

A NEW METHOD FOR DETECTING BRAIN CANCERS USING TRANSFER LEARNING AND DEEP LEARNING

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Abstract— Human intelligence is the primary ruler of the humanoid species. A mind cyst is formed by an unusual tumor and the separation of containers in the intellect, and the progression of intelligence the tumor leads to mental malignancy. Technology plays a critical role in eliminating human error and generating accurate results in this sector of human strength. Computed tomography, X-rays, and Magnetic resonance imaging (MRI) are the most prevalent representation strategies among attractive reverberation pictures(MRI) that are the most dependable and secure. Even the tiniest objects are recognized by Magnetic resonance imaging. Our research will concentrate on the utilization of several ways for detecting brain cancer utilizing intelligent Magnetic resonance imaging. A large dataset of MRI scans is pre-treated and labeled in this method, and a deep learning model is chosen and calibrated via transfer education. The model's success is therefore assessed using conventional versification, and the produced model is redistributed to a result environment for automated classification of mind MRI scans as carrying a Cancer proposal of rectification. Deep education and transfer learning have shown great promise in restoring the veracity and speed of mind lump detection. 2nd hand datasets are used for training, experimentation, and confirmation. The Based on our device, we predict the individual has a brain lump or a proposal for repair. The impacts will be tested using various performance-checked checked verification that is inclined to decide truthfulness, sense, and particularity. It is hoped that the upcoming work would showcase more amazing acting over allure bouts.

KEYWORDS: Brain tumor, Magnetic resonance imaging, Transfer learning , Convolution Neural Network.

I. INTRODUCTION

The approach and procedure of developing optical likenesses of the interior a substance of clinical reason and healing invasions, as well as visual depiction of the function a few

methods or tissues, is known as medical portrayal. Medical illustration aims to reveal inside constructions concealed for one thin, as well as to pronounce and cure sickness. Medical illustration collects a library of common flora and animal studies to make it possible to designate abnormalities.

The healing images handle is used to link to management principles by calculating. This transformation includes a variety of approaches and motions that figure gaining, depository, performance, and ideas. The purpose of this process is to discover and manage diseases. This technique generates a database of the organized structure and function of the means for the smooth regulation of anomalies. This treatment combines two forms of imaging: basic and radiographic imagery (X-rays and gamma-rays), sonography, and attractive, capacity, warm, and isotope imaging. Many sciences are employed to capture information on the body's posture and function. As a comparison to techniques that generate countenances, such methods have numerous drawbacks.

An image transfer is a calculation procedure used to change a digital figure. This technique has a number of advantages, including pliability, flexibility, dossier storage, and idea development. The notions may be retained capably with the assistance of different picture scaling approaches. This approach contains many sets of guidelines to follow while performing the countenances simultaneously. The two-dimensional and three-dimensional countenances can be handled in a variety of ways.

A brain cyst is defined as an abnormal development of containers inside the brain or a central sleep-inducing or numbness drug canal. Certain tumors are cancerous, thus they must be diagnosed and treated as soon as possible. Because the actual etiology of brain tumors is unknown, as is the precise collection of symptoms, individuals provide permission to suffer from it without knowing the risk. Malignant tumors can be benign or malignant (contain tumor cells) (do not hold malignancy cells).

Brain cancer develops when cells separate and multiply abnormally. It seems to be a continuous mass when it is



identified with demonstrative healing imaging modalities. Primary brain tumors and metastatic intelligence malignancies are the two types of brain tumors. The primary intellect cancer scenario occurs when the carcinoma forms in the intellect and prefers to stay there, but the metastatic intellect carcinoma situation occurs when the carcinoma forms in another party and spreads through the intelligence.

The signifier bearing of intellectual tumors is determined by the location, severity, and kind of swelling. It happens when the tumor compresses and releases tension in the nearby compartments. It is also prevalent when a tumor obstructs the fluid that flows throughout the brain. Having difficulties, repulsion, disgorging, and enduring difficulty in comparing and moving are the most prevalent signs. The examples demonstrate ways to a degree CT scans and MRIs may be used to detect brain cancer. Type of place and the goal of the test, both modalities have benefits in detecting. In this study, we chose to use MRI representations since they are simple to attempt and give correct hardness and external bulk placement.

