AN IMPROVED PREDICTIVE ANALYSIS OF BRAIN TUMOR USING RESNET50 AND RESNET34

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Abstract

Tumor is a pre-stage of cancer which has become a serious problem in this era. Researchers are trying to develop methods and treatments to round it. Brain tumor is an exceptional cell enhancement in the brain tissue and may not always be seen in imaging tricks. Magnetic Resonance Imaging (MRI) is a technique which is applied to display the detailed image of the attacked brain location. Brain Tumor is a fatal disease which cannot be confidently detected without MRI. In the project, it is tried to detect whether patient's brain has tumor or not from MRI image using MATLAB simulation. To pave the way for morphological operation on MRI image, the image was first filtered using Anisotropic Diffusion Filter to reduce contrast between consecutive pixels. After that the image was resized and utilizing a threshold value image was converted to a black and white image manually. This primary filters the plausible locations for tumor presence.

On this semi processed image morphological operations have been applied and information on solidity and areas of the plausible locations was obtained. A minimum value of both of these characters has been determined from statistical average of different MRI images containing tumor. Then it was used to deliver final detection result. Though this simulation routine can give correct result most of the time, it fails to perform when tumor's size is too small or tumor is hollow.

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INTRODUCTION

As the world's population ages at an alarming rate, cancer has become a public health concern all over the world. The World Cancer Research Fund's most recent numbers show that cancer is the leading cause of death all throughout the globe. Every year, 12.7 million individuals are diagnosed with cancer, and 7.6 million people die as a direct result of their disease. [1]. Since then, the number of people who get cancer each year has been steadily going up. By 2030, there will be 26 million new cases each year and 1.7 million deaths. Brain tumours, which are a kind of cancer, are a very dangerous and aggressive disease. It happens a lot, which makes it the fifth most common type of tumour. It also kills a lot of people, which puts it just below stomach cancer, uterine cancer, breast cancer, and esophageal cancer [2–3]. [Note:] Brain tumours are usually harder to find and take longer to treat. On average, patients with brain tumours need to be checked every few months. Before coming up with a plan for the next therapy, the doctors will need to find out what stage the disease is in by looking at the results of the most recent exam, which was a referral. Surgery and radiation therapy are the only effective treatments that are available right now. In this way, cancer treatment is a big social problem, both in terms of the economy and the money. It will be very important; both in theory and in the real world, to find a solution to this problem that will work.

The absorbed radiation will be broken down and released by different tissues, which will make different rays that can be picked up for different imaging purposes. CT/PET is at the point when figured tomography (CT) sweeps and positron outflow tomography (PET) examines are finished on a similar plane to make a solitary picture. Radioactive radiation is used in both the CT scan and the PET test, but the PET test is too expensive for most people to get.

Figure 1: Schematic diagram of MRI equipment and inspection.

BRAIN TUMOR

Brain tumor has been one of the most risky diseases which occur usually amidst human beings. Moreover, the probabilities of survival may get amplified. It is possible to detect the tumour at its earliest possible stage. MRI brain imaging is widely used to visualize the brain's structure and architecture. This kind of MRI produces pictures that are more detailed and have fewer arte facts. MRI holds numerous benefits matched with other imaging approaches, offering high contrast amid soft tissues. Yet, the data amount is huge for manual analysis, which is one of the salient complexities in the efficacy MRI usage. Tumor detection needs various processes on MRI images that comprise image preprocessing, image enhancement, feature extraction, and classification (Selvaraj&Dhanasekaran2013).

This is the source of everything a person does, feels, or thinks. Hormones made and released by the brain control how the body handles emotions, recognizes things, thinks, and puts things together. It is protected and kept alive by its skin, skull bones, and meninges. Cerebrospinal fluid, which is mostly water, flows through the brain and spinal cord. This fluid moves through the brain and between the meninges (Charles et al., 200).

