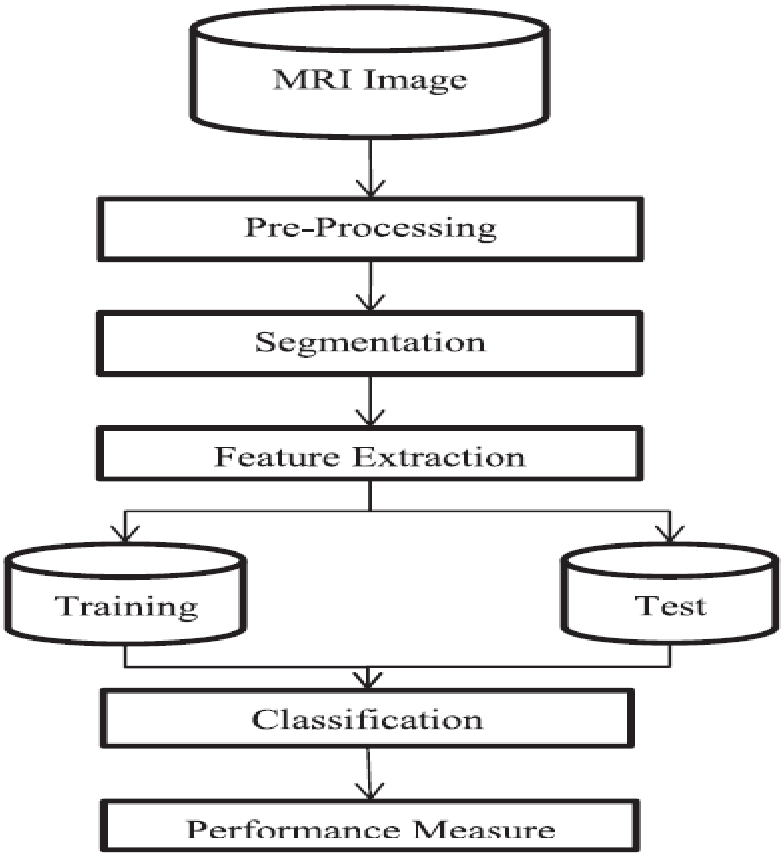

Figure 5: Block Diagram MRI image Segmentation and Classification (A. Karthik et al., 2025)

Feature extraction methods, such as texture analysis and shape profiling, play a vital role in identifying distinctive patterns associated with various brain tumour types. For classification, the proposed framework employs an Attention-Augmented Convolutional Neural Network (CNN) to capture complex features, which are further refined using a Random Forest classifier for ensemble learning. This combination ensures robust and accurate tumour categorization. In parallel, U-Net architecture is utilized for precise tumour segmentation, providing clinicians with comprehensive diagnostic insights that support more effective treatment planning.

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The article is organized around the discussion of three widely used imaging modalities for brain structure analysis. Magnetic Resonance Imaging (MRI) is one of the most effective techniques for early detection of brain abnormalities, offering high-resolution views of complex anatomical structures. However, the intricate nature of brain tissues makes tumour segmentation a challenging task.Computed Tomography (CT) scans, on the other hand, provide detailed information on soft tissues, blood vessels, and bones, and are more informative than traditional X-rays. CT scanning has become a routine diagnostic tool, with studies in the USA reporting approximately 62 million annual scans, including 4 million in children. Despite its advantages, CT uses higher radiation doses than standard X-rays, raising concerns about increased cancer risks from repeated exposure. Positron Emission Tomography (PET) offers another perspective by using radioactive tracers to evaluate the metabolic activity of brain tumours, thereby complementing structural imaging techniques. Compared to CT, MRI provides clearer visualization of soft tissues and structures that may not be visible otherwise, making it particularly valuable in tumour analysis.

