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A DEEP LEARNING APPROACH FOR DETECTION AND CLASSIFICATION OF BRAIN TUMOURS FROM MRI IMAGES

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ABSTRACT:
The World Health Organisation (WHO) identifies brain tumours as one of the leading causes of death in the world. This disease is challenging to identify because of its complexity and cunning character. Because of the high risk of clinical occurrences, persistent brain tumour illness is a severe public health issue worldwide. Despite the general consensus that persistent brain tumour disease has considerable interactions with elevated risks of vascular events, end-stage excretory organ disease, and all-cause mortality, there is still inadequate information on individuals. Deep learning (DL), a branch of machine learning, has recently shown impressive results, particularly in tasks like classification and segmentation. Imaging can be done in various ways to look for brain tumours. Magnetic Resonance Imaging MRI is widely utilized because it produces high-quality images without harmful ionizing radiation. MRI enables the early diagnosis and evaluation of brain tumours as a preventive medical measure. Brain tumour diagnosis is aided by MRI, which provides thorough information on human-sensitive tissue.
The Convolutional Neural Network (CNN) is a popularly used method and sought-after model for classification in modern times. Like the human brain, the CNN-based expert system's input, neurons, hidden layers, and output are all interconnected. The study focuses on developing and optimizing deep learning models to handle the complexity and heterogeneity of brain tumours. CNNs are commonly employed for their ability to automatically learn discriminative features from medical images, particularly MRI scans. These models leverage large datasets to understand representations that capture the subtle variations and distinctive patterns indicative of brain tumours.
Keywords: Brain tumour, Deep Learning, Machine Learning, Convolution Neural Networks (CNN), MRI

I. INTRODUCTION:

Every year there is a rise in the number of people diagnosed with a brain tumour. Uncontrolled cell development is the root cause of tumours. Malignant brain tumours are far more common than their benign counterparts. Primary tumours are those that originate within the brain or central nervous system (CNS). They develop directly in the brain tissue or its surrounding structures, such as the meninges, which are the protective membranes covering the brain and spinal cord[11].

On the other hand, secondary tumours refer to tumours that have spread from other parts of the body into the brain. These tumours are also known as metastatic tumours, as they result from the spread (metastasis) of cancer cells from their original site to the brain. Secondary tumours in the brain are not considered primary because they did not originate in the brain or CNS, but rather spread to it from elsewhere in the body [1].

Tumours of the brain are classified into four distinct grades, each corresponding to a different degree of tissue abnormalities. Grade 1 and 2 tumours are considered low-grade and pose little threat to the patient. Tumours with a grade of 3 or 4 are considered to be very malignant. Meningioma, which often develops around the top and outer curve of the brain, accounts for 36.1% of all primary tumours[2,3].

The brain holds significant importance as a vital organ within the human body, playing a crucial role in controlling and facilitating decision-making processes. As the central hub of the nervous system, it is imperative to ensure the protection and well-being of this essential component, safeguarding it against any potential harm or ailments. Tumours, resulting from the abnormal proliferation of cells, are the primary afflictions that can harm the brain. Among the various types of tumours, Meningioma, Glioma, and Pituitary tumours specifically affect the brain, distinguishing them from other types that may occur elsewhere in the body[4].

II. LITERATURE SURVEY:

a) MAGNETIC RESONANCE IMAGING (MRI):

MRI is a useful tool for detecting and treating brain tumours. Its ability to produce comprehensive anatomical images assists healthcare practitioners in accurately diagnosing brain tumours, planning therapies, and tracking disease development[7].

Here's an overview of how MRI used for BTD:

MRI is a non-invasive medical imaging technique that is widely used for detecting and visualizing brain tumours. It produces precise, high-resolution images of the brain, helping doctors to spot and characterise suspected tumours. Here are the key steps involved in MRI for brain tumour detection:

Image Acquisition: The individual is reclined on a table that may be slid inside the MRI scanner. The brain may be seen in great detail using magnetic fields and radio waves. Different MRI sequences are employed, such as T1-weighted, T2-weighted, and contrast-enhanced sequences, to capture various aspects of the brain tissue and enhance tumours visibility.

Image Interpretation: The acquired MRI images are then interpreted by radiologists or specialized computer algorithms. They analyse the images to identify any abnormal regions that may indicate the presence of a brain tumours. Tumours can appear as areas of abnormal signal intensity or mass-like structures within the brain tissue[9].

Tumours Characterization: Once a potential tumour is identified, further analysis is conducted to determine its characteristics. This includes assessing the tumours' size, location, shape, and relationship to surrounding structures. Additionally, contrast-enhanced MRI can help identify areas of increased vascularity or blood-brain barrier disruption, providing additional diagnostic information.

Treatment Planning: The MRI findings play a critical role in treatment planning. The detailed information obtained from the MRI images helps determine the best course of action, such as

surgical resection, radiation therapy, chemotherapy, or a combination of treatments. The MRI results guide the neurosurgeon or oncologist in devising a tailored treatment plan based on the tumours' location, size, and characteristics[8].