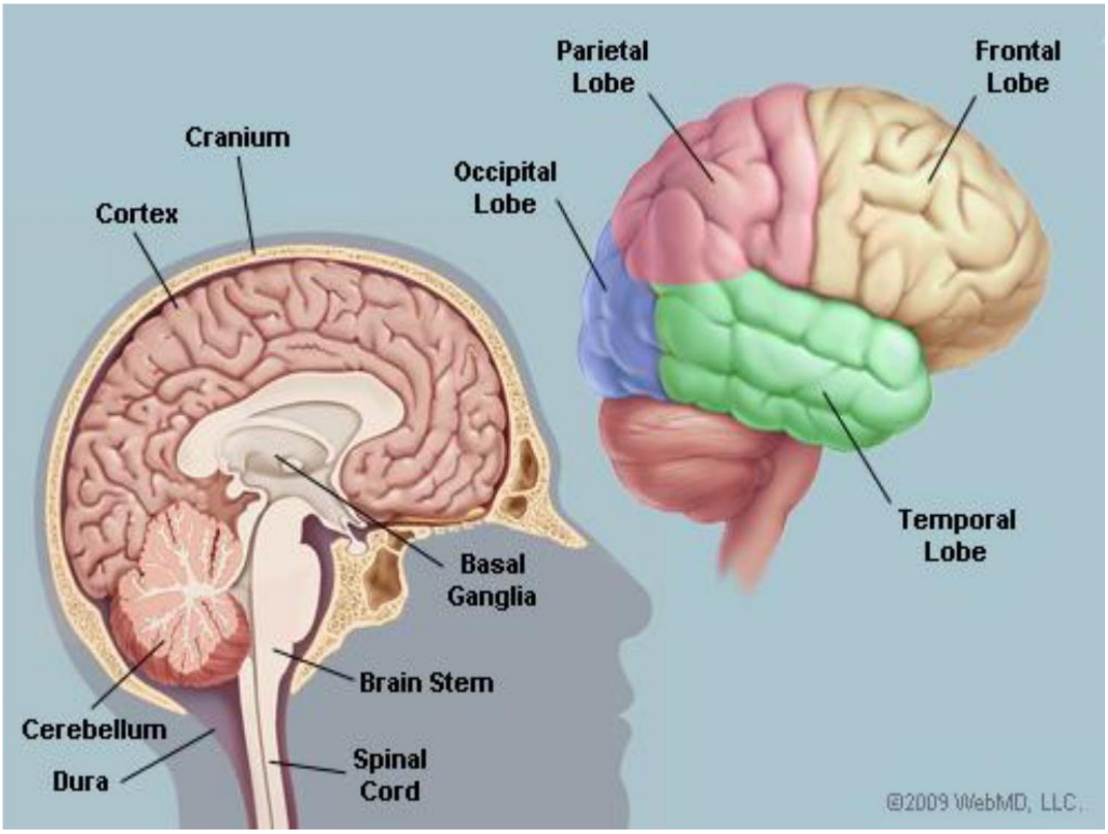

Figure 2: The structure of the brain

Brain is a complicated structure and also it is understood as the essential ingredient of the body. In order to protect the brain, nature encased it in a skull, making the investigation of its functions more difficult. Nonetheless, the brain is not immune and may be damaged by the formation of abnormal cells that alter its shape and activity, which is known as a brain tumour. Toxic tumours of the brain may arise from tumours in the central spinal canal or from those inside the skull itself. There are several therapeutic and diagnostic uses for automatic MRI fault detection. MRI and CT scans are the two imaging modalities that make it easier for researchers and doctors to evaluate the brain in a noninvasive way. Mostly, the tumor apportionment and classification is tough due to the MR pictures amount and furthermore obscured limits. As the mind is safeguarded with the skull, earlier diagnoses of brain tumor have been probable whilst the diagnostic apparatus have been focused at the intracranial cavity. Here , X-ray has been a clinical imaging approach, and the radiologists use it for the inner construction perception in the body. Moreover, MRI yields enormous information regarding the human soft tissues analysis also it helps in diagnosing the brain tumor. MR images are applied to assess and learn the brain behavior (Richa Agarwal & Amanpreet Kaur 2014).

TYPES OF BRAIN TUMOR

Table 1.1 shows the histological subtypes of brain tumors that are seen the most often. Meningiomas are the most common type of tumour, but they are almost never cancerous. They make up 35% of all cancerous tumors. Glioblastomas are the second most common type of cancerous tumour after lymphomas (16 percent). Pituitary tumors make up

13% of all tumors, but they almost never turn out to be cancerous. Nerve sheath tumours are the cause of 8% of all cancers. Medulloblastoma, craniopharyngioma, and germ cell tumors are the types of brain cancer that affect the fewest number of patients. The information here comes from the Central Brain Tumor Registry (CBTR) of the United States in the year 2012..

The above table is graphically represented in Figure 1.2 that clearly shows the various types of primary brain tumor and their affected rate in the human

