RECURRENT NEURAL NETWORK-BASED BRAIN TUMOR CLASSIFICATION USING 3D MAGNETIC RESONANCE IMAGING

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ABSTRACT

Brain tumor identification and segmentation using magnetic resonance imaging (MRI) represent difficult but critical tasks for a variety of applications in the area of medical analysis, including cancer detection and treatment. Brain tumor implies the collection of aberrant cells in certain brain tissues. The brain tumor may be malignant or cancer-free. Glioma, Meningioma are the most frequent kinds of brain tumors. Early identification of tumor cells plays an important role in patient therapy and recovery. Brain tumor diagnosis is typically subject to a highly complex and time-consuming procedure. MRI scans of different patients may be utilized to identify cancers at various stages. There are many kinds of functional extraction and classification techniques used to identify brain tumors from 3D MRI brain images. Specifically, in this article, we offer a preprocessing method that works just on a small portion of the image rather than the whole image to produce a flexible and efficient brain tumor segmentation system. This technique reduces the amount of computation time required and eliminates the overfitting issues that may occur in a deep-learning model. In the second phase, we suggest a simple and effective Recurrent Neural Network (RNN) while we are interacting with a smaller portion of brain images in each slice. The Recurrent neural network algorithm exploits combine local and global characteristics and it does so in two distinct ways. Additionally, it enhances the accuracy of brain tumor segmentation when compared to current state-of-the-art models. The image classification method for the RNN enables the early detection of the tumor with great accuracy. We presented a recurring neural network design for tumor cell identification, which is about 99.92% accurate. A recurring neural network (RNN) is a kind of artificial neural network where connections between nodes create a graph in a time sequence.

Keywords: *Magnetic Resonance Image, Malignant, Glioma, Meningioma, Recurrent Neural Network*

1. INTRODUCTION

A brain tumor is the aggregation or bulk of aberrant brain or central spinal canal cells. Our brain is encased by an extremely hard skull. Any development inside such a confined area may create numerous human issues. Both cancerous (malignant) and noncancerous brain tumors may be (benign). When benign or malignant tumors develop, the pressure inside the skull increases. This may cause brain damage and endanger life. Brain tumors typically occur in multiple places of varying sizes and forms. Tumors in the brain are classified as primary or secondary. Our brain has a primary brain tumor. Many primary tumors of the brain are benign. A secondary brain tumor, also known as a metastatic brain tumor, develops when cells of the disease migrate from another organ, such as the lungs or breast, to our brain. Early tumor cell identification can save a lot of human lives. Detection of the brain tumor and its stage is a time-consuming and complicated procedure. The patient refers to a 3D MRI when certain signs of tumor rashes have occurred. After examination of the brain images, if the tumor is detected, the brain biopsy of the patient takes effect. A biopsy is an intrusive operation and may take a certain response in certain instances even for up to a month. Detailed information on brain anatomy and abnormality detection in brain tissue is provided in the image of MRI. Scholars provided

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automated techniques, unlike brain tumor detection and categorization, utilizing images of brain MRIs from the time when medical images could be scanned and transported to the computer. Conversely, in recent years the Neural Networks (NN) and the Support Vector Machine (SVM) have been utilized for their excellent implementation. However, newly developed, Deep Learning (DL) models have set a stirring trend in machine learning, because underground architecture can effectively express complicated connections without having to use a huge number of nodes, such as the K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). As a result, they rapidly developed to become state-of-the-art in fields such as health information technology analysis, medical computer science, and bioinformatics.

Because tumors are so tiny in comparison to the rest of the brain, brain imaging data is skewed in favor of the tumors. As a result of this characterization, existing networks become biased towards the one class that is overrepresented, and training a deep model results in low true positive rates in many cases. Additional complexity in the current deep learning methods makes them more time-consuming to develop and maintain. To address the aforementioned problems, we utilized a strong pre-processing technique to eliminate a large amount of irrelevant information from the data set, which produced promising results even in the current deep learning models, as shown in our study. This approach avoids the need for a sophisticated deep-learning model to identify the position of the tumor and extract characteristics, which would otherwise result in a time-consuming procedure with a high failure rate. Furthermore, since the size of the area of interest has been reduced, the preprocessing phase in this approach has resulted in a reduction in overfitting issues. Furthermore, after the pre-processing phase, a cascade RNN method is used to extract both local and global features efficiently. A novel distance-wise attention mechanism is included inside the RNN model to make our model more resistant to variations in tumor size and location.