Follow-up and Monitoring: After treatment, MRI is used for follow-up and monitoring purposes. Sequential MRI scans are performed at regular intervals to assess treatment response, detect potential tumours recurrence, or evaluate the effectiveness of ongoing therapies. Changes in tumours size and appearance over time can be monitored through these follow-up MRI scans.

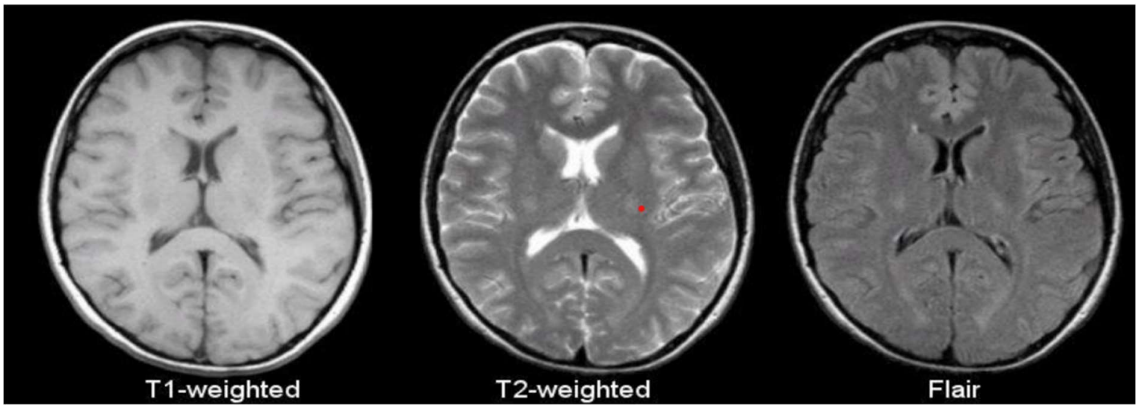


Figure.1 : T1, T2 , Flair image

T1-weighted and T2-weighted MRI sequences are the most typical. Figure.1 shows Bright FAT makes up the sole type of tissue in T1 weighted, while Bright FAT and Water make up both of the two categories of tissue in T2[5]. Repetition time (TR) is low when T1 weighting is used, whereas TE and TR are long when T2 weighting is used. The TE and TR parameters of the pulse sequence stand for the repetition time and the time to echo, respectively, and are measured in milliseconds (ms).[9] The echo time is depicted in the image as the interval between the centre of the RF pulse and the centre of the echo, and TR is the interval between the TE repeating sequence of pulse and echo. Figure.2 shows TE & TR Graph.

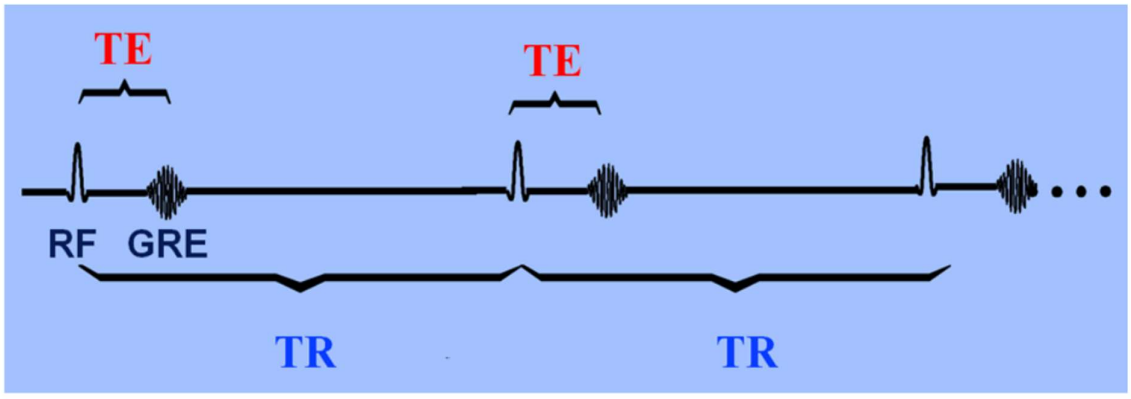


Figure. 2: Graph of TE & TR

various methodologies used in the detection and classification of brain tumours:

b) Medical Imaging Techniques:

i. MRI: It is widely used for BTD and characterization. It provides detailed anatomical information about the brain and helps visualize tumour location, size, and morphology.

ii. Computed Tomography (CT): X-rays are utilised in CT scans in order to obtain images of the brain in a cross-sectional format. They have the ability to provide information regarding the location, size, and density of the tumour.

iii. Positron Emission Tomography (PET): PET scans use radioactive tracers to detect metabolic activity in the brain. They help identify areas of increased glucose metabolism, which can indicate tumour presence[7].

iv. Functional MRI (fMRI): fMRI detects variations in blood flow to the brain in order to evaluate brain activity. It can be used to map tumour-related functional deficits or identify eloquent brain regions that should be preserved during surgery.

III. ROLE OF ML & DL:

i. Image Segmentation: ML algorithms are used to segment brain images, separating tumour regions from healthy tissues. This aids in precise tumour delineation.

ii. Classification Models: Machine learning models are trained on labelled datasets to classify brain tumours into different types or grades. These models can assist in tumour characterization and treatment planning[12].

iii. Radiomics: It produces thorough and high-resolution images of the brain, allowing healthcare practitioners to identify and characterise possible tumours. The features are then analysed using ML techniques to identify cancer characteristics.

d. Deep Learning: DL models, such as CNNs, can analyse brain images and automatically detect and classify tumours. They monitor the state of brain activity by analysing variations in blood flow.