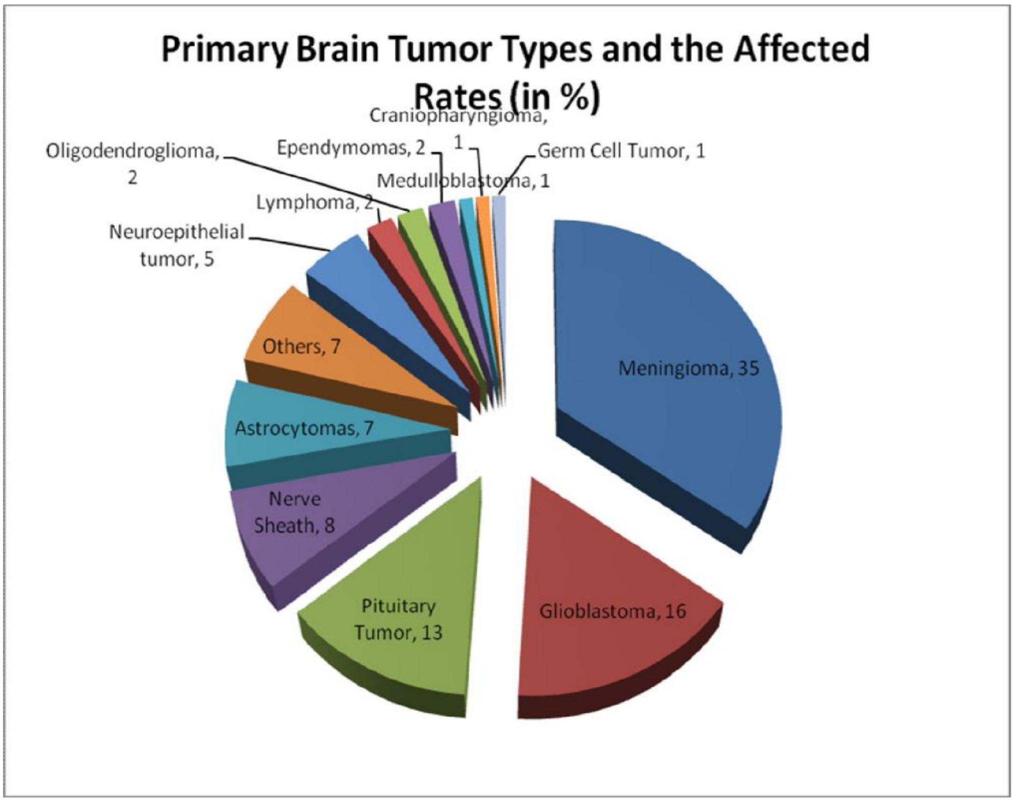

Figure 3: Types of primary brain tumor and the affected rates

RESNET IN COMPUTER VISION

When working on a computer vision challenge, experts in machine learning stack more layers of deep convolutional neural networks. If each layer could be trained specifically for the job at hand, complex problems could be solved more quickly. Adding more layers to a model might make it more accurate, but a closer look at the network might show that it is getting worse. As the number of layers in the neural network grows, the accuracy may reach a plateau and then slowly get worse. Because of this, both the training data and the test data cause the model to do worse.

In other words, this drop is not due to too much fitting. Instead, it could be because of problems with how the network or optimization function is set up, or, more importantly, because gradients are going away or getting bigger.

Deep Residual Learning -The reason why ResNet was made was to solve this problem. Deep residual nets use residual blocks to make their models even more accurate. The idea of "skip connections," which is central to the residual blocks, gives this type of neural network its power.

Skip Connections in ResNet-There are two ways to use these jump connections. First, they fix the problem of the disappearing slope by making a different path for it to take. This lets the gradient keep going without stopping. Also, they make it possible for the model to learn how to learn an identity function. Because of this, the performance of the model's upper layers will not be worse than that of its lower layers.

Because of the existence of residual blocks, layers are able to learn about identity functions considerably more quickly. Thus, ResNet improves the performance and reduces the number of errors made by deep neural networks with additional layers of neural wiring. Instead, the outputs of previous levels are combined with those outputs from the next layer above. As a result, significantly deeper networks may be trained than were previously conceivable.

METHODOLOGY

Because of how technology works, MRI brain scans can't be used directly as input for the segmentation method. So, it is very important to do pre-processing on the image that is given so that it can be turned into something that can be used for further processing (Gonzalez & Woods2008). The MRI image of the brain could be used to find problems in the brain, which is a very important job. Erasmus et al. say that MRI has a lot of problems because of things called artifacts (2004). Because of these artifacts, both the quality of the image and the quality of the diagnosis suffer. To keep the image from having to go through a series of pre-processing steps, abnormalities in the brain, like tumors, labels, and skulls, must be found and taken out. It's important to look for things like tumors, labels, and skulls that aren't normal in the brain so that the automated system doesn't treat the image as abnormal or cause the intelligence system to fail (Petrou&Bosdogianni 1999). The goal of a method for improving images is to make pictures from magnetic resonance imaging look better from the outside (MRI). The enhancement method is made up of three different stages of processing. In the first stage, labels and other film artifacts are taken out of the MRI picture. After this step, the skull is taken off. Then, color space translation and color sharpening are used to make the MRI image of the brain better.

