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An Ensemble Approach for Comprehensive Brain Tumour Detection Using MRI-Based Machine Learning Models

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Abstract: In the realm of medical imaging, the rapid evolution of techniques and exponential growth of data have emphasised the significance of automatic and reliable tools for brain tumour detection. This project proposes a system designed to detect brain tumours utilising Magnetic Resonance Imaging (MRI) data. Two distinct models leveraging advanced machine learning algorithms, particularly Convolutional Neural Networks (CNNs), are developed using multiple datasets. The BraTS dataset is used for segmentation tasks, providing detailed information about specific brain tumour regions. Concurrently, the Br35H dataset is used for binary classification, distinguishing the presence or absence of tumours. Furthermore, the brain tumour dataset from Kaggle adds another dimension to this study, offering diverse data samples. The proposed system encompasses a two-step approach. First, a segmentation model is fine-tuned on the BraTS dataset to identify specific regions within brain scans. Subsequently, a classification model is trained using both the Br35H and Kaggle datasets. Ensemble learning techniques, involving an ensemble of CNN architectures such as ResNet and VGG, along with the exploration of ensemble methods like AdaBoost, are employed for effective classification.

Keywords: BraTS 2021, Brain Tumour, Br35H, CNN, Machine Learning, MRI (Magnetic Resonance Imaging), ResNet

1. Introduction

Brain tumour has been a cause of significant concern within the medical community for decades. These growths, whether benign or malignant, can lead to a range of neurological complications, impacting various facets of a patient's life. From subtle symptoms like persistent headaches, changes in vision, and seizures to more pronounced issues such as cognitive deficits, behavioural changes, and motor function impairment, the presence of a tumour in the brain can be life-altering[16].

The advanced machine learning system for brain tumour detection provides significant advantages for both doctors and patients. For radiologists, it serves as an additional layer of analysis, boosting diagnostic precision and reducing oversight risks[17]. By quickly identifying potential anomalies, it ensures even subtle tumour signs are recognized, facilitating timely detection and effective treatment planning.

For patients, the system's quick and accurate diagnosis reduces result wait times and allows for earlier interventions, enhancing treatment outcomes. This also eases the stress and uncertainty tied to awaiting a diagnosis.

This paper shows the analysis of various models developed or used to detect brain tumours in recent research papers. This paper will help to understand the complex landscape of brain tumour detection methodologies and their implications in the medical field. The diverse range of models discussed, from convolutional neural networks (CNNs) to hybrid architectures, highlights the continual innovation in this critical domain. Analysing these models provides insights into their strengths and limitations, contributing to a deeper comprehension of the challenges associated with accurate brain tumour detection.

1.1. Challenges

Brain tumour detection, particularly when utilising imaging techniques coupled with computational methodologies, is riddled with complexities. One of the paramount challenges is the variability in image quality. Due to differences in imaging equipment, the positioning of the patient, or even the technician's method, there's a broad spectrum of quality in medical images. This variance can inadvertently result in the oversight of tumours or the occurrence of false positives[19]. Further complicating detection is the inherent complexity and variability of tumours. These malignant growths can manifest in diverse sizes, shapes, and locations. Some may nestle deep within the cerebral recesses or exhibit irregular peripheries, making their identification challenging.

Adding another layer of intricacy is the heterogeneity of tumours. A solitary tumour can comprise varied regions, like necrotic or active areas, each presenting differently on images[21]. When integrating machine learning into the detection process, the risk of overfitting emerges. This implies that while a model might exhibit

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stellar performance on training data, its effectiveness may dwindle on unfamiliar data[20]. Moreover, the integration of a detection system into clinical workflows can pose challenges, especially if it lacks compatibility with existing infrastructure or fails to offer user-friendliness.

Of equal importance is the concern of data privacy and security. Given the sensitive nature of medical images, ensuring that this data remains inviolable, especially in systems based on cloud infrastructures, becomes vital. Furthermore, the medical fraternity doesn't just need predictions; they need explanations. A system lacking in interpretability, which provides binary outcomes without indicating areas of interest or elucidating confidence levels, might be met with scepticism.