Because of the aforementioned issues, we have proposed an alternate method for brain tumor screening and classification that eliminates the need for a segmentation step entirely. The use of holistic 3D images without extensive annotation at the pixel or slice level, in particular, is proposed. The 3D holistic images are represented as sequences of slices in our method. For each image, it uses an auto-encoder that is built on a deep DenseNet to extract features from the image. This saves us from having to use the original noisy and high-dimensional data. To manage the sequential data for the classification task, it is natural to use a Recurrent Neural Network (RNN), more particularly the Long Short-Term Memory (LSTM) model, once the characteristics of slices have been extracted. A purely convolutional model is also applied to sequential data, which is achieved via the combination of 2D slice features, which are handled as if they were another piece of image data. Based on recent research into utilizing a solely convolutional auto-encoder for sequence representation learning, we developed this method.

Our contributions to this effort are divided into three categories:

- In contrast, to pixel-wise or slice-wise labeling, the suggested models simply need a holistic labeling of patients. In the course of therapeutic practice, holistic labels are considerably more easily obtained.
- We have amassed a dataset of 600 MRI scans, which includes images of normal control subjects as well as images of three different kinds of brain cancers (meningioma, glioma, and metastatic tumor).
- Deep neural networks (DNNs) are used to create a new architecture that treats 3D input as a series of slices, with RNNs or CNNs used to learn sequence-to-label mapping and a DenseNet-based auto-encoder used to extract features.

Both the DenseNet-LSTM and DenseNet-DenseNet suggested models are shown in two experiments: tumor screening and tumor type classification, which are carried out on public and private datasets, respectively.

1.1 Findings

In this paper, we interpret the research on Recurrent Neural Network (RNN)-based brain tumor classification using 3D Magnetic Resonance Imaging (MRI) to provide a cutting-edge approach to medical image analysis. Readers can expect an in-depth exploration of the methodology, data preprocessing, and the RNN architecture that enhances diagnostic precision. By the end, they will understand how RNNs effectively classify brain tumors with 3D imaging data, overcoming traditional limitations. The findings of this study can be leveraged by researchers and medical practitioners to develop more accurate diagnostic tools, optimize treatment planning, and contribute to advancements in AI-driven healthcare solutions.

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1.2 Claim

This study presents the claim that Recurrent Neural Networks (RNNs), when applied to 3D Magnetic Resonance Imaging (MRI), offer superior accuracy and efficiency in brain tumor classification compared to traditional methods. By leveraging the sequential data processing capabilities of RNNs, the proposed approach demonstrates improved detection and classification performance. However, as research in this area advances, this claim may be contested, particularly with the emergence of new architectures like transformers or hybrid models. In the result analysis, we emphasize the assumptions, limitations, and comparative benchmarks, encouraging further scrutiny and refinement as knowledge and technology in medical imaging and AI evolve.

2. RELATED WORKS

The segmentation of Fuzzy C-means (FCM) is used to distinguish the brain tumor from the non-tumor area. Multilevel Discrete Wavelet Transform also extracts the wavelet feature (DWT). The Deep Neural Network (DNN) is also integrated for high-accuracy brain tumor classification. This approach is contrasted with the classification techniques of KNN, Linear Discriminate Analysis (LDA), and SMO. A 96.97% accuracy rate in DNN-based brain tumor categorization study. However, the complexity is great and the performance is extremely low [1].

In [2], new modeling of bio-physio-mechanical tumor development is given to evaluate the tumor progression of patients step by step. The important tumor mass impact will be applied to gliomas and solid tumors with distinct margins. The discreet and continuous techniques for simulating tumor development are merged. The suggested method offers the chance to tacitly record tumor-bearing brain images based on an atlas. This method is primarily utilized for the segmentation of brain tissue. But the time for calculation is high.

In [3] novel multi-fractal (MultiFD) extraction features and enhanced AdaBoost classification methods are utilized to identify the brain tumor and divide it. The multi-FD extraction method extracts the texture of the brain tumor tissue. The enhanced classification techniques for AdaBoost are utilized to detect a tumor or non-tumor tissue in the cerebral tissue. Complexity is complex.

The local independent classification projection-based technique (LIPC) is utilized to categorize the brain voxel. This technique also extracts the route characteristic [4]. Therefore, no explicit regularization in LIPC is necessary. The precision is poor.

In [5], the novel Cellular Automata (CA) procedure is given as a seeded tumor segmentation approach compared with the graph-cutting-based segmentation method. For effective brain tumor segmentation, seed selection and volume of interest (VOI) are determined. Segmentation of the tumor cut is also included in this study. The complexity is small. However, the accuracy is poor.

New segmentation of brain tumors, also known as multimodal brain tumor segmentation methodology is presented in [6]. Combining several segmentation algorithms to obtain great performance compared to the current technique. The intricacy is considerable, though.