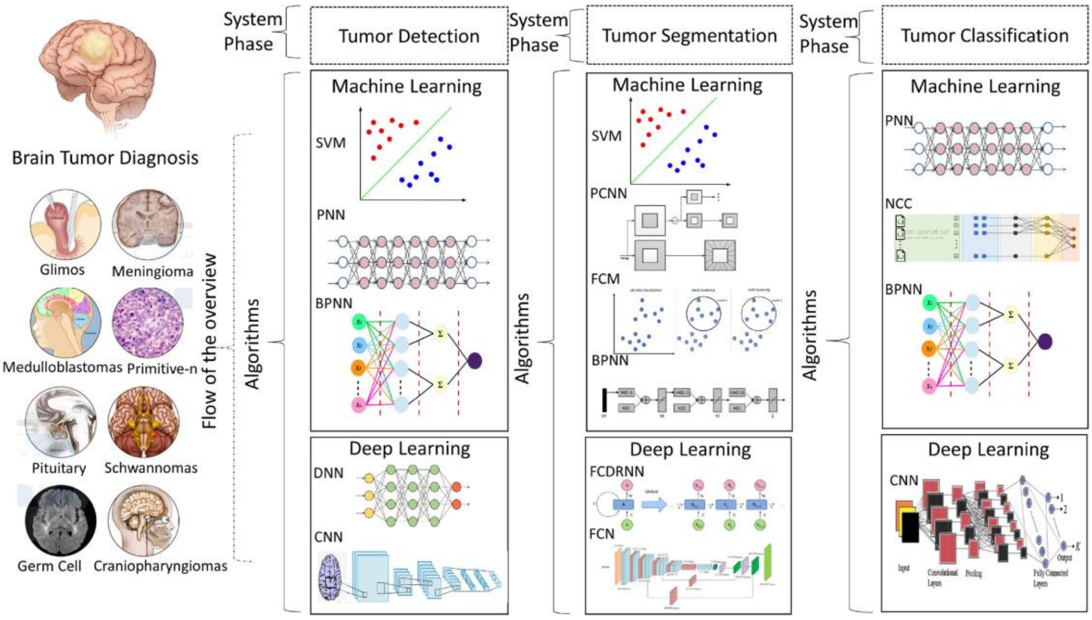

Figure 6: Methods for identifying, classifying, and segmenting brain tumours based on two different types of information (Amreen Batool et al., 2024)

Positron Emission Tomography (PET) employs a nuclear medicine tracer, most commonly fluorodeoxyglucose (FDG), and is considered a powerful metabolic imaging technique. Despite its diagnostic value, FDG-PET has certain drawbacks. The radioactive tracers used in PET may cause adverse side effects, including post-scan allergic reactions, while the spatial resolution of PET images is generally lower compared to MRI. In contrast, MRI technology has made remarkable contributions to medical imaging by enabling detailed analysis of different anatomical structures, particularly the brain. Advances in computational techniques now allow specialists to extract and interpret large volumes of information from MRI scans. MRI plays a critical role in locating and determining the extent of brain tumours, making it indispensable for accurate diagnosis and treatment planning. The subsequent sections of this review examine different tumour types and emphasize the importance of advanced imaging modalities in brain tumour analysis.

U-Net, a widely recognized architecture for biomedical image segmentation was introduced by Ronneberger in 2015. Unlike conventional fully convolutional networks, U-Net achieves faster performance by using only the valid portions of each convolution. Its distinctive design incorporates skip connections between the contracting (encoder) and expanding (decoder) paths, which significantly enhance segmentation accuracy. The encoder consists of four modules, each containing two convolutional layers followed by a max-pooling operation, with the number of feature channels doubling at each step. The central bottleneck stage comprises two convolutional layers and an up-convolutional layer, bridging the encoder and decoder pathways. The decoder pathway mirrors the encoder with four up-sampling modules, each containing deconvolution layers concatenated with corresponding feature maps from the encoder, followed by two convolutional layers. The proposed study investigates a modified U-Net structure for brain tumour segmentation, featuring a contracting encoder on the left, a symmetric expanding decoder on the right, and a merging layer at the end to improve localization accuracy. Figure 8 illustrates this customized U-Net architecture.

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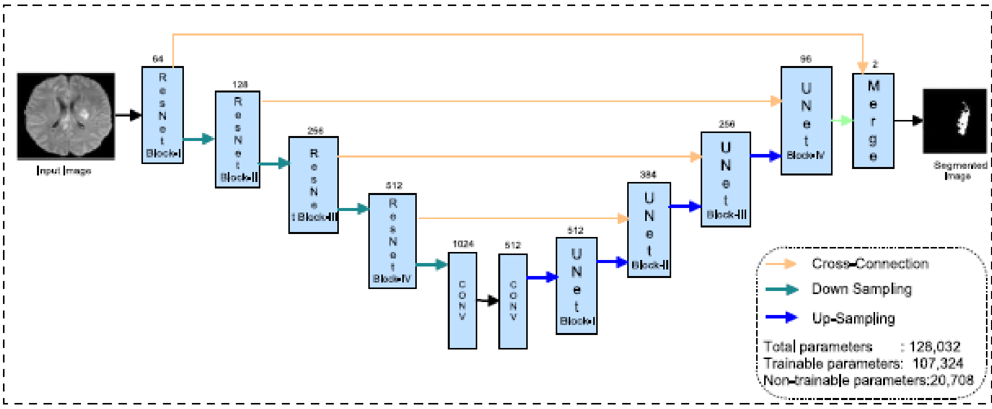

Figure 7: Proposed modified U-Net architecture (PedadaKameswaraRao et al., 2023).

In the modified U-Net architecture, the encoder is replaced with a ResNet34 framework pre-trained on the ImageNet dataset, enabling efficient feature extraction and image classification. The decoder comprises multiple U-Net blocks along with a merging layer. Each U-Net block receives up-sampled outputs from the preceding block, as well as activation features transferred from the corresponding intermediate layers of the encoder, thereby enhancing feature reconstruction and segmentation accuracy.