Biomarkers and Molecular Analysis:

a. Genetic and Molecular Profiling: Genetic and molecular analysis of tumours tissue can provide insights into the specific genetic alterations or biomarkers associated with different types of brain tumours. This information aids in classification and personalized treatment decisions[13].

b. Liquid Biopsies: Liquid biopsies involve analyzing tumours-specific genetic material, such as circulating tumours DNA (ctDNA) or circulating tumours cells (CTCs), in a patient's blood or cerebrospinal fluid. These non-invasive tests can provide information about tumours presence, genetic alterations, and treatment response.

Clinical Assessment and Neurological Examination:

a. Patient History and Symptoms: When it comes to forming a first suspicion of a brain tumour, clinical examination and patient history are both extremely important factors. Headaches, seizures, cognitive shifts, or focal neurological abnormalities are some of the symptoms that may point to the presence of a tumour.

b. Neurological Examination: A thorough neurological examination helps assess the patient's motor, sensory, and cognitive functions. Specific neurological deficits can provide clues about tumours location and its effects on brain function.

The early suspicion of a brain tumour relies heavily on clinical examination and patient history. Tumours can cause a variety of symptoms, including headaches, seizures, mental abnormalities, and localised neurological impairments. Each approach has its strengths and limitations, and a multidisciplinary approach involving radiologists, neurosurgeons,

oncologists, and pathologists is typically employed for comprehensive evaluation and management of brain tumours[11].

IV. ROLE OF DIFFERENT CNN MODELS FOR THE BTD & CLASSIFICATION:

U-Net*:* U-Net is a popular architecture widely used for medical image segmentation, including brain tumours segmentation. Its encoder-decoder architecture enables accurate tumour segmentation in brain imaging.

VGG (Visual Geometry Group)Net: VGGNet is a deep CNN a style of architecture renowned for its efficiency and ease of construction. It is made up of several convolutional layers followed by fully connected layers. VGGNet has been applied for brain tumours classification tasks.

ResNet (Residual Neural Network)*:* ResNet is a deep CNN model that introduces skip connections to alleviate the vanishing gradient problem. Its residual blocks allow the network to learn more effectively, making it suitable for brain tumours detection and classification.

InceptionNet: InceptionNet, or GoogLeNet, is characterized by its inception module, which incorporates multiple parallel convolutional operations of different kernel sizes. This architecture is known for its ability to capture both local and global features, making it applicable to brain tumours analysis.

DenseNet (Densely Connected Convolutional Networks): DenseNet connects layers densely, allowing each layer to receive feature maps directly from all preceding layers. This architecture promotes feature reuse and gradient flow, making it suitable for brain tumour classification problems[8].

3D CNNs: While most CNN architectures are designed for 2D images, 3D CNNs are specifically designed to analyze volumetric medical images, such as brain MRI scans. These models capture spatial information in all three dimensions and have shown promising results in brain tumours detection and classification.

V. CNN in BTD:

A CNN is a deep learning system that can take in an input image, assign priority to various features and objects in the image, and distinguish between them.

A CNN requires far less pre-processing than other classification methods. CNN can learn these filters and attributes, whereas filters in primitive systems are hand-engineered. CNN have proven to be effective in analysing medical imaging data, including MRI scans, for accurate tumour detection. The convolution process's purpose is to extract high-level characteristics from the input image, such as edges. CNN need not be restricted to only one convolutional layer. The first CNN is typically used to record the low-level Edges, colour, gradient direction, and other details. We get a network that comprehends the dataset's images as well as we do when there are more layers since the design adapts to high-level features as well[15]. The method yields two types of results: one in which the dimensionality of the convolved feature decreases in relation to the input and one in which it increases or remains constant. In the first

situation, Valid Padding is utilised, and in the second, Same Padding is used[13].