In [7], the survey shows the segmentation of the brain tumor. Discussion of a range of segmentation techniques, including Region segmentation, threshold segmentation, Fuzzy C segmentation, Atlas-based segmentation, Margo Random Field (MRF), Model deformation, and Geometric model deformable. The accuracy, robustness, and validity of all techniques are evaluated.

In [8], brain tumor diagnostics, hybrid feature selection with ensemble classification is used. For decision rules, the GANNIGMAC, decision tree, and Bagging C wrapper method are utilized. Simplify the rules of decision by employing a combination hybrid feature selection (GANNIGMAC + MRMR C+ Bagging C + Tree of Decision).

In [9], the idea of fuzzy control is utilized in the segmentation and categorization of brain tumors. The Fuzzy Interference System (FIS) is a unique method used mostly for the segmentation of the brain. Supervised categorization is utilized to construct a fuzzy controller membership function. The performance is great and the precision is poor.

In [10], the adaptive histogram equalization is utilized to enhance the image contrast. Fuzzy C-means (FCM) is then segmented to isolate the tumor from the whole image of the brain. Gabor is then removed to screen the aberrant brain cells. Finally, the fuzzy K Nearest Neighbor (KNN) classification is used to detect brain abnormalities in MRI. The intricacy is great. However, the accuracy is poor. A new automated categorization of brain tumors is done using a neural network of convolutions.

To imitate the knowledge of doctors, Zhang, and colleagues [11] developed a TSBTS network (task-structured brain tumor segmentation network) that explored both the task-modality structure and the task-task structure. Because they represent diverse pathological features, the task-modality structure distinguishes between markedly different mammogram images by weighing the dissimilar modality dataset, whereas tasks resemble the much more distinct area with one component of both the tumor and use it to find a whole other part in its vicinity.

It was discovered in [12] that a learning technique for expressing relevant characteristics from the knowledge transfer across various modality data might be used. They utilized a feed-forward neural network (GAN) learning method to extract inherent patterns from each modality's data to make the knowledge transfer easier and more seamless.

Zhou et al [13] developed only One Multithread Network (OM-Net) to address the issue of unbalanced data in the medical brain volume, which they called "the imbalanced data problem." OM-Net learns racist discriminatory and joint features by using common and task-specific parameters in the learning process. Combining attempting to learn retraining as well as online learning data transfer methods are used to improve the performance of OM-Net. Also included is the CGA module, which allows for the sharing of prediction results across jobs when the CGA module is on.

Havaei et al [14] suggested that the Deep CNN structure be used to extract simultaneously domestic and international contextual information at the same time and that this be done concurrently. Their model makes use of a simple yet effective feature extraction technique.

Coupé et al [15] presented an Assemblymen model for 3D whole-brain MRI segmentation, which is based on the parliamentary decision-making idea and utilizes the parliamentary decision-making concept. This parliamentary network is capable of resolving previously unsolved issues, making complicated choices, and reaching a meaningful parliamentary majority. AssemblyNet uses a majority voting system to make decisions by pooling information from adjacent U-Nets. This network is capable of overcoming the issue of having insufficient training information.

2.1 Solution Interpretation Criteria and Comparison with Previous Literature

- Results are evaluated based on metrics like accuracy, precision, recall, and F1-score, ensuring robust performance evaluation of the RNN model. These metrics align with those used in prior studies for fair comparison.
- Unlike conventional models, the solution's ability to capture sequential dependencies in 3D MRI data is analyzed, providing a novel performance perspective absent in most prior research.
- The model's robustness across diverse datasets is tested to ensure its adaptability, a step that refines and extends interpretations from earlier literature in this domain.

3. PROPOSED WORK

The human brain is represented via neural network architecture and execution. Feedback, feedback, and recurrent networks are three neural networks. The Feed Forward Neural Network is further broken down into a single network layer and a multilayer network. The hidden layer is not shown in the single-layer network. However, it includes just the layer of input and output. The multilayer, however, includes the input layer, the hidden layer, and the output layer. As a recurring network, the loop-based feedback network is termed. The image cannot be scaled in the conventional neural network. The image may be scaled in the neural network, however, (i.e.), it takes 3D input volume to 3D output volume (length, width, height). The RNN comprises an Input Layer, a Recurrent Linear Unit (ReLU) Layer, a Pooling Layer, and a fully linked Layer. The supplied image in the layer is divided into several tiny parts. The wise element activation function is performed at the ReLU layer. The layer of pooling is optional. The pooling layer is, however, primarily utilized for sampling. The class score or label score value is generated based on a probability from 0 to 1. Fig.1 shows the block diagram of the categorization of brain tumors based on neural network convolution. The number of images is separated into various categories by utilizing names such as the tumor images and the brain images of non-tumors, etc. Finally, the neural convolution network is utilized for the automated categorization of brain tumors. The data set for the brain image is obtained from the image net. If you wish to train from the start layer, we must train the whole layer (i.e. the calculation time is thus minimal, while the performance in the suggested automated classification method for brain tumors is high.

