Research Article

Tversky Loss Analysis In Brain Tumour Detection Using CNN And Resnet Models

Dr. C. Bharanidharan[1], Udaiyar karthik murugan[2], Murugan V[3], Yuvabharadhi G[4], S. Arulanandan[5]

[1,2,3,4,5] Department of AI&DS, Panimalar Engineering College, Chennai , India.
Corresponding author mail id: bharani88.c@gmail.com

ABSTRACT

The World Health Organisation (WHO) identifies brain tumours as one of the leading causesof death in the world. This disease is challenging to identify because of its complexity andcunning character. Because of the high risk of clinical occurrences, persistent brain tumourillness 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 onindividuals. Deep learning (DL), a branch of machine learning, has recently shown impressiveresults, particularly in tasks like classification and segmentation. Imaging can be done invarious ways to look for brain tumours. Magnetic Resonance Imaging(MRI)is widely utilizedbecause it produces high-quality images without harmful ionizing radiation. MRI enables theearly 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 modelfor 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 featuresfrom medical images, particularly MRI scans. These models leverage large datasets tounderstand representations that capture the subtle variations and distinctive patterns indicativeof 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.

Then again, optional cancers allude to growths that have spread from different pieces of the body into the mind. These growths are otherwise called metastatic cancers, as they result from the spread (metastasis) of disease cells from their unique site to the mind. Optional growths in the mind are not viewed as essential since they didn't begin in the cerebrum or CNS, yet rather spread to it from somewhere else in the body [1].

Cancers of the mind are ordered into four particular grades, each relating to an alternate level of tissue irregularities. Grade 1 and 2 growths are viewed as poor quality and posture little danger to the patient. Tumors with a grade of three or four are regarded as extremely malignant. Meningioma, which frequently creates around the top and external bend of the cerebrum, represents 36.1% of all essential tumours[2,3].

The mind holds critical significance as an imperative organ inside the human body, assuming a urgent part in controlling and working with dynamic cycles. As the focal center point of the sensory system, guaranteeing the insurance and prosperity of this fundamental part, defending it against any expected damage or ailments is basic. The most common conditions that can harm the brain are tumors, which are caused by an abnormal proliferation of cells. Meningioma, glioma, and pituitary tumors are distinct from other types of tumors that can occur anywhere in the body because they only affect the brain [4].

II .Related Works :

a) MAGNETIC Reverberation IMAGING (X-ray):

X-ray is a valuable device for distinguishing and treating mind growths. Its capacity to create extensive physical pictures helps medical care experts in precisely diagnosing mind growths, arranging treatments, and following sickness development[5-7].

An overview of how MRI is used for BTD is as follows:

X-ray is a painless clinical imaging strategy that is broadly utilized for recognizing and envisioning mind cancers. It produces exact, high-goal pictures of the cerebrum, assisting specialists with spotting and portray thought cancers. The essential steps in MRI for the detection of brain tumors are listed below:

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.