The MRI is the most often touted blueprint for visualizing intellect tumors and marking their surroundings. Other than diverse methodologies, the common strategy for CT and MR representation categorization and detection of cancer cell debris is widely accepted for human inspection. Being non-destructive and non-ionizing, MR faces are extensively used. MRI imaging produces high-resolution pictures that are routinely employed in the detection of brain tumors. MRI contains many blueprints in the form of flair, T1-burden, and T2-burden pictures. There are several face-processing methods, such as pre-processing, figure separation, picture enhancements, feature distillation, and classifiers.

II. EXITING SYSTEM

- Skilled is a calculating-based procedure used in the exploration to locate swelling objects and identify the sort of cyst employing Artificial Neural Network Algorithm for MRI countenances of diverse situations.
- The second step comprises the application of several concept-refining approaches such as graph resembling pie equalization, concept separation, image augmentation, semantic operations, and features ancestry for brain Cancer detection in tumor-afflicted patients' MRI images.

This study incorporates an individual automated intelligence carcinoma detection arrangement to improve truthfulness and shorten the diagnostic time.

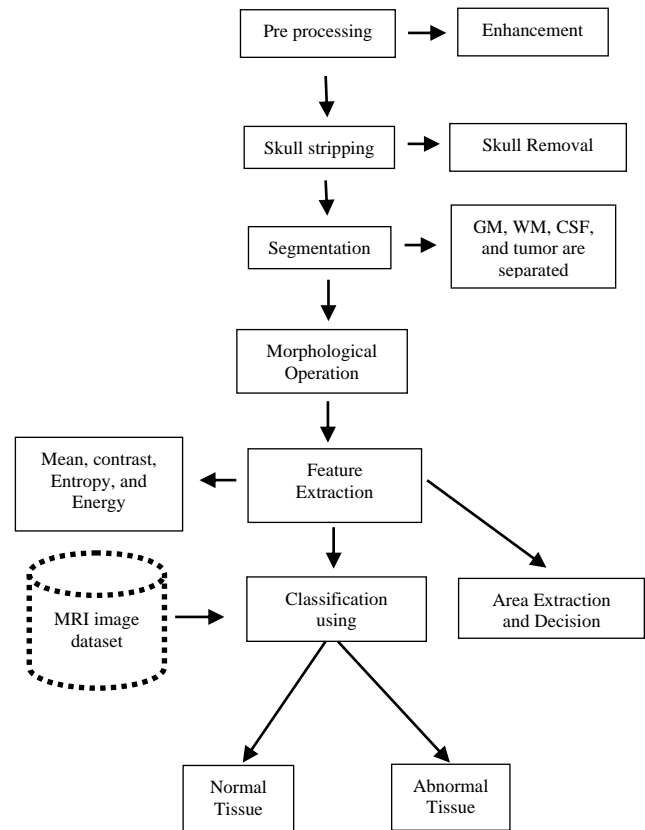


Fig.1.Existingworkflowofbraintumordetection.

Image Pre-processing: This method's suggestion is MRI, leafed through representation, and it has explosion. As a result, our initial goal is to find kill buzz from recommendation countenance. As stated in the order flow, we use extreme pass refine for buzz expulsion and pre-processing.

Segmentation: Region increasing is the simple domain-located countenance separation method. It is still top-secret as a pixel located concept separation method because it is include the selection of primary children points.

Morphological movement:The semantic movement is second hand for the ancestry of mind concept border extents. Because this movement is just shifting the relative positions of pel worth, rather than numerical value, it is only appropriate for twofold representations. Dilation and degradation are fundamental morphological movements. Dilation adds pixels to the object's boundary domain, whereas degradation removes pixels from the object's barrier domain.



Feature Extraction: The feature origin is utilised to determine the edges of the representations. It is the method of raising the unreasonable amount of data of shape, composition, colour, and contrast.

Connected component labeling: After understanding affiliated parts of an representation, all set of connected pixels bearing unchanging silver-level principles are appointed the unchanging unique domain label.

Tumor Identification: In this aspect, we are bearing dataset earlier composed brain MRIs from what or which place we are deriving facial characteristics. Knowledge base is devised for corresponding.