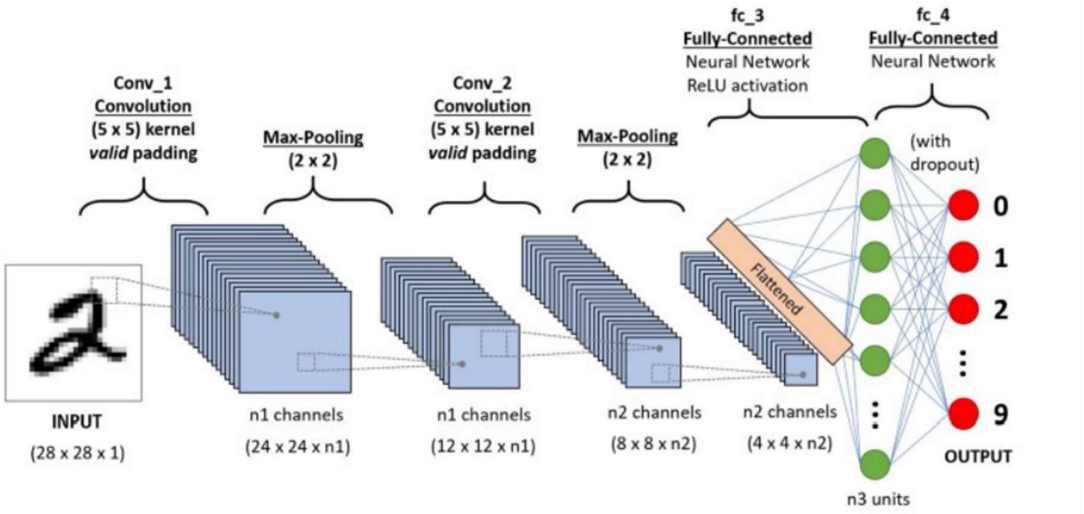


Figure.3 CNN Basic Architecture

The pooling layer, similar to the convolutional layer, plays a crucial role in reducing the spatial dimensions of the convolved features. This reduction in size not only reduces the computational requirements but also aids in capturing dominant features that are invariant to rotation and position. Pooling can be categorized into two types: maximum pooling and average pooling. Maximum pooling selects the maximum value within each kernel-covered region of the image. It not only reduces the dimensionality of the data but also acts as a noise suppressor by discarding noisy activations. On the other hand, average pooling computes the average of all values within the kernel-covered region, primarily focusing on dimensionality reduction without effective noise suppression. Due to its noise suppression capability and better performance in capturing dominant features, maximum pooling generally outperforms average pooling. It effectively reduces noise an spatial dimensions, making it a popular choice in various computer vision tasks[6].

VI. ResNet (RESIDUAL NEURAL NETWORK)

ResNet is a deep NCC architecture that was introduced in 2015 by Kaiming He et al[3]. It introduces a special residual learning approach to solve the difficulty of training very deep neural networks[6]. ResNet uses a technique called skip connections to solve the vanishing gradient problem. Skip connections are direct connections between layers in a neural network. These connections allow the gradient to flow through the network without being multiplied by a small number many times. This makes it possible to train deep neural networks with many layers[6].ResNet has several benefits over other CNN architectures. First, it is able to train deeper networks, which can achieve better performance. Second, it is more robust to overfitting. Third, it is easier to train than other deep neural networks[8]. Figure .4 shows Residual Learning Block Layer.

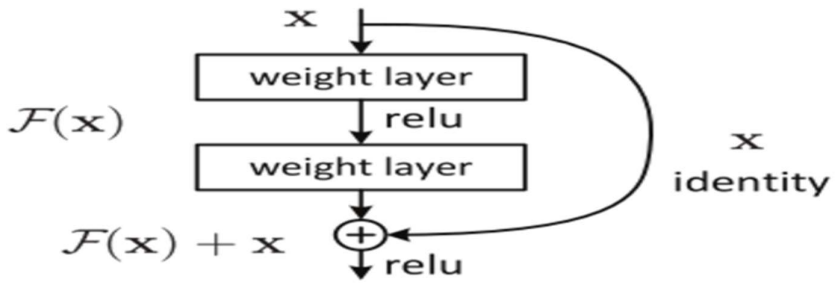
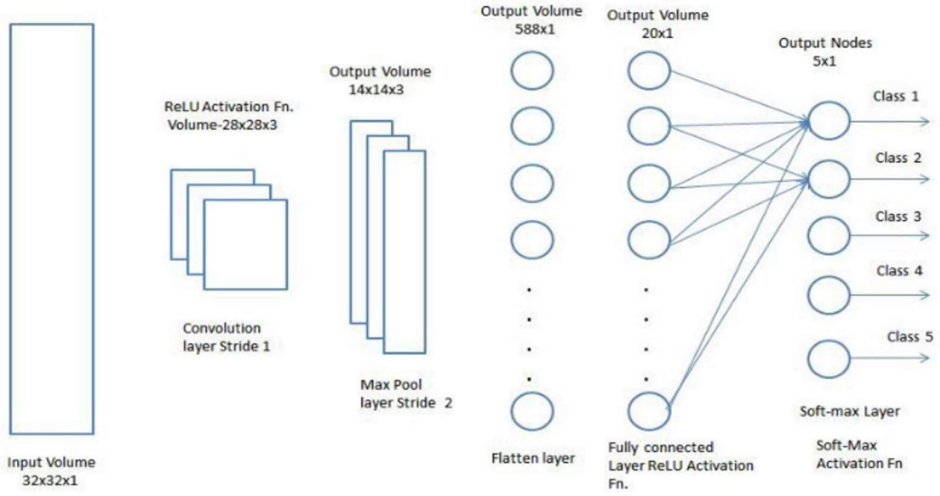


Figure 4. Residual Learning: Block of a Layer

ResNet has been used for image classification, object recognition, and semantic segmentation, among other computer vision applications [9]. It has also been utilised for problems involving natural language processing, such as machine translation and text categorization[12].Here are some of the most popular ResNet architectures:

- ResNet-18 ResNet-34 ResNet- 50
- ResNet-101 ResNet-152 ResNet-200

ResNet is a powerful deep learning model that has had a major impact on the field of



computer vision. It is used by many of the leading companies in the world, including Google, Facebook, and Amazon[15]. Figure 5. Shows Architecture of ResNet50[14].