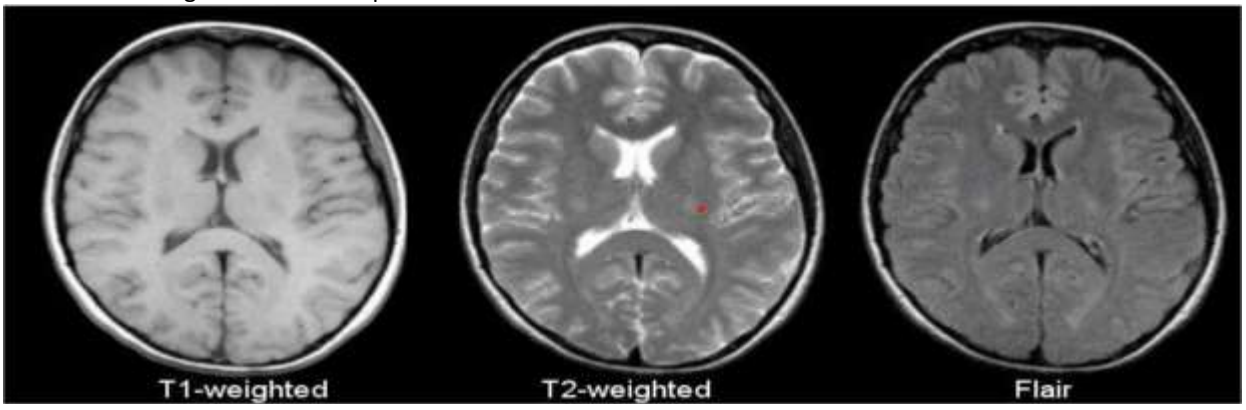
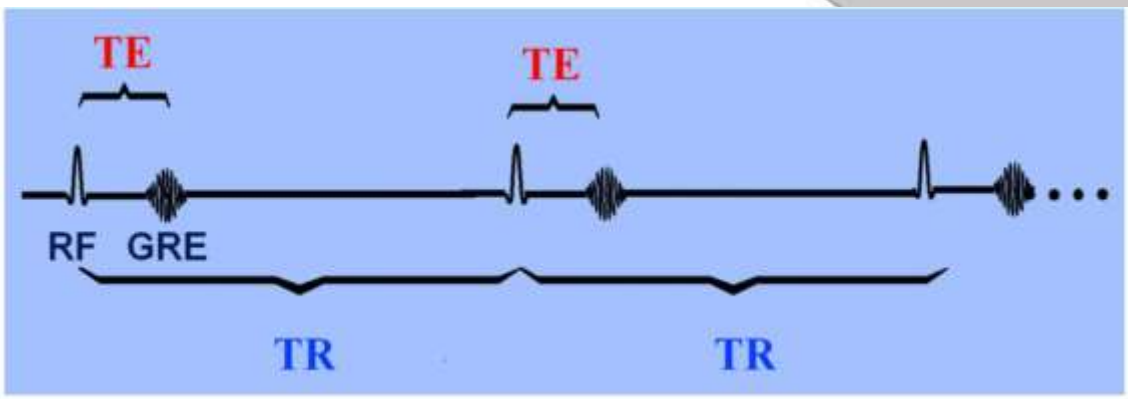


Figure.1 : T1, T2 , Flair image

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 weightingis used, whereas TE and TR are long when T2 weighting is used. The TE and TR parametersof 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 betweenthe 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:



a) **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.

v.

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. Molecular and Genetic Profiling: The specific genetic alterations or biomarkers associated with various types of brain tumors can be discovered through genetic and molecular analysis of tumor tissue. This data supports characterization and customized treatment decisions[13].

b. Liquid Biopsies: Fluid biopsies include breaking down cancers explicit hereditary material, like circling growths DNA (ctDNA) or flowing cancers cells (CTCs), in a patient's blood or cerebrospinal liquid. The presence of tumors, genetic modifications, and treatment response can all be determined by these non-invasive tests.

Clinical Evaluation and Neurological Assessment:

a. Patient History and Side effects: Clinical examination and patient history play a critical role in establishing a first suspicion of a brain tumor. Some of the symptoms that may indicate the presence of a tumor include headaches, seizures, cognitive shifts, and focal neurological abnormalities.

b. An Examination of the Brain: The patient's motor, sensory, and cognitive abilities are assessed through a comprehensive neurological examination. Explicit neurological deficiencies can give signs about growths area and its consequences for cerebrum capability.

Clinical examination and patient history play a significant role in establishing an early suspicion of a brain tumor. Growths can cause different side effects, including migraines, seizures, mental irregularities, and confined neurological impedances. For comprehensive evaluation and treatment of brain tumors, a multidisciplinary approach involving radiologists, neurosurgeons, oncologists, and pathologists is typically used[11]. Each approach has advantages and disadvantages.

The vanishing gradient problem is solved by ResNet using skip connections. In a neural network, skip connections are direct connections between layers. The gradient can move through the network without being repeatedly multiplied by a small number thanks to these connections. This enables the training of deep neural networks with numerous layers[6]. ResNet outperforms other CNN architectures for a number of reasons. To begin with, it can prepare further organizations, which can accomplish better execution. Second, it is more hearty to overfitting. Thirdly, training it is simpler than with other deep neural networks [8].