A pressing concern in this domain is the scarcity of appropriately annotated data. To train sophisticated algorithms, vast amounts of labelled data are imperative. However, procuring such data, complete with precise annotations, is both resource-intensive and time-consuming. Furthermore, the realm of medical devices and diagnostic tools is stringently regulated. Navigating this regulatory maze to secure approvals can be tedious[5].

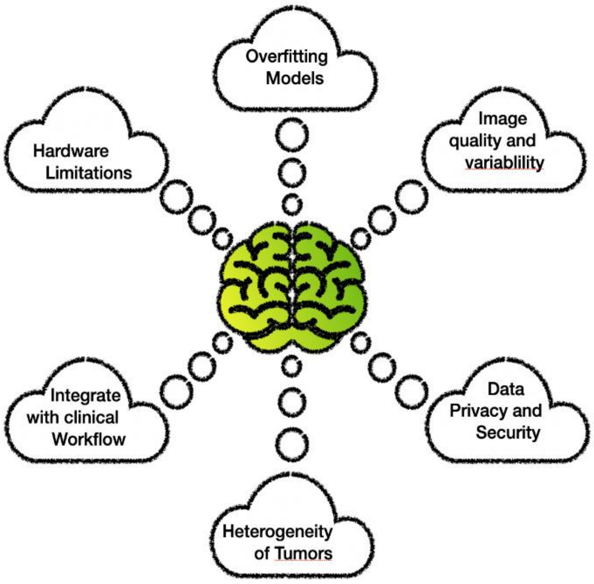

Fig. 1. Challenges of Brain Tumour Detection

Lastly, there's the ever-present challenge posed by hardware constraints. The computational heft required by deep learning models, especially those geared for image analysis, isn't universally accessible to all healthcare institutions, making widespread implementation a daunting task.

2. LITERATURE REVIEW

Yashwant Kurmi et al. [1] With an aim to devise a method that can proficiently detect unhealthy brain tissue in MRIs, the research embarked on an initial approach to pinpoint key regions by harnessing basic image data. Recognizing the need for a more nuanced understanding, this rudimentary data was subsequently transformed into a richer set of features. For an in-depth analysis, techniques such as the Fisher vector and autoencoder, among other tools, were put into play. When the developed model was put to the test across five distinct MRI sets, the results were compelling. The system achieved an accuracy rate of 94.5% in tumour identification and an impressive 91.76% in the subsequent classification of these detected tumours.

Arkapravo Chattopadhyay and Mausumi Maitra [2] address the critical aspect of brain tumour detection in medical imaging, specifically utilising a 9-layer Convolutional Neural Network (CNN) model. Their methodology involves preprocessing input MRI images, implementing convolutional kernels with ReLU activation, and incorporating batch normalisation for enhanced algorithm speed. The model's architecture includes max pooling to reduce feature map dimensions and dense layers for classification, achieving an impressive 99.74% accuracy using RMSProp as the optimizer.

G. Hemanth et al. [3] Highlighting the escalating concern of uncontrolled brain tumour growths in healthcare, the study introduces a method leveraging Convolutional Neural Networks (CNN) with 3 x 3 kernels. The procedural journey encompasses stages like data collection, pre-processing, filtering, segmentation, feature extraction, and CNN classification. Remarkably, the first CNN architecture yielded an accuracy of 99.33%, while the subsequent model closely followed with an approximate accuracy of 92.66%.

V. Divya Dharshini et al. [4] Addressing the challenge where 5% of tumour cases remain undetected due to MRI artefacts, the study's primary goal is to ensure precise tumour detection, even in the presence of these artefacts. The approach amalgamates edge division and morphological techniques with traditional image processing steps, like filtering and segmentation. Utilising the MATLAB software for execution, the method achieved an impressive detection rate of 94.22% by leveraging the OTSU Algorithm.