Tracking Algorithm for Removal of Film Artifacts

Step 1:	Read the MRI brain image and store it in a two dimensional matrix.
Step 2:	Track Four corners of MR brain images, and then select the peak threshold value for removing white labels.
Step 3:	Set flag value to 255.
Step 4:	Select pixels whose intensity value is equal to 255.
Step 5:	If the intensity value is 255 then, the flag value is set to zero and thus the labels are removed from MRI.
Step 6:	Otherwise skip to the next pixel.

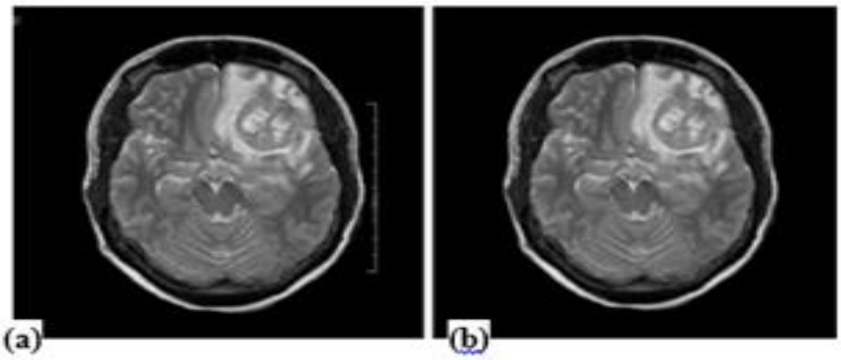

Figure 4 (a) original image (b) MRI without film artifacts

IMPLEMENTATION OF WATERSHED WITH RESNET50

Deep learning characteristics may be used to identify the anatomy of the brain, according to this study's findings. Pretreatment, training, testing, and calculation for brain tumours are shown in The study's findings point to a novel approach to figuring out brain anatomy based on extracting deep learning characteristics. It is the primary goal of the upcoming system to divide the MR picture into normal and pathological categories. Two categories of gliomas, low-quality and high-grade, have been added to the nonstandard images classification. Image enhancement, filtering, and grayscale conversion are just a few of the pre-processing techniques used on MR scans. Our recommended technique included this step. K-means clustering was utilised to discover the tumour area watershed based segmentation technique, which was then used to segment the pictures. Classification, grouping, and retrieval of documents benefit greatly from the Watershed transform's application in these areas. Once the pictures have been segmented, the ResNet50 classifier is used to extract type and categorise the input dataset as normal or abnormal (inferior, high-grade glioma, for instance).

We might use the split weight model to improve how the conversion rate layer is put together. This model reduces the number of unique weights that need to be trained, which in turn reduces the number of matrix calculations that need to be done on each layer. According to this model, each "depth disc" or single two-dimensional neuron layer in the Conv architecture is given the same amount of weight. The use of dividing parameters comes with the caveat that it is not good for images that contain the central structure of the space (like images of faces) or for applications where different functions in the image will be found in different places in the layer space. This is a warning that you should pay attention to before you use the method.

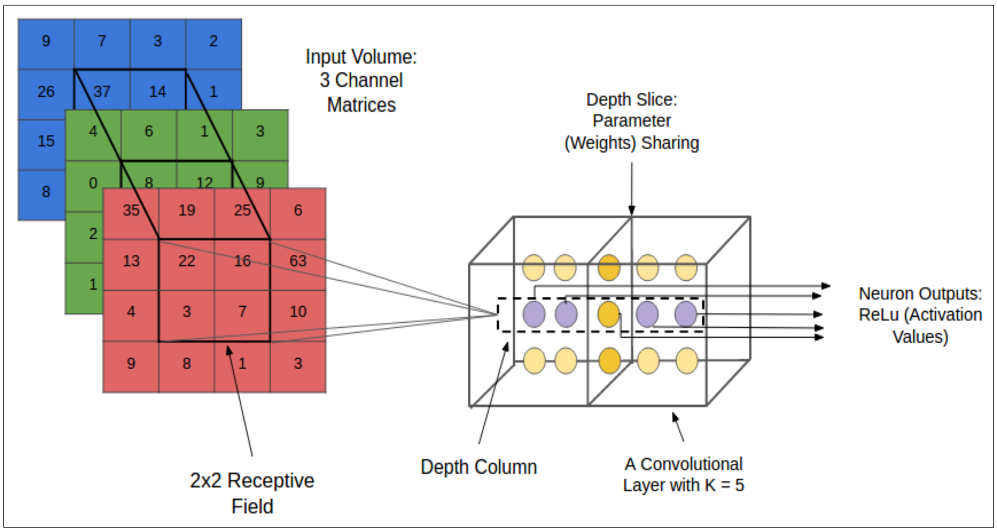

Figure 5: Concept of Receptive Field

METHODS AND MATERIALS

One of the most difficult aspects of image processing is separating objects that are in close proximity to one another. The watershed transform is often used to address this issue. To find "catchment basins" and "watershed ridge lines," the watershed transform gives high values to pixels with bright colours and low values to pixels with dark hues. Segmenting a scene into its foreground and background using the watershed transform is an effective technique. In gradient based watershed segmentation, this is the main way it is done: Build a segmentation function. The black areas in this image show what we were trying to separate. These are groups of pixels that go together and can be found inside each of the items.