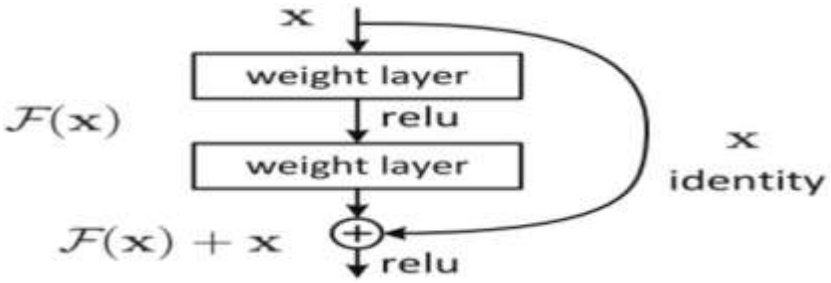


Figure 3 Relu Layer

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

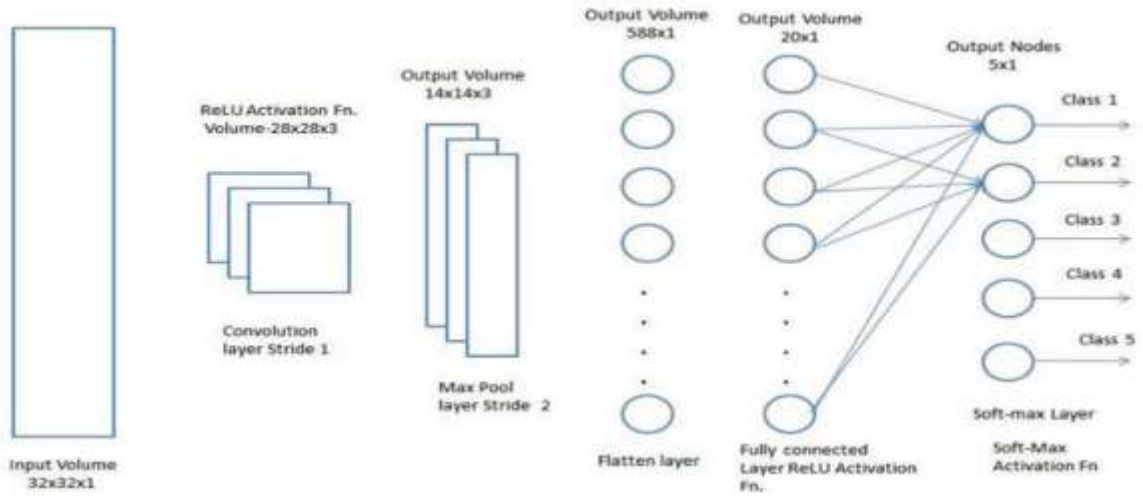


Figure 4. Residual Learning: Block of a Layer

computer vision. It is used by many of the leading companies in the world, including Google, Facebook, and Amazon[12]. Figure 5. Shows Architecture of ResNet50[11].

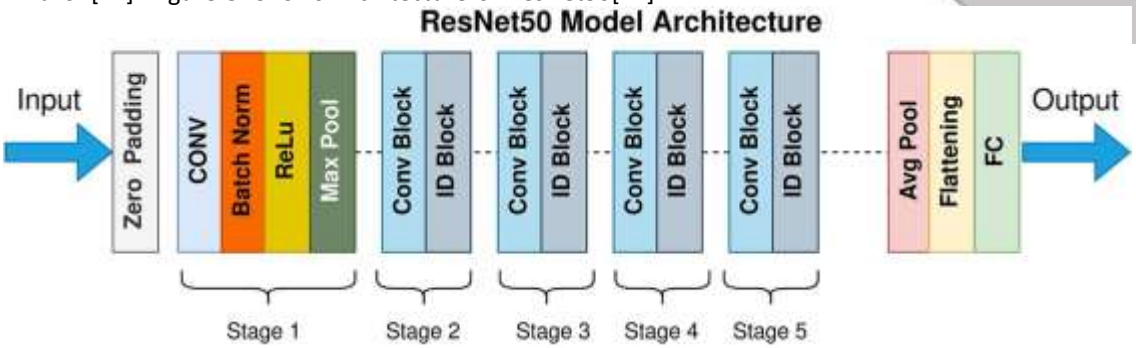


Figure 5. Architecture of ResNet

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 blockfrom, the network performed worse than its 110-layer sibling. Residual block types are depicted in Figure 6.