Mahmud, Mamun, and Abdelgawad [5] study the potential of artificial intelligence, particularly deep learning, in early brain tumour identification by magnetic resonance imaging (MRI). They compare their proposed convolutional neural network (CNN) architecture to well-known models such as ResNet-50, VGG16, and Inception V3. Evaluating parameters like accuracy, recall, loss, and AUC, the study reveals their CNN model beats others, reaching 93.3% accuracy, 98.43% AUC, 91.19% recall, and 0.25 loss using a dataset of 3264 MR images. The suggested model shows promise for improving medical image analysis by being dependable for early detection.

The difficult problems of brain tumour localization and segmentation in magnetic resonance imaging (MRI) for medical analysis are discussed by Ranjbarzadeh et al. [6]. In light of the intricacy of current methods—which frequently involve lengthy training periods and experience overfitting—the authors suggest a versatile and effective strategy for segmenting brain tumours. Their technique is a preprocessing strategy that targets particular areas of the image, cuts down on computation time, and lessens overfitting in a Cascade Deep Learning model. In the second step, a Cascade Convolutional Neural Network (C-CNN) is introduced, which mines both local and global information through two different paths, tailored for smaller regions of each slice of the brain picture. The authors present a unique Distance-Wise Attention (DWA) method that takes into account the position of the brain inside the model as well as the tumour's centre to improve segmentation accuracy. The BRATS 2018 dataset experiments show competitive results, with mean dice scores of 0.9203, 0.9113, and 0.8726 for the tumour core, augmenting tumour, and total tumour, respectively. The proposed model showcases improvements compared to state-of-the-art models, supported by comprehensive quantitative and qualitative assessments.

MD Abdullah Al Nasim et al. [7] present a comprehensive study on brain tumour segmentation using a 2D U-Net model based on Convolutional Neural Networks (CNN). The research addresses the challenges in accurately segmenting brain tumours, including necrotic, edematous, growing, and healthy tissue, using MRI images. The proposed model is trained and evaluated on the BraTS datasets for the years 2017 to 2020. The study discusses the significance of automated segmentation in medical imaging, especially for gliomas, which are primary brain tumours. The authors compare their 2D U-Net model with other CNN-based models such as FCNN and RCNN, demonstrating superior performance in terms of accuracy, Mean IoU, Precision, Sensitivity, Specificity, and Dice Score on the BraTS datasets. The results indicate the model's effectiveness in differentiating tumour sub-regions across various datasets. The paper concludes by emphasising the potential of CNN-based models, particularly U-Net, over traditional machine learning methods for brain tumour segmentation, and outlines future work to explore 3D U-Net models to address information loss in the 2D approach.

Babayomi, Olagbaju, and Kadiri [8] address the critical issue of brain tumour detection, emphasising the importance of early diagnosis for improved prognosis. Conventional diagnostic methods involve extensive manual examination of brain scans and test results, leading to mental strain and time consumption. Leveraging the advancements in deep learning, the study proposes a model named C-XGBoost for early brain tumour detection, combining extreme gradient boosting (XGBoost) and convolution neural network (CNN). The C-XGBoost model demonstrates lower complexity than pure CNNs, making it easier to train and less prone to overfitting. It works well for managing unstructured and unbalanced data, which is typical for tasks involving the classification of medical images. The study achieves encouraging findings using a dataset of brain MRI scans that includes and does not include malignancies. Using DenseNet-121 transfer learning, the suggested model outperforms a non-hybrid CNN-based model with an accuracy of 98.8%, achieving a F1 score of 0.97 and an accuracy of 99.02%. Lower training and validation loss show greater generalisation to the test set for the C-XGBoost model. Overall, the study showcases the proposed model's potential as a reliable technique for early detection of brain tumours, offering high accuracy in medical image analysis.