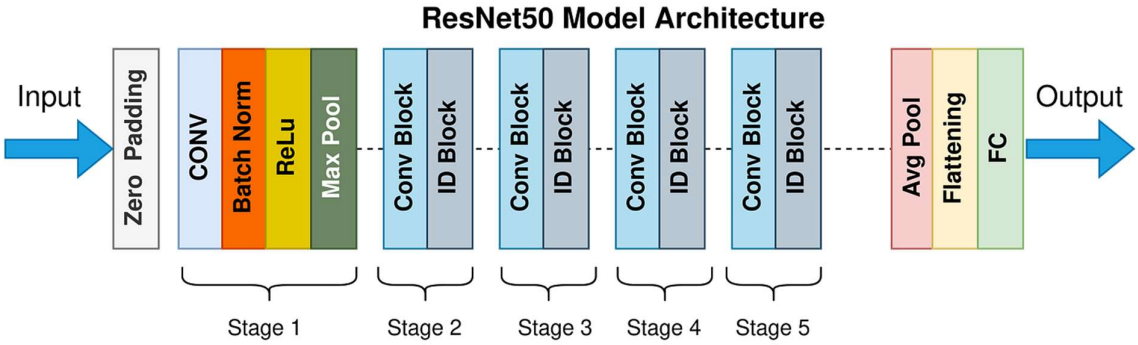


Figure 5. Architecture of ResNet

Based on this understanding, the authors of [4] presented a pre-activation variation of the residual block [8] in which gradients can freely flow through the shortcut connections to any other previous layer. In fact, when training a 1202-layer ResNet with the original residual block from [?], the network performed worse than its 110-layer sibling. Residual block types are depicted in Figure 6.

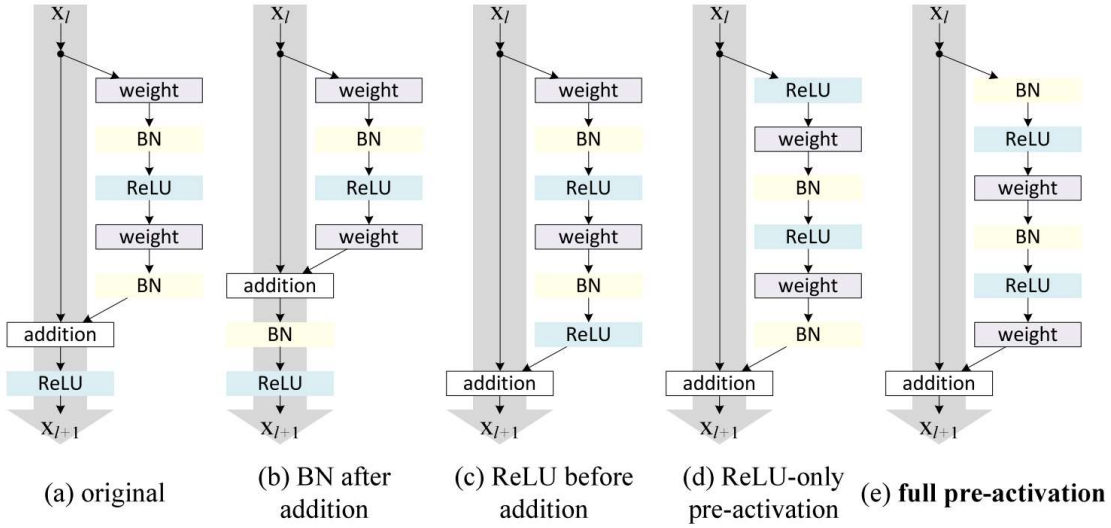


Figure 6. ResNet with ReLU

VII. MOTIVATION AND OBJECTIVE:

The proposed application's purpose is to help neurosurgeons and radiologists discover brain tumours in a cost-effective and non-invasive manner. The research goals are as follows:

- Using matching mask images, train a classifier to detect MRI brain pictures with and without malignancies.
- To apply a segmentation technique to MRI scans in order to identify the tumour from normal brain regions.

VIII.PROPOSED METHODOLOGY:

In this paper, we present a completely automated system for classifying brain tumours. This study investigates the connections between two forms of brain tumours that can develop.

Following are steps implemented in this proposed work. Figure 7 shows complete architecture of proposed model[11].