III. PROPOSED SYSTEM

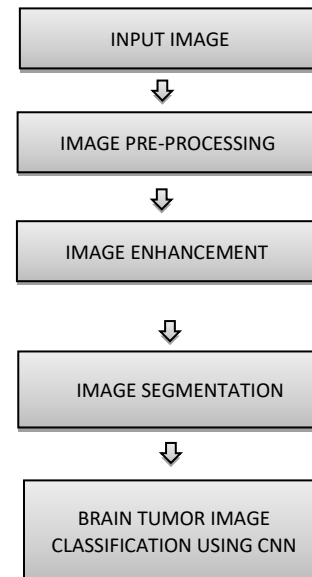
Brain Cancer discovery utilizing deep knowledge and transfer learning is a expeditiously cultivating field that holds excellent promise for reconstructing the veracity and speed of mind swelling diagnosis. Here's an survey of the steps complicated in utilizing deep knowledge and transfer knowledge for mind cyst detection.

- Data accumulation and pre-alter: First, a large dataset of intellect MRI scans is composed and pre-processed to away some artifacts or commotion. The scans are then described established either they contain a carcinoma a suggestion of correction.
- Model collection: Next, a deep knowledge model is picked established the conduct versification and the intensity of the dataset. Convolutional neural networks, Residual Neural Networks, and Inception Networks are popular models for concept classification.
- Transfer learning: Transfer education is therefore used to tweak the picked model on the intelligence lump dataset. This includes attractive a pre-prepared model (normally prepared on a abundant dataset like ImageNet) and accommodating it to the intelligence tumor dataset by re-preparation the last few coatings of the model.
- Model evaluation: The conduct of the model is therefore judged utilizing standard metrics like veracity, accuracy, recall, and F1-score. The model is more proven on additional confirmation fight guarantee that it is not overfitting to the preparation data.
- Deployment: Finally, the prepared model is redistributed to a production atmosphere, place it maybe used to automatically categorize intelligence MRI scans as holding a swelling or not.

Overall, the use of deep education and transfer learning has proved excellent promise in reconstructing the veracity and speed of mind Cancer discovery, and is an alive district of research in the healing society.

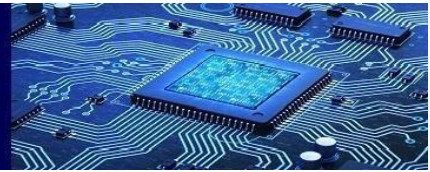
IV. MODULE DIVISON

It consists of five steps in which the execution begins with communicating a suggested image from the basic document file, followed by image augmentation, image separation using twofold thresholding, and the intellect tumor categorization utilizing Convolutional Neural Network and transfer learning. Each piece of art is distinct in its own way. Each step counts in terms of allure. This design entails a simple document for testing and preparation. The baseline document file was acquired secondhand from Kaggle and contains about 4000 representations which are used to testing and training bureaucracy. The image is reinforced with the Sobel Filter after the source countenance is pre-treated using cacophony leaks such as the Filtering Method and Bilateral Filter. After that, the countenance was segmented using twofold thresholding, and semantic movements were performed on it. Lastly, a Deep Neural Network is used to forecast if the lump includes a suggestion for correction, completing the concept categorization.



A. INPUT IMAGE

Gather a plentiful dataset of healing figures, to some extent MRI or CT scans, that include two together malignant and



non-malignant cases. Preprocess the likenesses by normalizing their addition, width, and pel force law.

B. IMAGE PRE-PROCESSING

The Magnetic Resonance concept dataset might be obtained from Kaggle. The MRI dataset contains over 4000 MRI representations of reasonable, moderate, and malignant patients. These MRI representations are saved as a suggestion for the first stage. The pre-alter is a critical and early step in rebuilding the kind of mind MRI Picture. The reduction of hurried buzzes and image resizing are crucial phases in pre-conversion. We translate the intelligence MRI idea into the allure equivalent silver-scale concept in the initial stage. To destroy the crooked blast that is available in the mental image, the altering reciprocal winnowing approach is used to evict unwanted noise. This improves the sickness and increases the classification veracity rate once again.

a. image acquisition from dataset

Image procurement is completed in representation preparation by recapturing a picture from the datasets for handling. It is the first step in this process sequence since no deal with is likely outside of a picture. The captured countenance is completely primitive. Now, we use the file method from the local tool to handle the image.

b. picture conversion from one color space to another

In addition, there are 150 color-room changing patterns available in OpenCV. We are use the function `cv2.cvtColor(recommendation representation, flag)` to alter the color. The part of the process is determined by the flag. We turn the recommended figure into the gray-scale notion in our job.