Brain tumour segmentation in MRI is addressed in the study "Automatic Brain Tumour Segmentation using Fully Convolution Network and Transfer Learning" by Sinan Alkassar, Mohammed A. M. Abdullah, and Bilal A. Jebur [9]. The VGG-16 network is used together with fully convolutional network and transfer learning techniques. Using pixel-wise classification and encoder-decoder networks, the suggested approach delivers state-of-the-art results on the BRATS 2015 database, with a Dice score of 0.89 for whole tumour segmentation and a global accuracy of 0.97785. On CPU and GPU architectures, comparisons with current approaches show that the mean Dice score of 89% is superior. The MATLAB-based studies confirm the high classification performance using samples of brain tumour segmentation findings and a confusion matrix.

N. Sravanthi et al. [10] Addressing the challenge of detecting early-stage brain tumours obscured by MRI noise, the study proposes a system specifically designed for processing and pinpointing tumours in images. The implemented techniques include conversion to grayscale, noise-removal filters, and image segmentation for robust edge detection. Enhanced by the integration of various algorithms, the system demonstrated marked improvement in tumour identification accuracy. All methodologies and algorithms were cohesively built and tested within the Matlab platform.

Geethanjali N et al. [11] in this paper proposed a model for performing challenging tasks like brain tumour classification. The dataset used in this is the MRI dataset which is available on the Kaggle website. While developing the model the data was first pre-processed by using various image processing techniques like filtering, blurring, cropping, etc., then the data was split into training and testing sets which were then given to the CNN models like Resnet50, DenseNet and EfficientNetB1. The models achieved an accuracy of 91%, 99.31% and 90.24% respectively. In short, this paper demonstrates the efficacy of their brain tumour classification model, leveraging MRI data and employing advanced CNN architectures

The proposed [12] method utilises the Resnet50 architecture, a champion in the 2015 ILSVRC ImageNet competition, known for its success in biomedical data. Employing a pre-trained model aims to capitalise on prior knowledge. The model is modified by removing the last 5 layers and introducing 10 new layers, enhancing its depth. In hybrid CNN architectures, layer order is crucial, adhering to established CNN theory. Evaluation against established models, including Alexnet and InceptionV3, highlights the hybrid model's superior performance in brain tumour detection, achieving a peak accuracy of 97.2%. The study suggests potential integration into computer-aided systems for improved early and accurate brain tumour diagnosis, paving the way for further exploration of hybrid structures.

Tonmoy Hossain et al. [13] This research addresses the challenging task of brain tumour segmentation in medical images. The study employs Fuzzy C-Means for 2D MRI image extraction and subsequently applies both traditional classifiers (e.g., SVM, KNN) and a Convolutional Neural Network (CNN). The CNN, implemented using Keras and Tensorflow, achieves a commendable accuracy of 97.87%, surpassing the performance of traditional classifiers. This demonstrates the effectiveness of deep learning approaches in accurately identifying brain tumours.

Joel Menachery, Ishan Kumar Anand, and Michael Moses Thiruthuvanathan use Magnetic Resonance Imaging (MRI) pictures to study brain tumour identification and segmentation techniques[14]. They emphasise the significance of early detection for effective treatment and explore various deep learning models, including DenseNet201, Inception V3, ResNet50, and MobileNet. The study aims to find a more accurate and efficient method for detecting brain tumours, comparing the models based on training accuracy, with ResNet50 leading at 85.30%. The research contributes to advancing deep learning applications in medical image analysis for improved brain tumour detection.

In this paper, Soheila Saeed et al. [15] suggested a model in which they used 2D CNN and Convolutional auto-encoder neural networks after applying augmentation techniques on the preprocessed MRI data. This was done using a dataset of 3264 T1-weighted, contrast-enhanced MRI pictures. The suggested auto-encoder neural network and the 2D CNN produced results with accuracy of 95.63% and 96.47%, respectively.

2.1. Limitation of existing systems

The existing brain tumour detection systems are riddled with several limitations that hinder its efficacy. Firstly, the systems are marked by a noticeable inconsistency in human interpretation. Radiologists, based on their individual expertise and subjected to fatigue or the overwhelming volume of scans, might interpret MRI scans differently, introducing potential inaccuracies in tumour detection.