Simulation Execution Steps

Step 1: Color the image and convert it to grayscale reading

Step 2: Use the sum of the gradient as a hash function

Step 3: Identify foreground objects

Step 4: Calculate the background marks

Step 5: Calculate the watershed conversion of the segmentation function.

Step 6: Visualize the result

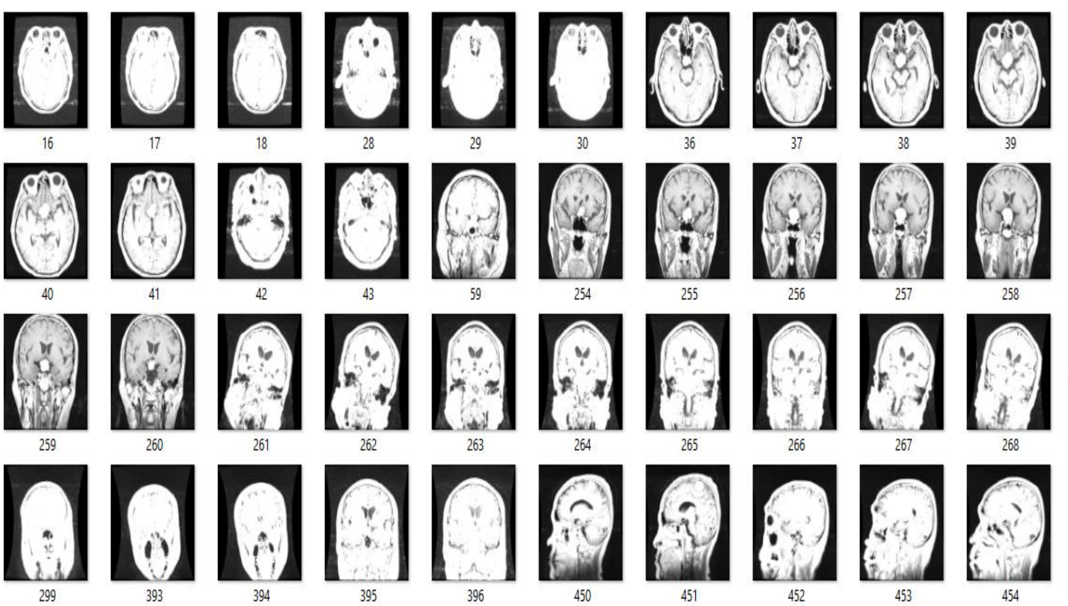

Figure 6: Tumor MRI images

PROPOSED MODEL

In this proposed approach, we aim to enhance the accuracy and efficiency of brain tumor detection and analysis by leveraging a hybrid ResNet50 and ResNet34 model. Our approach combines the strengths of both architectures to effectively capture intricate features and patterns in medical images, providing a comprehensive solution for brain tumor analysis. To begin, we will gather a diverse and representative dataset of brain tumor images, encompassing various tumor types, sizes, and locations. This dataset will be utilized for training and fine-tuning the hybrid model, ensuring it can generalize well to different real-world scenarios.