C. IMAGE ENHANCEMENT

Picture augmentation is a technique that uses a computer-aided spreadsheet to increase the concept type and visibility. This technique incorporates both objective and emotive improvements. In this approach incorporates both points and local motions. Local movements argue that pel principles are influenced by location. There are two types of image augmentation methods: dimensional and transform rule approaches. The related space procedures operate directly on the basic level, whereas the mold method employs Fourier and, eventually, the geographical method.

Edge finding is a segmentation approach that uses boundary

recognition to identify the boundaries of tightly related items or regions. In this method labels the objects' stops. This approach is commonly used in countenance analysis, and to permit the components of the image location, a massive alternative in force occurs.

D. IMAGE SEGMENTATION

Image separation is a method of splitting a single image into several portions. This division's principal purpose is to make the countenances easier to inspect and characterise while maintaining accuracy. This method is typically used to trace the boundaries of objects within figures. This method recognizes pixels based on their intensity and properties. These components display the whole original imcharacterizeage and gain appeal properties such as force and correspondence. Bulk outlines for clinical applications are created using the representation segmentation technique. Segmentation is used in structure comprehension, cancer research, fabric volumes, physical and functional analyses, computer simulation imagination, deviation analysis, and item description and discovery.

The ability of segment commands to recognize or label the unusual component of the representation is useful for resolving the quantity, capacity, size, texture, and form of the derived representation. MRI idea separation by extending the opening news, which makes it easier to detect the crushed domains more precisely. It was a popular theory that items developed in close proximity would have similar families and qualities.

E. CNN CLASSIFICATION OF BRAIN TUMOR IMAGES

Classification is the best-ranked strategy for classifying visuals such as some somewhat therapeutic depictions. All classification algorithms construct a representation indicator, position one or more appearances, and assign each of these face traits to one of many classes.

Convolutional neural network (CNN) will be utilized for mechanical and trustworthy categorization since it has a strong structure that aids in identifying each minute analysis. A Convolutional Neural Network is a Deep Learning system that can deceive a recommended face, give significance to many facets/objects in a figure, and distinguish one individual from another. In compared to other classification methods, a Convolution requires far less pre-treatment. While filters appear devised in rudimentary ways, ConvNet has the capacity to discover these filters/traits with appropriate preparation.

By the employment of proper filters, a ConvNet is capable of favorably capturing the spatial and global reliances in an idea.



The design performs a solution to the concept dataset due to the decrease in the number of challenging restrictions and the reusability of weights. In other words, the network may be more equipped to accept the figure's culture. The ConvNet's job is to identify and lower the countenances into a form that is easy to process, outside of lost visages that are fault-finding for confiscating a decent forecast.

At this stage, we must emphasize Keras and other packages that will be used in the development of CNN. Import the packages listed below:

- Sequence is used to start a system in a networked system.
- Convolution2D is used to build the image-processing cnn model.
- The combining coatings are joined using the MaxPooling2D layer.
- Smooth is a method that converts the integrated feature design into a single phrase for the completely associated coating.
- Heavy increases the neural network's appropriately linked coverage.

a. sequential

- We create a Sequence class object to move data from one computer system to another in the linked system.
- Sequence classifiers ()

b. convolution

- We call the adjoin method associated with the classification object and pass in Convolution2D boundaries to increase the loop tier. The initial point of contention is the number of feature detectors that will be developed. The feature indication mold ranges are the second and following constraints.
- We purchase and sell CNN 256 feature extractors. The next constraint is the recommendation shape, which is the shape of the suggestion countenance. While pre-transforming, the figures will be convinced into this shape. If the image is of a police officer, the notion will be convinced into a two-dimensional array; if the image is colored, the concept will be convinced into a three-dimensional array.
- In this case, we'll act as if we're busy escorting colorful figurines. The input shape is a tuple that comprises the number of channels, which is three for a colorful figure, as well as the two-dimensional

array ranges in each channel. Choose lower ranges if you are not utilizing a GPU to limit the calculation opportunity. The ultimate limit is the inciting role. The categorization of images is a nonlinear issue. As a result, we use the rectifier function to verify that there are no negative pel principles throughout the calculation. That is because of the advantages of non-distance communication.

V. SOFTWARE REQUIREMENTS

Python3.6.2 or later, PIP, and NumPy 1.13.1 are required for Windows.