Additionally, the prevailing manual review process, being inherently time-consuming, leads to significant delays in diagnosis. Such delays not only disrupt the efficient planning of therapeutic strategies but can also jeopardise patient prognosis, potentially escalating the associated health risks. Furthermore, the conspicuous absence of automation exacerbates these challenges. This manual-centric approach does not fully harness the potential of advanced computational techniques, making the process both slower and potentially less accurate, especially when confronted with vast imaging datasets. This lack of automation not only amplifies the operational bottlenecks but also leaves a gaping need for a system capable of rapidly and accurately processing extensive imaging data, thereby underscoring the urgent need for improvements and innovations in the field.

Table 1. Overview of Analysed papers

	Dataset	*Methods Used*	*Results/Accuracy*	*Purpose*
[1]	Five MRI datasets	Support vector machine, and Multilayer Perceptron	Segmentation: 0.945, Classification: 0.9176	Classification and Segmentation
[2]	2020 BraTS	9 layer CNN model with 14 stages	0.9974	Classification
[3]	UCI datasets	Convolution Neural Network	0.91	Classification
[4]	MRI images from Brain Web data set	OTSU threshold segmentation.	0.9485	Classification
[5]	3264 MR images from kaggle.com	ResNet-50, VGG16, and Inception V3	0.933	Classification
[6]	BRATS 2018	Cascade Convolution Neural Network (C-CNN), and distance-wise attention (DWA)	Whole Tumour: 0.9203, Enhancing Tumour: 0.9113, Tumour core: 0.8726	Segmentation
[7]	BraTS 2017-2020	U-Net	0.9330	Segmentation
[8]	Brain scan images from the figshare public repository	DenseNet20-based non-hybrid CNN model, DenseNet201 based C-Xgboost model	CNN model: 0.9880434, XGBoost: 0.99021739	Classification
[9]	BRATS 2015	VGG-16	Accuracy: 0.97785, Dice score: 0.89	Segmentation
[10]	Grayscale MRI images	Support Vector Machine	0.97	Segmentation
[11]	MRI dataset from Kaggle	Resnet50, DenseNet, EfficientNetB1	Resnet50: 0.91, DenseNet: 0.9931, EfficientNetB1: 0.9024	Classification
[12]	MRI dataset from Kaggle	Modified Resnet50	0.9701	Classification
[13]	BRATS	5 Layer Convolutional Neural Network	0.9787	Classification
[14]	MRI dataset from Kaggle	ResNet50, DenseNet201, InceptionV3, MobileNet	ResNet50: 0.8909, DenseNet201: 0.9315, InceptionV3: 0.9391, MobileNet: 0.9492	Classification
[15]	3264 T1-weighted contrast-enhanced MRI images	2D CNN, Convolutional auto-encoder neural network	2D CNN: 0.9647, Convolutional auto-encoder neural network: 0.9563	Classification