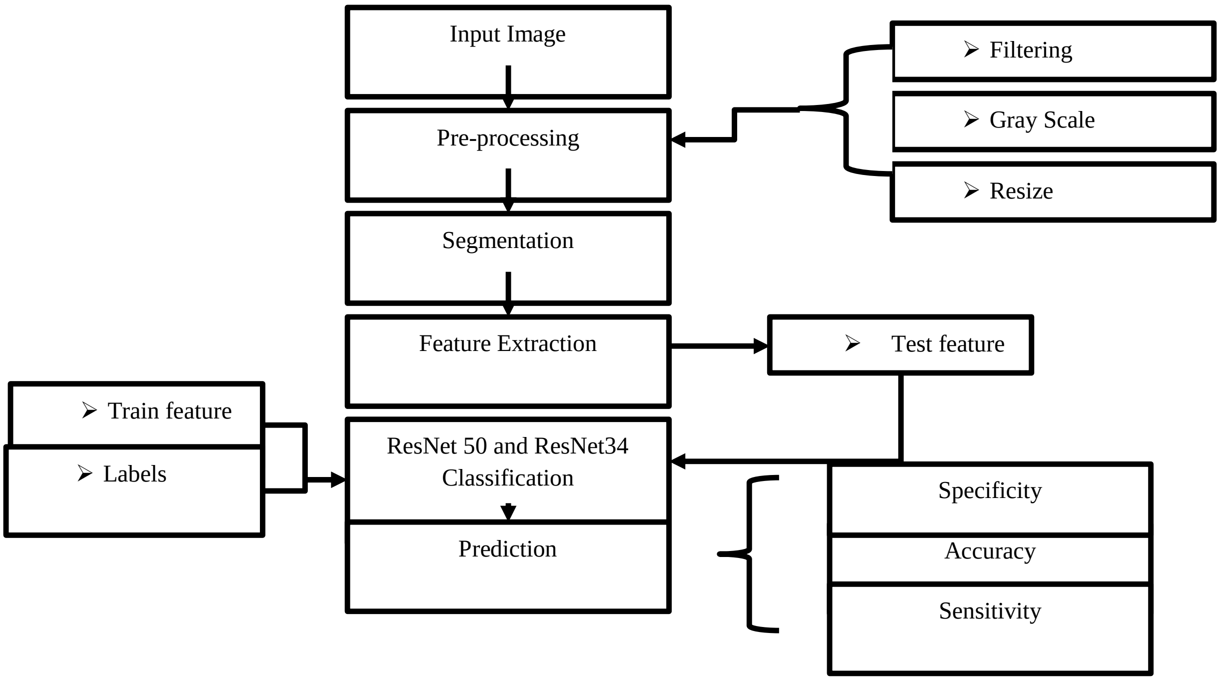

Figure 7: Proposed floe diagram

During the pre-processing stage, we will apply appropriate techniques to prepare the input images for analysis. This may include resizing, normalization, and augmentation to enhance the model's performance and robustness. Additionally, we will explore techniques like multi-modal fusion, integrating different imaging modalities such as MRI, CT, and PET scans, to capture complementary information and improve the accuracy of tumor detection and classification. The hybrid model will consist of the ResNet50 and ResNet34 architectures, carefully combined to optimize performance. Training the model will involve an iterative process, where we fine-tune the model's parameters using the labeled brain tumor dataset. Techniques such as transfer learning can be employed, leveraging pre-trained weights from large-scale datasets like ImageNet to improve the model's initial performance and accelerate convergence.

DATASET

The brain data set that was looked at included 233,306 T1-weighted MRI images with contrast that were looked at for this revision. [5] This dataset includes three different types of tumours: meningiomas, gliomas, and tumours of the pituitary gland. This particular data set uses an image resolution of 512 by 512 pixels and a voxel spacing size of 0.49 by 0.49 millimeter squared. The image resolution is made up of three types of planes: axial (lateral planes), coronal (frontal planes), and sagittal (lateral planes). The axial planar allotment is made up of 708 gliomas, 1426 meningiomas, and 930 pituitary tumours, in that order. The number of categories is used to decide how these things are split up. The min-max normalisation method is used on the data that each pixel contains.