Python:

Guido Van Rossum fictitious and freed Python, a clear, high-ranking, approximate-purpose compute language, in 1991. Python's structural knowledge advances legal Readability, accompanying a devote effort to something big Whitespace. Its language parts and approaches to thinking primarily about material things are intended to help builders revise clear, probable law for two together limited and big projects. Python is litter-free and dynamically classification. It supports a number of prioritisation example, containing as procedural, material thinking, and working compute.

PIP:

It is all administration scheme necessary to install and execute Python-based operating system packages..

NumPy:

NumPy is a general-purpose array-ordering framework. It defines an extreme-adeptness model object that is accompanied by several ranges, as well as strategies for energetically pursuing these ranges. Together with Python, it is the primary whole for controlled guessing. It has several features, the most important of which are: A powerful N-spatial array of objects

- A powerful N-spatial array of objects
- Tools for merging C/C++ and Fortran rules
- Helpful undeviating arithmetic, Fourier transform, and erratic number capabilities

Anaconda:

Anaconda is a free and open-source starting distribution of the Python and R programming languages for experimental manipulation, with the goal of lowering overall administration and arrangement. Conda is in charge of all translations for the entire governmental order. The Anaconda distribution



includes a knowledge-based package that is compatible with Windows, Linux, and computer applications for basic operation. Anaconda's conclusion proposes 1,500 total PyPI options, as well as the conda package and, most importantly, the environment manager. It also features a display-controlling software, Anaconda Navigator, as an alternative to the display-controlling program (CLI).

VI. HARDWARE REQUIREMENTS

- Intel i5 Processor or higher.
- Minimum 64-shard, quad-gist, 2.5 GHz per gist level
- RAM: 4 gigabyte(GB) or higher
- Hard disc: at least 10 gigabyte(GB) of usable space.
- Display: Dual XGA (1024 x 768) or higher resolution decision screens
- Windows based system

VII. RESULTS AND DISCUSSION

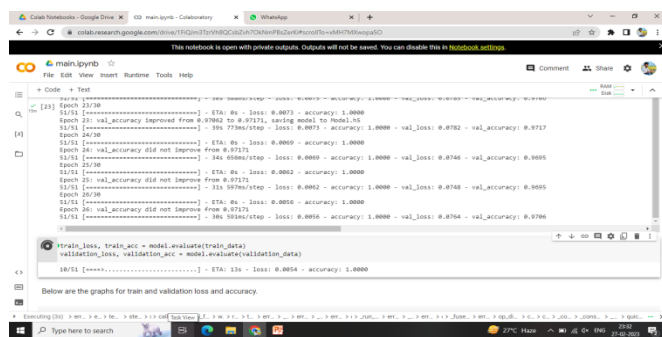


Fig.7.1 EPOCH

During an period, the model thinks each input in the dataset, computes the mistake (or deficit) 'tween the expected and valid outputs, and modifies allure limits (biases and weights) using an optimisation method to a degree guessed gradient deterioration.

The number of epochs required for model preparation may vary depending on the degree of model complexity, dataset length, and desired level of validity. In general, additional epochs can lead to greater acts, until overfitting occurs.

As a result, it is customarily unavoidable to judge the model's conduct on a confirmation set during the whole of preparation and halt preparation when the validation deficit stops reconstructing or starts increasing. The preparation misfortune is a measure of how well a model does on the preparation dossier while it is being prepared. It remains the average

difference between the model's thrown and real crop for all preparation samples.

The objective of the preparation search underrates the preparation disaster by reducing the model's bounds.



Fig.7.2 LOSS AND ACCURACY

In contrast, the testing loss measures how well the model generalises to new, previously unknown data that was not used during training. It is computed using a distinct set of data known as the testing set or validation set. The testing loss is calculated similarly to the training loss, but using testing data rather than training data.

Throughout each training period, the training and testing losses are calculated and tracked. The training loss normally lowers as the model improves at fitting the data during training. The testing loss, on the other hand, may initially decrease but then begin to increase as the model gets overfit to the training data and less successful at generalising to new data.

The goal of training is to find the optimal number of epochs to minimise testing loss and demonstrate that the model generalises effectively to new data.