The loss function is computed using the method of gradient descent. The raw image pixel is mapped using a scoring function with the class scores.

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The data samples are pre-processed beforehand. Jupyter Notebook is used for code execution and compilation. The modules of the prediction models are discussed below.

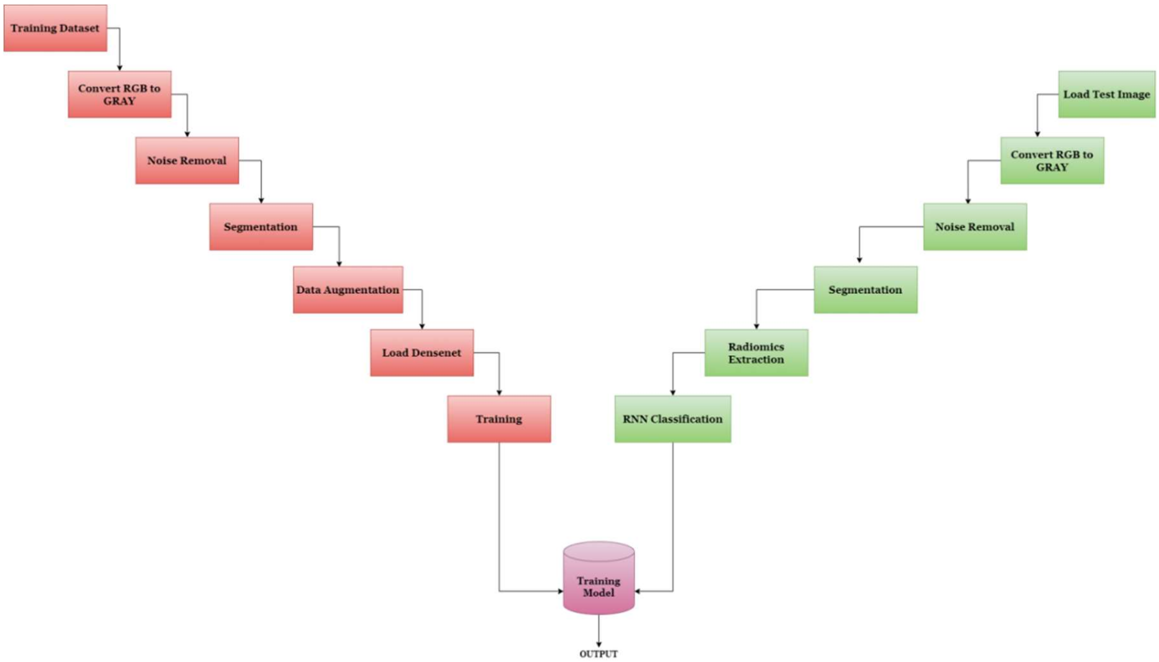

Figure 1: Proposed Block Diagram

3.1 Novelty for Justification

The novelty of this work stems from its application of Recurrent Neural Networks (RNNs) to brain tumor classification using 3D Magnetic Resonance Imaging (MRI), a less-explored domain for RNN architectures. Unlike widely used convolutional neural networks, this study highlights the sequential nature of volumetric MRI data, utilizing RNNs to capture temporal and spatial dependencies more effectively. By introducing innovative preprocessing techniques and optimizing RNN architecture for 3D medical imaging, the approach not only improves classification accuracy but also addresses challenges like data dimensionality and feature representation. This unique application positions RNNs as a promising tool for advancing AI-driven medical diagnostics.

3.2 Pre-processing

Unlike many other current deep learning methods that utilize the whole image to extract important features, we simply concentrate on a small portion of the image to extract critical characteristics. Furthermore, by using such a technique, we avoid the requirement to use a recurrent model with a very high level of detail.