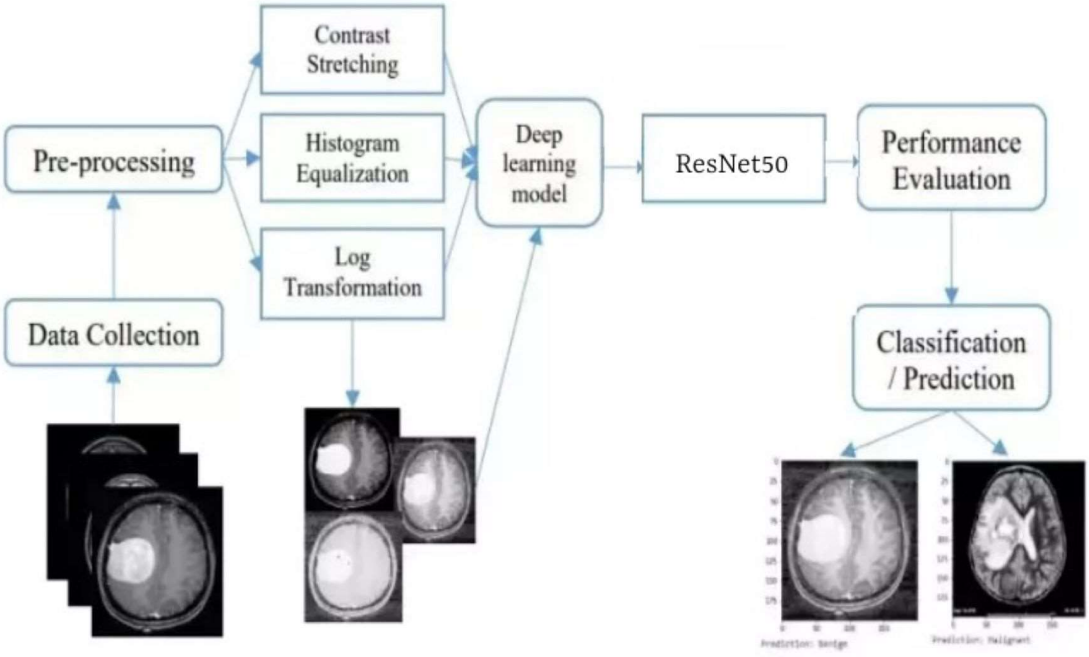


Figure 7. Architecture of Proposed Model

Step-1: Data Collection:

TCIA provided the MRI pictures coupled with the necessary FLAIR segmentation masks. The FLAIR sequence is an accurate technique for generating excellent digital tumour responses (Rucco, Viticchi, and Falsetti, 2020). The Cancer Genome Atlas (TCGA) LGG collection includes images from 109 patients. Figure.8 shows BT MRI Images[11].

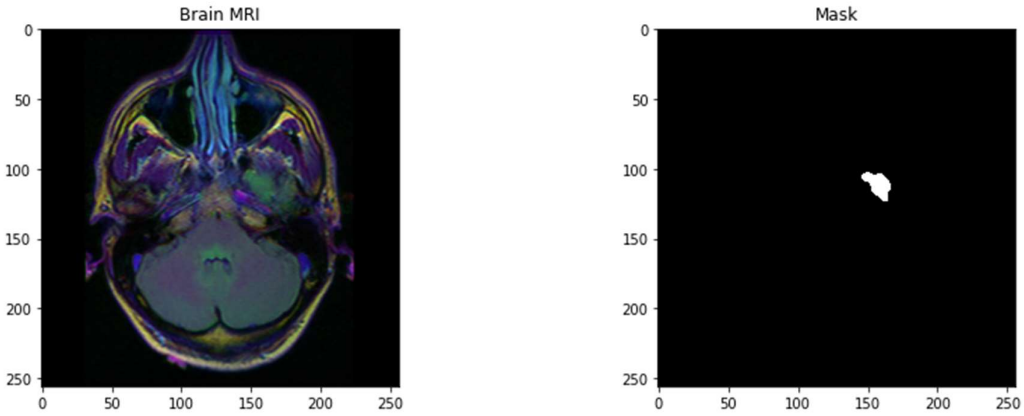


Figure 8: Brain tumour MRI images & their respective masks from the patient

Step-2: Preprocessing

It is used to improve the picture dataset, normalise images, and generate image data. For improvement in images, we used contrast stretching, histogram Equalization, and logarithmic transformation. Voxels are the standard for measuring brain data. The data is organised as 3929 pairs (MRI_scan, MRI_mask). These images are from 109 different patients. Out of a total of 3929 tuples, 1373 have information about tumour tissue, while the remaining 2556 do not.

Step-3: Train, Test & Validation of data:

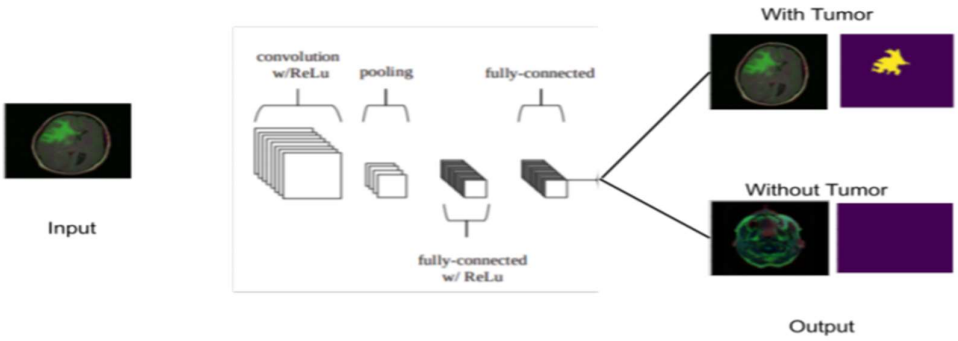
The dataset can be broken down into TS(training set), VS(validation) & TS(testing set).