Table 1: Comparison among state – of – the – art Brain Tumour detection Methods

Ref.	Year	Pre-processing	Methods	Datasets	Results
(M.S. Mithun et al.,2024)	2024	Tumour region extraction and tumour classification	Artificial neural networks (ANN) and Magnetic Resonance Imaging (MRI)	Publicly accessible REMBRANDT dataset, which is a database.	The method can detect 98.97% brain tumours on REMBRANDT dataset
(Mohammed Zakariah et al., 2024)	2024	Planned to segment brain tumours without external input and with high accuracy using dual vision approaches	Dual Vision Transformer-DSUNET model	BRATS dataset	The method can detect 99.93% brain tumours on BRATS dataset
(Muhammad Sami Ullah et al., 2024)	2024	Brain tumour segmentation and classification from MRI scans	Residual Networks (ResNet)	A publicly available dataset named Figshare brain tumour dataset has been used	The method can detect 95.42 %. brain tumours on Figshare brain tumour dataset
(A. Karthik et al., 2025)	2025	Texture analysis and shape profiling, are applied to reveal critical patterns indicative of different brain tumour type.	Attention-Augmented Convolutional Neural Network (CNN), Random Forest, and U-Net.	MRI dataset.	The method can detect 99.5 %. brain tumours on MRI dataset.
(AmreenBatool et al., 2024)	2024	Detect abnormalities in the brain at earlier stages	Positron Emission Tomography (PET) is an imaging technique that uses radioactive tracers to analyze brain tumour metabolic features.	figshare SARTAJ dataset	The method can detect 98.56 %, brain tumours on figshare SARTAJ dataset

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(PedadaKameswaraRao et al., 2023).	2023	Brain image segmentation	U-Net architecture for segmentation	BraTS 2017 and BraTS 2018	The method can detect 93.4% and 92.8% brain tumours on BraTS 2017 and BraTS 2018

IV. DISCUSSION AND ANALYSIS

Machine learning (ML) and deep learning (DL) have emerged as transformative approaches in brain tumour detection and classification, offering faster, more reliable, and automated alternatives to conventional diagnostic techniques. Leveraging models such as Convolutional Neural Networks (CNNs) and transfer learning, these methods can analyze medical images—particularly MRI scans—with high accuracy, reducing the limitations of manual interpretation. This review paper provides an overview of current ML/DL methodologies, their effectiveness, and the challenges associated with their clinical adoption for brain tumour analysis.

Overview of Brain Tumours

The paper introduces brain tumours, their major types (e.g., gliomas, meningiomas), and tumour grading systems, emphasizing the clinical importance of early and precise detection.

1. Fundamentals of Machine Learning

Key ML concepts such as supervised and unsupervised learning are discussed, along with algorithms including Support Vector Machines (SVM), Logistic Regression, and K-Nearest Neighbors (KNN), which have been widely used in medical image analysis.

2. Deep Learning for Brain Tumour Analysis

A significant portion of the review highlights DL techniques, with particular focus on CNNs, which automatically learn hierarchical image features for tumour classification and segmentation tasks.

3. Transfer Learning

The paper discusses the role of transfer learning, where pre-trained models such as VGG16 and ResNet are fine-tuned on brain tumour datasets, enabling effective training even with limited medical data.

4. Image Processing Techniques

The importance of pre-processing steps—such as denoising, contrast enhancement, segmentation, and feature extraction—is emphasized, as these steps greatly influence the performance of ML/DL models.

5. Performance Evaluation

Different approaches are assessed using metrics such as accuracy, sensitivity, specificity, and F1-score, which provide insights into diagnostic reliability.

6. Comparison with Traditional Methods

The review compares ML/DL-based approaches with manual diagnostic practices, highlighting their advantages in terms of speed, consistency, and reduction of human error.

7. Challenges and Future Directions

Limitations such as the requirement for large annotated datasets, lack of generalization across imaging modalities, and biases in training data are discussed. The review also identifies future research avenues, including federated learning for privacy-preserving data sharing and the development of explainable and more robust AI models.

8. Specific Algorithms and Models

The performance of widely used models and algorithms—such as CNN variants (AlexNet, VGG16, ResNet), SVM, Logistic Regression, and ensemble methods—is also explored in detail.

V. CONCLUSION

Machine learning (ML) and deep learning (DL) approaches are becoming increasingly important for brain tumour detection and classification in medical imaging, particularly with MRI scans. These techniques enable faster, automated, and more accurate diagnosis, supporting earlier and more effective treatment interventions. Despite their promise, several challenges persist, including the segmentation of complex tumour morphologies, managing image noise, and optimizing model efficiency. Ongoing research focuses on developing more robust ML/DL architectures, incorporating explainability to enhance clinical trust, and leveraging multi-modal imaging for improved diagnostic accuracy. Overall, this review underscores the transformative role of ML and DL in brain tumour diagnosis while highlighting the need for continued advancements to overcome current limitations and ensure successful clinical translation.

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