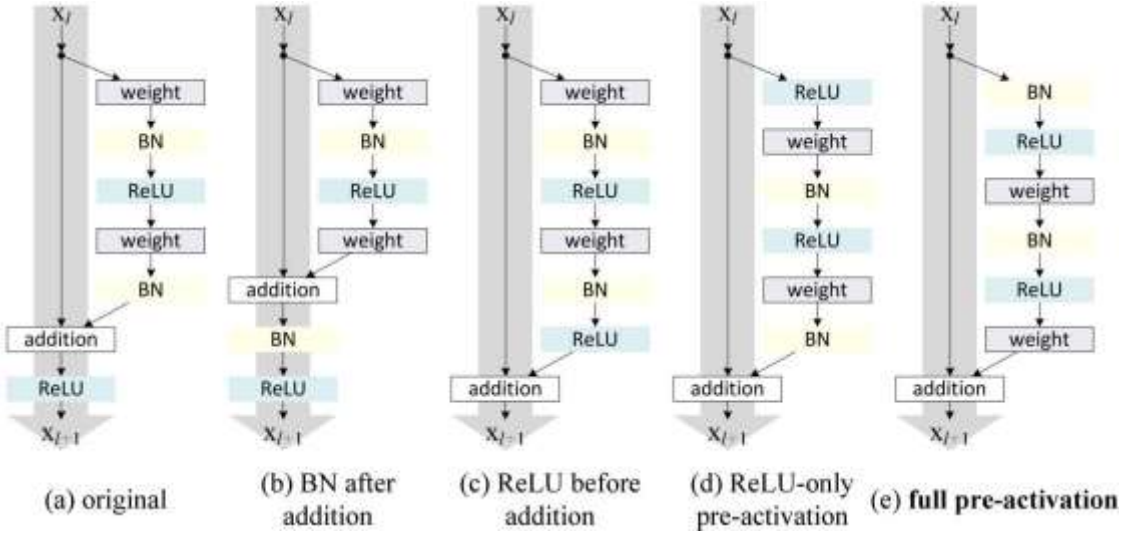


Figure 6. ResNet with ReLU

V.MOTIVATION AND OBJECTIVE:

The proposed application's purpose is to help neurosurgeons and radiologists discover braintumours 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 andwithout malignancies.
- To apply a segmentation technique to MRI scans in order to identify the tumour fromnormal brain regions.

VI PROPOSED METHODOLOGY:

In this paper, we present a completely automated system for classifying brain tumours. Thisstudy 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].