3. Proposed Methodology

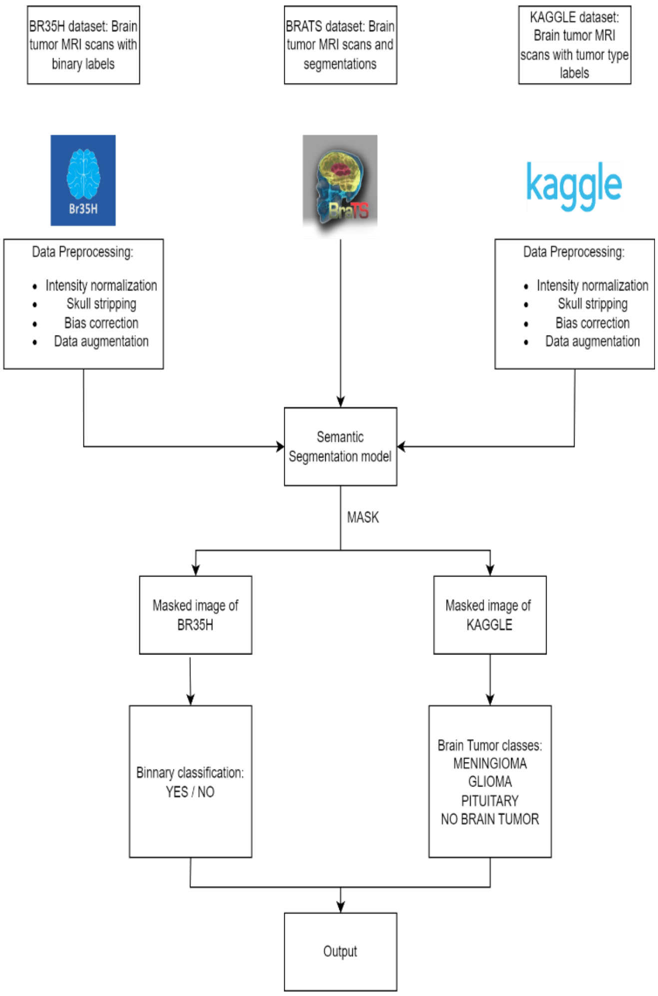

Fig. 2. Proposed Methodology

The proposed method aims to solve two main tasks: brain tumour segmentation and tumour type classification using BraTS brain tumour segmentation dataset and brain tumour MRI dataset. The approach begins with data acquisition and preprocessing, focusing on the BraTS dataset for segmentation and another dataset for tumour type classification. For segmentation, a U-Net model is trained to achieve accurate detection of tumour boundaries. The segmentation model and its output are used to label tumour types in another dataset. Pretrained models such as ResNet50 and EfficientNetV2 are used to determine the presence of a tumour. When tumours are detected, a secondary model is used to classify tumour types. A series of CNN architectures including VGG16 and EfficientNetV2 are tested to improve performance. The accuracy and reliability of the methodology are evaluated and its applicability to binary classification of brain tumours (Br35H) and identification of tumour types is verified. This comprehensive approach uses both segmentation and classification methods to provide a robust solution for brain tumour analysis.

In selecting the Enhanced U-Net for segmentation and ResNet50 for classification, our choices are grounded in their exceptional performance demonstrated in various studies. The Enhanced U-Net, as proposed by MD Abdullah Al Nasim et al., exhibits superiority over other CNN-based models, including FCNN and RCNN, showcasing remarkable accuracy and precision in segmenting diverse brain tumour sub-regions[7]. Furthermore, its adaptability across multiple datasets, as evidenced by its training and evaluation on BraTS datasets for consecutive years, reinforces its reliability. ResNet50, as highlighted by Mahmud, Mamun, and Abdelgawad, consistently outperforms established models such as Inception V3, ResNet-50 and VGG16 in terms of accuracy, recall, AUC, and loss[5]. Its effectiveness in early brain tumour detection and its potential integration into computer-aided systems, as suggested by Geethanjali N et al.[11] and Ahmet Çinar and Muhammed Yildirim[12], further solidify its suitability for our research. These choices align with our objective of achieving accurate segmentation and classification in brain tumour detection while considering their robustness, adaptability, and potential for future advancements.

3.1. Data Collection and Preprocessing

For this phase, we'll begin by collecting multiple datasets: the BraTS dataset for segmentation purposes, the Br35H dataset for binary classification, and the brain tumour dataset from Kaggle for understanding various brain tumour types. After acquisition, our focus will shift to data preprocessing. This process encompasses several stages. First, cleaning the datasets to eliminate errors or inconsistencies, ensuring the quality and reliability of the data. We will then perform normalisation, adjusting the data values to fit within a consistent range. Furthermore, data augmentation techniques will be applied to artificially enhance the dataset's size, promoting variety and mitigating overfitting risks. These steps ensure we maintain a consistent, high-quality dataset pivotal for effectively training our models.