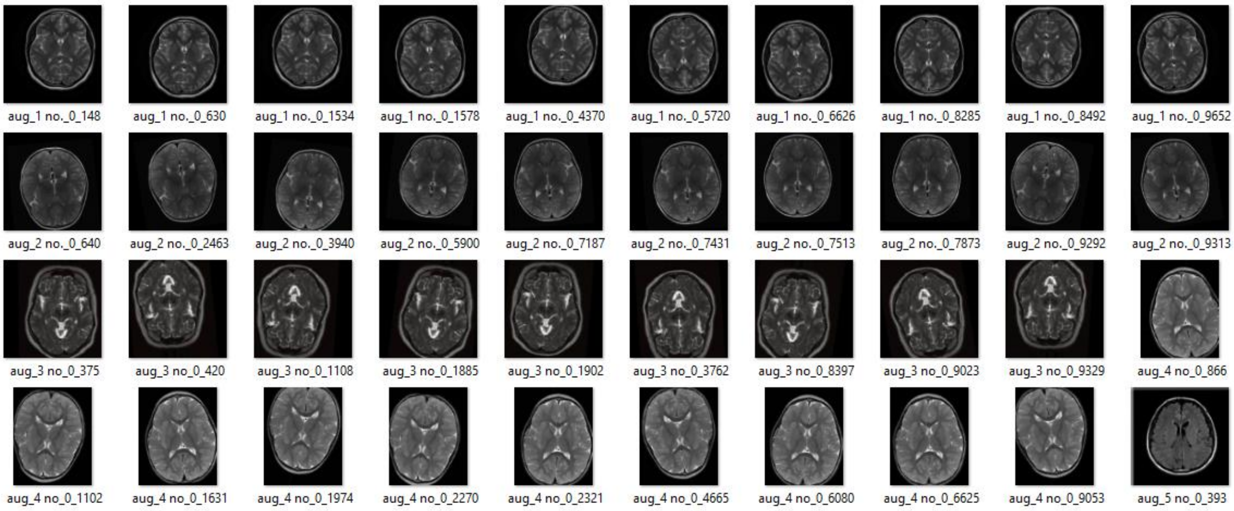

Figure 8: without tumor images

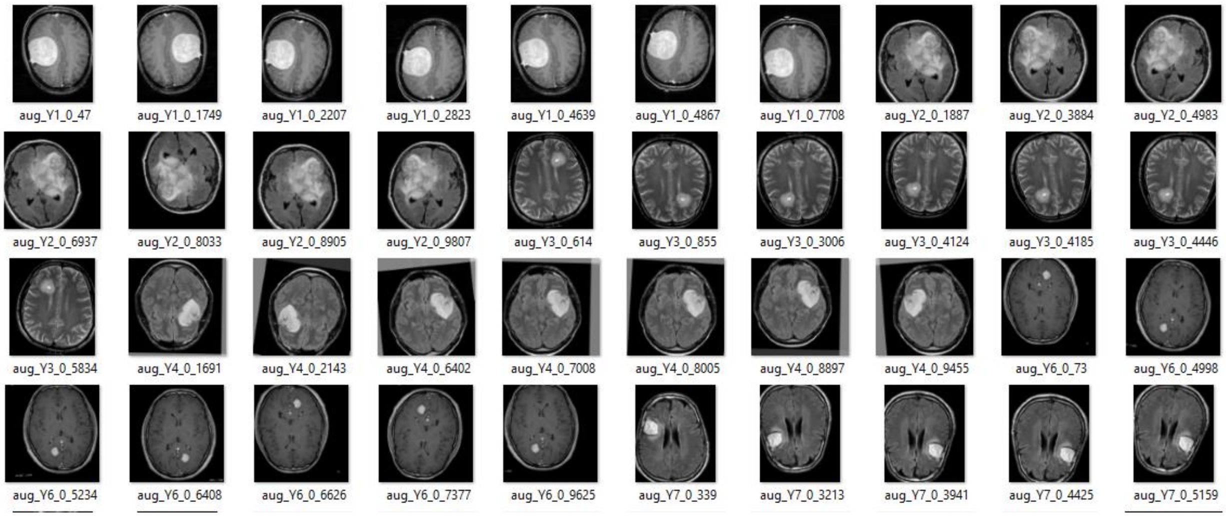

Figure 9: tumor images

USE THE GRADIENT MAGNITUDE AS THE SEGMENTATION FUNCTION

Figure 10: Gradient Magnitude as the Segmentation Function

The gradient magnitude is a measurement that shows how big the difference in intensity is in an image. A real-valued number called the gradient

magnitude can be used to measure how "strong" the change in intensity is. Using the orientation of the gradient, you can figure out which way the change in intensity is pointing.

Step 3: Mark the Foreground Objects

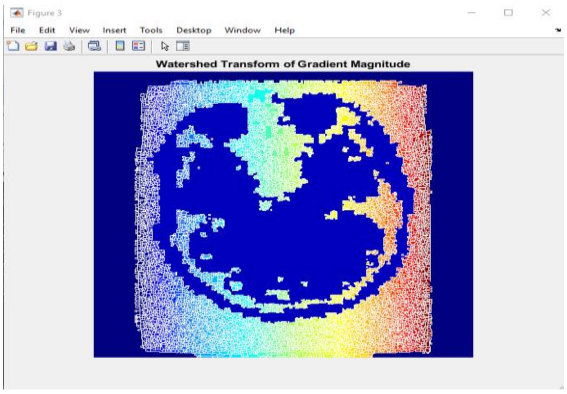

Figure 11: the watershed transform

Figure 5 shows how theimagewas broken up: the watershed transform was done in a way that applied it directly to the gradient magnitude.
There are many methods for locating the foreground markers, which must be connected blobs of pixels in each foreground item. The picture was "cleaned" using morphological

methods including "opening-by-reconstruction" and "closing-by-reconstruction." These operations will produce flat maxima within each object, which may be discovered by using the imregionalmax function.
The Hybrid CNN+CATBOOST+LGBM model performs well on all datasets, with high accuracy values ranging from 90.15% to 96.23%. The model also shows good performance in terms of specificity, precision, recall, and F1-score, with high values across the different datasets. It is important to note that the specific dataset characteristics and class imbalances can influence the performance metrics. However, based on the provided information, the model demonstrates consistent and strong performance across the datasets.