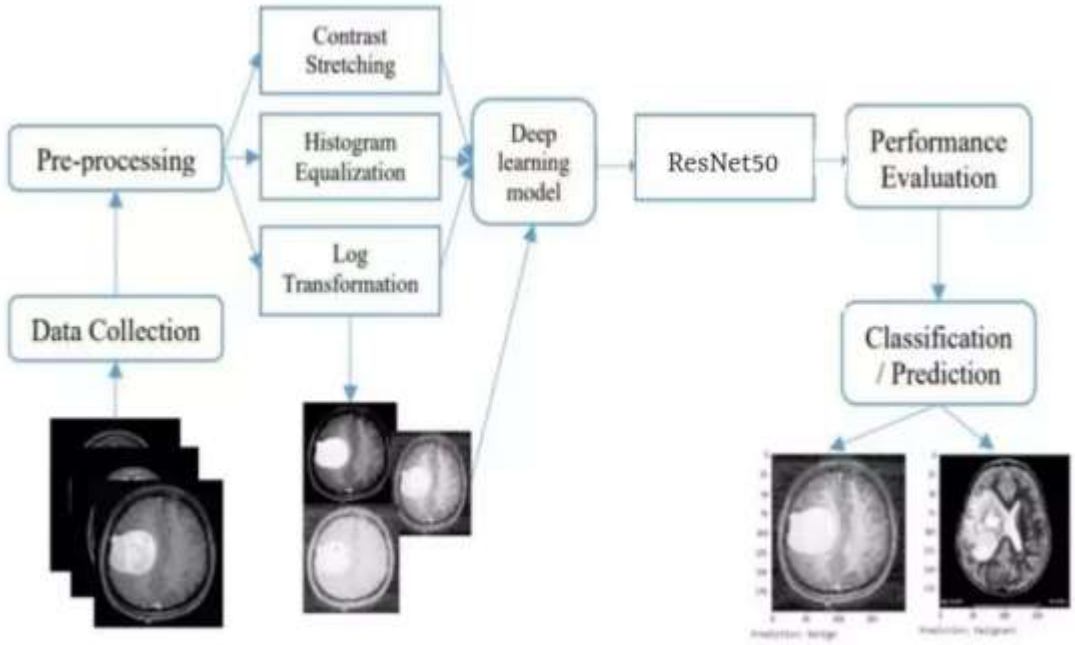
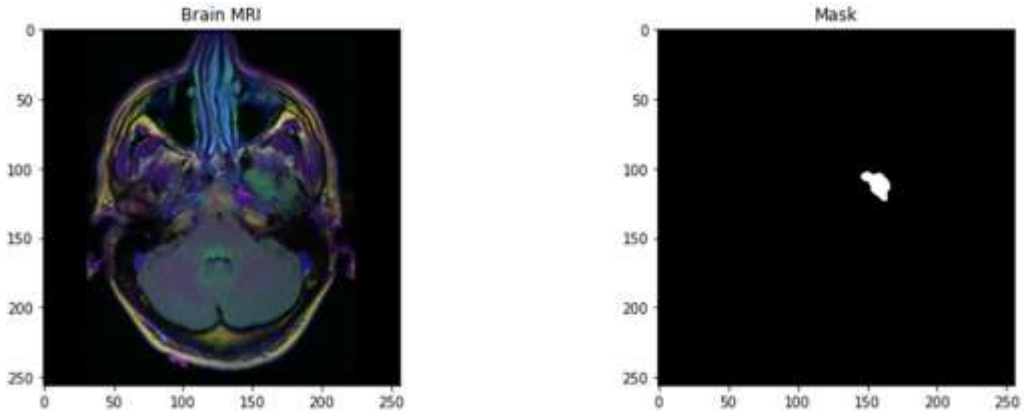


Figure 7. Architecture of Proposed Model

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[13].

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 leftover 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.

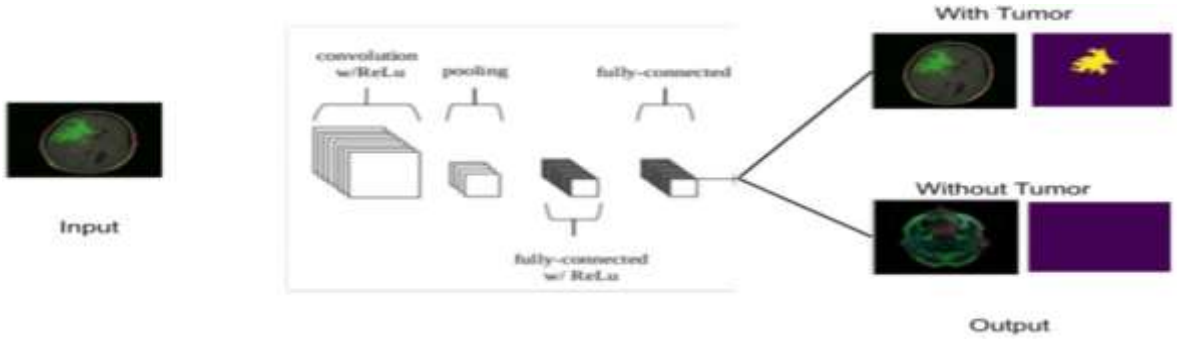


Figure 9: Resnet50 Model Architecture

Input ,padding,Convolution layers, Batch normalisation, Activation (ReLu), and Max pooling
are the layers that make up the residual network. In addition to these layers, We've increasedthe amount of trainable parameters by increasing the total number of parameters by adding additional layers such as Average Pooling,

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 10. ResNet

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[13]. The Performance of ResNet50 afteradding all the layers shown in Figure 11.