Step-4: Deep Learning Model – CNN

The tumour status of MRI brain scans can be determined using a CNN model. Applications for object recognition frequently employ CNN models (O'Shea and Nash, 2015). Convolutional, pooling, and fully connected layers are the three types of layers that make up CNNs. Figure shows the basic architecture of CNN[4]. CNN uses convolution and down sampling to layer-by-layer change the original input in order to provide class scores for the classification of brain MRI data[14].

Step-5: Resnet50 model

The model is trained with the Resnet50 as its foundation rather than creating a brand-new network. The basis model is the Resnet50 model because it has shown effective outcomes in biomedical information and because It's preferable to reap the benefits of a pool of pre-trained



networks. Additionally, in a residual network, the model learns from the residual that is left over after subtracting the characteristics that were learned from the inputs of the layers. Figure shows The architecture of Resnet50[10]. Figure 9. And Figure 10. Shows the Resnet models.

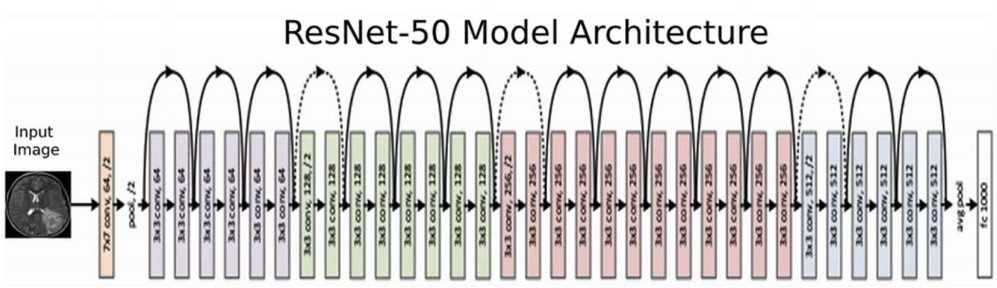


Figure 9: Resnet50 Model Architecture

Input ,padding,Convolution layers, Batch normalisation, Activation (ReLu), and Max pooling

Figure 10. ResNet

are the layers that make up the residual network. In addition to these layers, We've increased the amount of trainable parameters by increasing the total number of parameters by adding additional layers such as Average Pooling, Flatten, Dense, Dropout. Six distinct types of layers make up the ResNet[13].

Input, Padding, Convolution, Batch normalization, Activation (ReLu), and Max pooling. After these Average Pooling, Flatten, Dense, Dropout were added. The purpose of this is to raise the

ceiling on the number of parameters that can be trained[14]. The Performance of ResNet50 after adding all the layers shown in Figure 11.

Model: "resnet50"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 256, 256, 3)	0	
conv1_pad (ZeroPadding2D)	(None, 262, 262, 3)	0	input_1[0][0]
conv1_conv (Conv2D)	(None, 128, 128, 64)	9472	conv1_pad[0][0]
conv1_bn (BatchNormalization)	(None, 128, 128, 64)	256	conv1_conv[0][0]
conv1_relu (Activation)	(None, 128, 128, 64)	0	conv1_bn[0][0]
pool1_pad (ZeroPadding2D)	(None, 130, 130, 64)	0	conv1_relu[0][0]
pool1_pool (MaxPooling2D)	(None, 64, 64, 64)	0	pool1_pad[0][0]
conv2_block1_1_conv (Conv2D)	(None, 64, 64, 64)	4160	pool1_pool[0][0]

Figure 11. Performance of ResNet50

Step-6: ResUNet segmentation for tumour localization

ResUNet is divided into two parts: contraction path and expansion path. Each contraction block receives input from res-blocks and 2x2 max pooling. Each block doubles feature mappings, helping the model understand complicated features. The expansion or decoder component of this architecture is where the majority of the significance rests. Each res-block in the contraction path receives the up-sampled input from the layer below it and adds it to the features it receives as an output[15]. This function guarantees that the features learned during the contraction phase are utilised throughout the reconstruction phase of the picture. The output of the res.block is fed into a 1x1 convolution layer at the end of the expansion route to provide an output of the same size as the input[15].

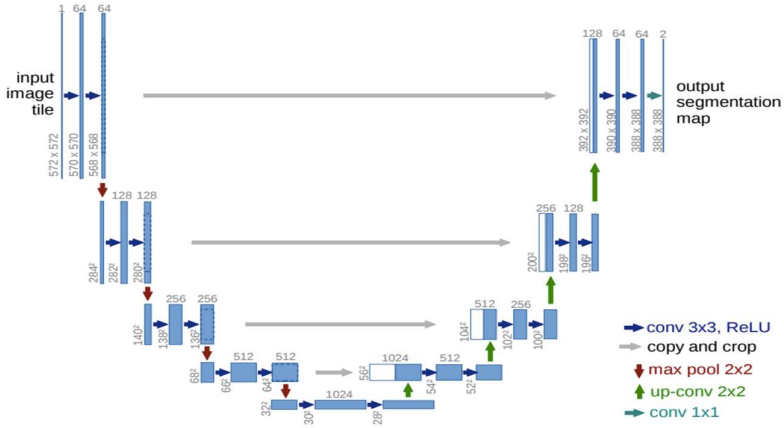


Figure 12. ResUNet Architecture.