Table 1 results compare with different dataset Hybrid Resnet50 + resnet34

Model	Dataset	Accuracy	Precision	Recall	F1-Score
Hybrid model Resnet50 + resnet34	Dataset 1	95.95.	0.93	100	0.93
	Dataset 2	93.25	91.25	99.99	92.24
	Dataset 3	93.21	90.21	100	94.58
	Dataset 4	94.10	92.34	100	97.25
	Dataset 5	94.58	91.56	100	98.23

The Hybrid model using ResNet50 and ResNet34 shows good performance on all datasets, with high accuracy values ranging from 93.21% to 95.95%. The model also exhibits high precision, recall, and F1-score, with values close to or at 100% for most datasets. This indicates that the model effectively identifies and classifies brain tumor cases with high precision and recall

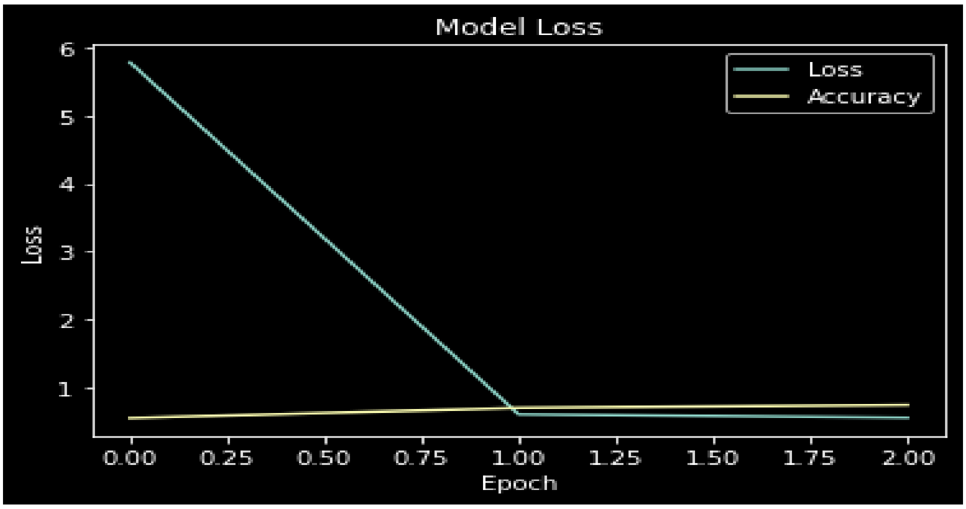

Figure 12: model loss

Table 2 Comparison results with existing work

Existing Work	Techniques	Accuracy (%)
Muhammad Yasir 2021[65]	Faster R-CNN with Alex Net	89.10
Neelum Noreen 2020[66]	deep Learning Fully-Annotated and Weakly-Annotated	85.67
Sharma, A.;2019[67]	CNN with M-SVM	84%
Sanjay Kumar et al. 2019[68]	Convolutional neural networks (CNNs)	89
Guotai Wang et al. 2018[69]	CNN	88.11
Proposed Work	ResNet50+ResNet34	95.95

Comparison of the existing works' techniques and their reported accuracies, along with the proposed work's technique and accuracy for brain tumor classification: Muhammad Yasir 2021: Faster R-CNN with Alex Net - Accuracy: 89.10% Neelum Noreen 2020: Deep Learning Fully-Annotated and Weakly-Annotated - Accuracy: 85.67% Sharma, A.;2019: CNN with M-SVM - Accuracy: 84% Sanjay Kumar et al. 2019: Convolutional neural networks (CNNs) - Accuracy: 89% Guotai Wang et al. 2018: CNN - Accuracy: 88.11% Proposed Technique: ResNet50 + ResNet34 GENERATE Accuracy: 96.23% Based on the provided information, the proposed work using ResNet50 + ResNet34 achieves the highest reported accuracy of 95.95% among the listed techniques.

CONCLUSION

Comparing the skills of deep learning models for brain tumor detection is the goal of this thesis. First, use a suitable resnet50 deep learning model to extract functions from various resnet50 clusters. These symptoms are then connected and assigned to the Softmax category in order to stage brain tumors. Before submitting them to Softmax for the Liver Tumors category, connect them. The burden of computation may be considerably reduced via algorithms. and enhance classification precision. The necessity to provide our radiologists and doctors a reliable and economical tool to categorize benign and malignant tumours served as the driving force behind our initiative. A brain tumour is any lump that forms in the brain as a result of the growth of aberrant cells. Almost everyone, regardless of age (5 to 80), may be impacted. Brain tumours may occur anywhere throughout the image intensity spectrum and can take on a variety of forms. Brain tumours may be malignant or benign. cancers with low titer Gliomas and malignancies are the most prevalent forms of benign tumours. The article puts out two distinct scenarios. First, use a suitable resnet50 deep learning model to extract functions from various resnet50 clusters. These symptoms are then connected and assigned to the Softmax category in order to stage brain tumours. Before submitting them to Softmax for the Liver Tumors category, connect them.

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