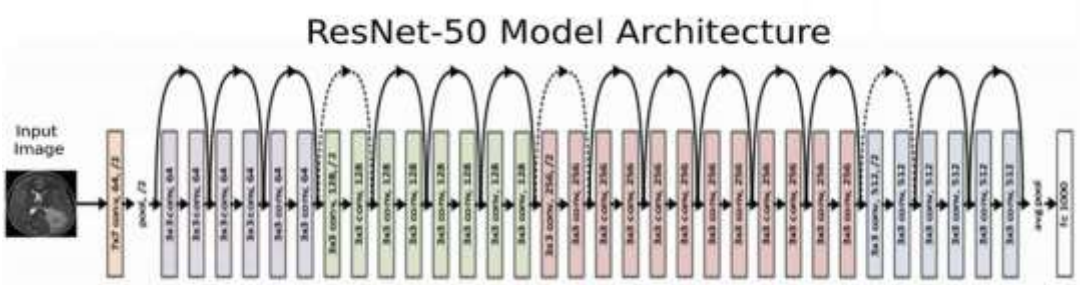


Figure 11. Performance of ResNet50

Step-6: ResUNet segmentation for tumour localization

ResUNet is partitioned into two sections: withdrawal way and extension way. 2x2 max pooling and input from res-blocks are provided to each contraction block. The model gets a better understanding of complex features because each block doubles feature mappings. The majority of this architecture's significance lies in the expansion or decoder component. The up-sampled input from the layer below each res-block in the contraction path is added to the features it receives as an output by each res-block in the path[12]. This function makes sure that the picture's features learned in the contraction phase are used in the reconstruction phase. At the conclusion of the expansion route, the res.block's output is fed into a 1x1 convolution layer to produce an output of the same size as the input[12].

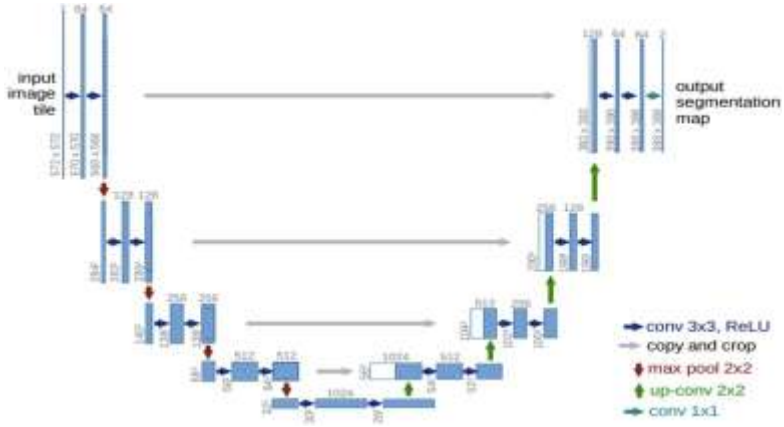


Figure 12. ResUNet Architecture.

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. 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 whendealing 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 abilityto 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 themodel's performance.

v. Loss Function:

The Focal Tversky loss function is an adaptation of the Tversky loss function, 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.

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 Tverskyloss 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.

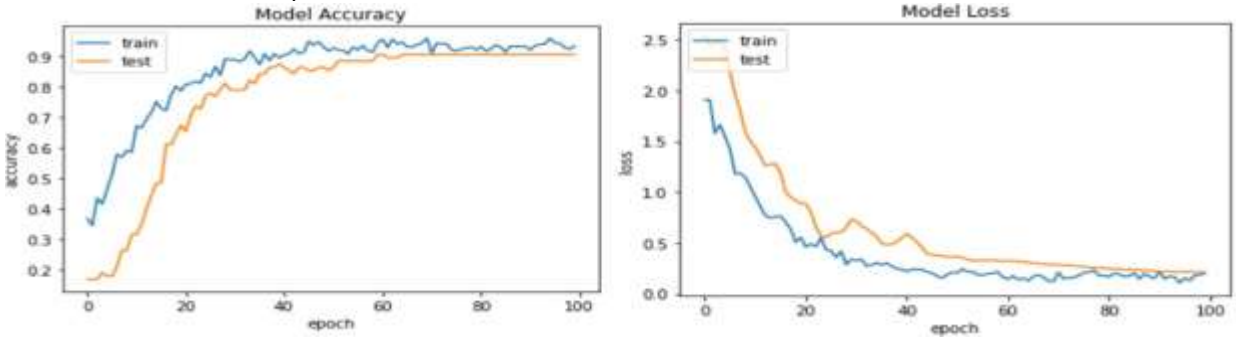


Figure 13: Focal Tversky Loss

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.

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