3.2. Transfer Learning for Segmentation

Our approach leverages the power of transfer learning for the segmentation process. By utilising pre-existing information, transfer learning expedites model training and gets around the problem of scarce labelled medical data. Positive transfer learning is a useful strategy for biomedical image analysis since it increases model accuracy for novel tasks [20].

A pre-trained deep learning model, with the potential choice being the U-Net architecture, will be fine-tuned using the BraTS dataset. The primary goal here is to train this model so it can accurately pinpoint the regions within brain scans that are associated with different tumour types

3.3. Labelling tumour types

Once segmentation is accomplished, the model will be applied to label the tumour types present in the second dataset. Emphasis will be on automating this process to maximise efficiency and ensure precise classification.

3.4. Classification Model Training

For the classification process, our methodology will harness the potential of an ensemble of Convolutional Neural Network (CNN) architectures. Examples include the likes of ResNet and VGG, complemented with the AdaBoost algorithm. The main objective during this phase is to train the model to expertly categorise the labelled brain tumour images into their respective types.

3.5. Model Evaluation and Validation

To ascertain the effectiveness of our models, both the segmentation and classification models will undergo a rigorous evaluation process. We will assess their performance using various metrics such as accuracy, precision, recall, and the F1-score. Beyond evaluation, we will validate the models on separate test datasets, ensuring their robustness and reliability.

3.6. Hardware and Software Setup

Optimal hardware configuration is pivotal for efficient model training. Therefore, our recommended hardware setup will comprise an RTX GPU coupled with a high-performance CPU.
On the software front, the system will necessitate the installation of Python 3.8 or a more recent version. Essential libraries like Tensorflow, Keras, Scikit-Learn, Numpy, and Pandas will also be part of the software stack, ensuring a seamless model training and evaluation process.

3.7. System Testing and Optimization

After setting up the system components, thorough testing will be undertaken to ensure that all components integrate flawlessly. There will also be a focus on fine-tuning any hyperparameters, optimising memory usage, and addressing performance bottlenecks to ensure efficient operation.

4. Data

4.1. Dataset Used: BraTS Brain tumour Segmentation Dataset

The BRATS 2020 dataset is a collection of brain tumour MRI scans used for the evaluation of state-of-the-art methods for the segmentation of brain tumours in multimodal magnetic resonance imaging (MRI) scans

4.1.1. Contents in the dataset:

Id: Identifier for the data point.
MRI Scans: Brain tumour MRI scans are included in the dataset. Four MRI modalities are included in each scan: T1, T1Gd (post-contrast T1-weighted), T2, and T2-FLAIR1: These scans were obtained using a variety of scanners from different institutions and distinct clinical protocols.
Tumour Masks: The dataset includes complete masks for brain tumours in addition to the MRI scans. The labels on these masks correspond to distinct tumour sub-regions, including the necrotic and non-enhancing tumour core (NCR/NET — label 1), the peritumoral edema (ED — label 2), and the GD-enhancing tumour (ET — label 4).
Segmentation Tasks: The evaluation of segmentation in the dataset is predicated on the segmentation of brain tumours that are inherently heterogeneous, specifically gliomas.

4.2. Dataset Used: BR35H Brain tumour Detection Dataset

The BR35H dataset is a collection of brain tumour MRI scans used for the detection and classification of brain tumours.
Contents in the dataset:
Id: Identifier for the data point.
MRI Scans: The dataset contains 3060 Brain MRI Images. Each scan is a grayscale image of a slice of the brain, with pixel intensity representing different tissue types.
Tumour Labels: There are two categories in the dataset (yes and no). There are 1500 brain MRI images with tumours in the yes folder and 1500 brain MRI images without tumours in the no folder.
Detection Tasks: The BR35H dataset is used in machine learning and artificial intelligence research to develop automated classification techniques for detecting brain tumours.

4.3. Dataset Used: Brain MRI Images Dataset from kaggle

The Human Brain MRI Images Dataset is a collection of human brain MRI images classified into 4 classes.