Step-7: Evaluation Metrics:

Evaluation metrics such as accuracy and loss for assessing ResUNet's performance model are explained here.

When evaluating a classification model, several metrics are commonly used to assess its performance[31]. Here are some of the most commonly used evaluation metrics for classification models:

i.Accuracy: Accuracy measures the proportion of correct predictions over the total number of predictions.

Accuracy = (TP + TN) / (TP + TN + FP + FN),

where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives. However, accuracy may not be the most reliable metric when dealing with imbalanced datasets.

ii.Precision: Precision measures the proportion of correctly predicted positive instances (true positives) out of all instances predicted as positive. It provides insights into the model's ability to minimize false positives.

Precision = TP / (TP + FP).

Precision is especially useful when the cost of false positives is high.

iii.Recall (Sensitivity or True Positive Rate): Recall calculates the proportion of correctly predicted positive instances (true positives) out of all actual positive instances. It indicates the model's ability to identify positive instances

Recall = TP / (TP + FN). Recall is valuable when the cost of false negatives is high.

iv.Confusion Matrix: A confusion matrix compares predicted labels to actual labels to summarise model performance. It provides a detailed breakdown of true positives, true negatives, false positives, and false negatives, allowing for a comprehensive evaluation of the model's performance.

v. Loss Function:

The Focal Tversky loss function is an adaptation of the Tversky loss function[14], which is commonly used in medical image segmentation tasks[11]. The Tversky index is a similarity metric that balances false positives and false negatives by incorporating two separate weighting factors, namely the Tversky index α and the weight β[14].

The Focal Tversky loss function introduces a modification to the Tversky loss by incorporating a focal parameter γ. The focal parameter is used to assign higher weights to difficult or misclassified samples, which helps the model focus more on challenging regions during training. This modification aims to address class imbalance and improve the model's performance in accurately segmenting smaller or challenging regions of interest.

The formula for the Focal Tversky loss function is as follows:

$$FTL = (1 - Tversky)^{\gamma}$$

where Tversky represents the Tversky index between the predicted and target segmentation maps. The value of γ controls the focusing effect, where a higher γ assigns more weight is given to problematic samples. The Focal Tversky loss function encourages the model to prioritize the accurate segmentation of challenging regions while de-emphasizing well-classified regions. By doing so, It contributes to the model's enhanced accuracy. to handle class imbalance and focus on important areas during the training process [10]

It's worth noting that the Focal Tversky loss function is just one example of how the Tversky loss can be modified or extended to address specific challenges in segmentation tasks. There may be variations or alternative formulations of the focal variant depending on the specific requirements of the task or research study[6]. Figure. 13 shows the Focal Tversky Loss.

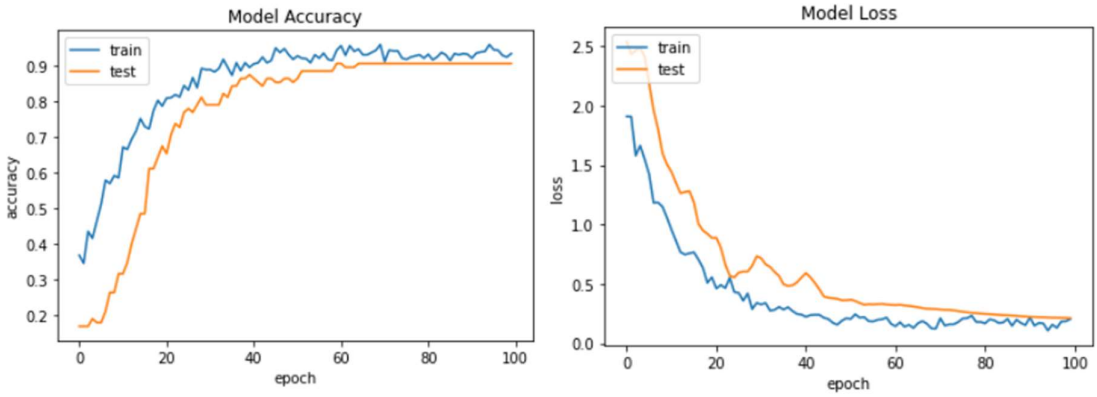


Figure 13: Focal Tversky Loss.

IX. CONCLUSION

This study aims to create a reliable, accurate, and simple autonomous brain tumour classification and localisation system. First, ResNet50-based CNN classifies brain tumours. Classification determines tumour existence. High computational time, precision, and low complexity. ResUNet-based segmentation, another convolution neural network-based classification, is used to locate the tumour in the image and draw an edge around it. The brain MRI scans show the projected tumour position as a mask. Finally, the focal Tversky loss function improves accuracy. 96% training accuracy. The proposed method will assist doctors diagnose tumours and treat patients more accurately due to the importance of physician diagnosis[1].

X.FUTURE WORK:

Unclassified and misclassified materials require special attention. Low-scoring detections have unclassified samples. Despite having malignancies, such samples may be considered "no tumours." Healthy pictures may help in the future. Preprocessing methods may highlight photos' hidden elements. Genetic algorithm, particle swarm optimisation, simulated annealing, etc. may be used in the future to determine the ideal parameter set for classification accuracy.

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