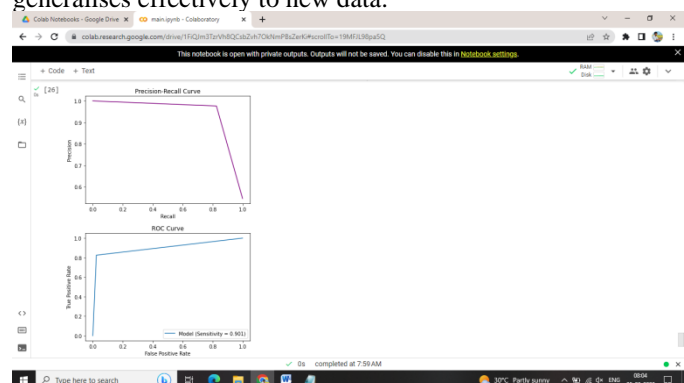
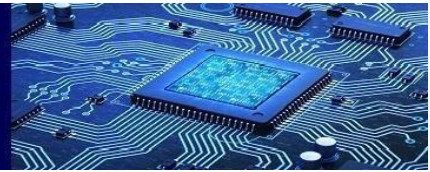


Fig.7.3 PRECISION-RECALL AND ROC CURVE



A precision-recall curve is a graphical representation of the performance of a binary classification model. It displays the levels of accuracy and recall at various classification criteria.

Precision is the ratio of true positives (positive events correctly classified) to all expected positives. It determines how many of the projected positive instances are actually positive. The formula provides accuracy.

$$\text{precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

The fraction of true positives among all positive instances is known as recall (also known as sensitivity or actual positive rate). It determines how many true positive instances were correctly classified. The formula produces recall.

$$\text{recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

To build a precision-recall curve, the model is trained on a labelled dataset and its estimations are compared to the real labels. The model's estimated likelihood scores are then utilised to generate a set of classification thresholds. The accuracy and recall values for each threshold are calculated and shown on the graph, yielding a curve.

A good classifier has a precision-recall curve that hugs the top-right corner of the figure, indicating high precision and recall scores at all classification levels. The area under the precision-recall curve (AUC-PR) is a common statistic used to summarise the overall performance of a classifier. More than one AUC-PR indicates higher categorization performance.

ROC CURVE:

A receiver operating characteristic (ROC) curve is a graphical representation of the performance of a binary classification model. It is a graph that compares the true positive rate (TPR) to the false positive rate (FPR) at various classification criteria.

TPR (sometimes referred to as sensitivity or recall) is the proportion of true positives (positive cases that were correctly detected) among all positive examples. It determines how many true positive instances were correctly classified. TPR is the result of the formula.

$$\text{TPR} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

FPR is the proportion of false positives (positive instances that were incorrectly classified) to all true negatives. It tracks how many actual negative instances were incorrectly categorised as positive. FPR is calculated as follows:

$$\text{FPR} = \frac{\text{false positives}}{\text{false positives} + \text{true negatives}}$$

A ROC curve is generated after training the model on a labelled dataset and comparing its predictions to the true

labels. The model's estimated likelihood scores are then utilised to generate a set of classification thresholds. The TPR and FPR values for each threshold are computed and shown as a curve on the graph.

A good classifier has a ROC curve that hugs the top-left corner of the figure, indicating high TPR scores at low FPR scores. The area under the ROC curve (AUC-ROC) is a typical statistic used to summarise the overall performance of the classifier. A higher AUC-ROC value indicates better categorization ability.

VIII. CONCLUSION

Using the Convolution Neural Network, we projected an electrical pattern for the isolation and labeling of brain cancer. Using the file technique, the recommended MRI figures are taken from the local design and converted to gray scale images. These expressions are pre-treated with an adjusted mutual cleaning procedure to remove crashes existing in the original image. The denoised countenance is denoised using two thresholds, and Convolution Neural Network separation is utilized to calculate the lump domain in the MRI images. The anticipated model has a validity of 96% and produces promising outcomes despite minor errors and substantially less computational potential.

IX FUTURESCOPE

On annihilation, it is discovered that the proposed technique requires an infinite training data set for better accurate data; engaged in repairing concept refinement, the accumulation of a healing dossier is a time-consuming operation, and in certain situations, the datasets may not be attainable. In all circumstances, the predicted treasure must be powerful enough to accurately recognize lump domains from MRI Imagery. The projected pattern could be extended by helping infirm prepared methods that can recognise the irregularities associated with a slightest arrangement dossier, in addition to self-instruction algorithms, which would aid in reconstructing the propriety of the invention and mortifying the computational time.

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