4.3.1. Contents in the dataset:

Id: Identifier for the data point.
MRI Scans: The dataset contains 7023 MRI scans of human brain tumours. Each scan is a grayscale image of a slice of the brain, with pixel intensity representing different tissue types.
Tumour Labels: The dataset is divided into four categories: glioma, meningioma, no tumour, and pituitary. Each category represents a different type of brain condition or tumour.
Classification Tasks: Brain MRI Images Dataset is used in machine learning and artificial intelligence research to develop automated classification techniques for detecting and classifying brain tumours into these four categories.

5. Proposed System

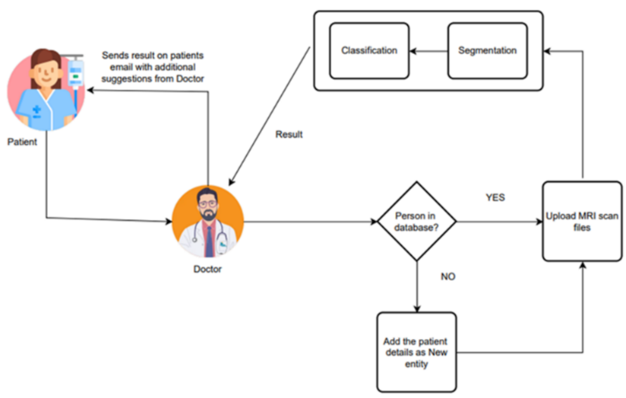

Fig. 3. Proposed System

In the above flowchart , the process of brain tumour detection is shown, which is designed to help medical experts diagnose brain tumours by analysing MRI data. An MRI scan is the first phase, which produces finely detailed images of the brain. These MRI scan files are then uploaded to the detection system for further examination.
During the segmentation stage, the MRI images are processed using a specific model that finds and highlights possible areas of interest in the brain scans. Furthermore, this segmentation model generates a mask that identifies the kind of tumour cell that is present in these areas, offering detailed information about the characteristics of the tumours that have been found.
Next, the classification system is applied, which consists of two different models. The Binary Model predicts if a tumour is present or not, providing a basic evaluation. In order to address the challenges presented by the small dataset size and potential recall concerns in a multi-class setting, the system deploys the Multiclass Model if the binary model indicates the presence of a tumour. In addition to classifying the tumour type, the Multiclass Model also differentiates between pituitary tumours, meningiomas, gliomas, and no tumour.
The results are obtained after the classification process is finished. Notably, the patient is not informed of the results directly in the flowchart. Rather, the doctor receives them initially for confirmation. When a tumour is detected by the Binary Model, the Multiclass Model is employed by the system to provide comprehensive details regarding the particular kind of tumour. These results are then returned to the physician for a comprehensive examination.
Equipped with this extensive data, medical practitioners can make

well-informed medical judgments and suggest additional courses of treatment. A reliable and accurate diagnostic procedure is ensured by the integration of segmentation and classification models and the meticulous verification performed by medical professionals. Furthermore, the system illustrates the potential application of Explainable Artificial Intelligence (XAI) approaches, mainly because of the segmentation mask. Making decisions about the treatment of brain illnesses more quickly and accurately is made possible by this comprehensive approach.

6. Conclusion

In conclusion, the proposed advanced machine learning system for brain tumour detection and classification addresses critical challenges related to the accuracy and efficiency of brain tumour diagnosis. Using datasets like BraTS and transfer learning techniques, it uses models like ResNet50 and EfficientNetV2 for tumour presence detection and U-Net for segmentation. Potential ensemble methods such as AdaBoost and combinations of CNN architectures further increase its capabilities. This system streamlines the diagnostic process, reduces variability in human interpretation, minimises delays in treatment planning, and ultimately improves patient outcomes.

By automating and speeding up brain tumour diagnosis, it reduces patient stress and gives healthcare providers a more reliable tool to make accurate and timely assessments..

Conflicts of interest

The authors declare no conflicts of interest.

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