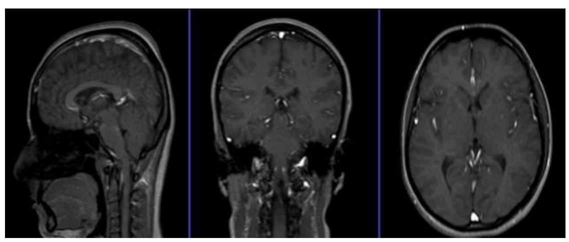

Figure 2: 3D Brain preprocess image

In the MR imaging method, some images are given by setting certain parameters such as pulses and gradients of radiofrequency. For normal instances, T1 images are used in this research. To minimize the number of normal brain images, six segments were chosen from the MR images of each normal participant with roughly identical spacing (person). In addition, one or more slices of an MRI image are utilized in the suggested technique and all slices or 3D images must not be used.

Data preprocessing is an extremely important stage in the process of processing the raw input data so that it is more accessible to neural network computation. Images acquired with MRI equipment may include a variety of artifacts, which are produced by differences in acquisition protocols and device configurations. Because of its simplicity of use and availability as an open standard, the non-

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parametric non-uniform normalization (N3) method has emerged as the treatment of choice for bias field correction among a variety of approaches for bias field correction. In addition to normalization, another common preprocessing method is to reduce an image dataset to a mean of zero mean and unit variance of one.

3.3 Split-up Dataset

We took 600 MRI images from the IXI dataset in this study. 80% of the images are utilized for model training and 20% of the images are used to evaluate the suggested prediction model. Over the last several years, there has been a significant increase in interest in the field of automated brain tumor segmentation research. As the volume of research output increased, the objective assessment of various algorithms became more difficult to do since researchers utilized private datasets with a variety of characteristics. Table 1 shows the detailed distribution of the database, with each row representing a unique record. After separating training and testing data, the database includes raw images that have been preprocessed, segmented, and augmented using segmentation and augmentation techniques. The structure suggested by hypertweaking the parameter and optimizing the algorithm is described in detail below. At the conclusion, the results of training and testing are given.

Table 1: Database Distributions.

Classes	Database Distributions		
	Total Image	Training Images	Testing Images
Benign	600	480	120
Malignant	600	480	120

3.4 Techniques for the Segmentation of Brain Tumors

3.4.1 Post-Processing

The post-processing phase is carried out to improve the segmentation findings even more. When employing techniques such as conditional random fields (CRF), Markov random fields (MRF), connected component analysis, and morphological operators, it aids in decreasing the number of misclassifications or false positives in the segmentation findings. With the use of CRF and MRF-based methods, false positives may be successfully eliminated by integrating model predictions with low-level image information, such as local interactions of pixels and edges, while making finer changes. These methods, on the other hand, are computationally costly [16]. It is possible to do linked components analysis by first identifying and extracting related components and then using a simple thresholding method to eliminate unnecessary blobs. Using morphological procedures such as erosion and dilation in succession on the segmentation image is another method for eliminating false positives from the edges of a segmented image shown in Figure 3.

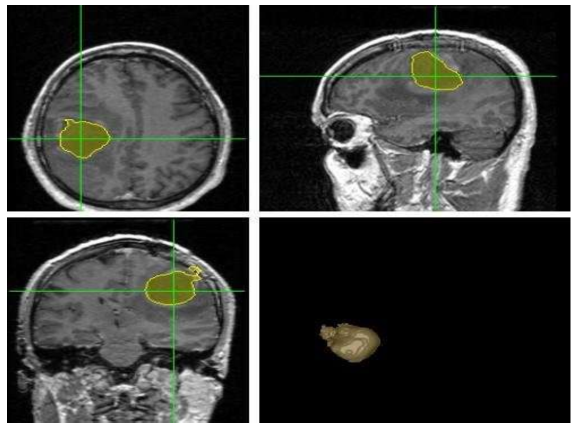

Figure 3: 3D Brain Segmentation Image

3.4.2 Unbalanced distribution of classes

In the segmentation task, the class imbalance issue, in which there is an uneven distribution of voxel classes in the training dataset, has an impact on the performance of the segmentation job. In an attempt to solve this issue, several methods have been investigated in the scientific literature.

Many studies included loss-based ways of resolving the issue of class imbalance, which were previously unexplored territory. There have been several publications that have included a weighted-loss function, in which voxels (or pixels) belonging to various classes are given weights according to their distribution in the training data. This guarantees that each class in the segmentation issue contributes to the model's loss in an identical amount, regardless of how many classes there are. Kuzima and colleagues coupled the CE loss with the Dice-based loss as a method of solving the issue of class imbalance. Other studies investigated the possibility of hard negative mining as a solution to the issue of class imbalance. Two-phase training [1, 5, 57] is another method of dealing with the issue of class imbalance [1, 5, 57]. In the first phase, the network is trained with patches that have equal class distribution, and in the second phase, the network is trained with patches that have genuine class distribution. Hierarchical segmentation may also be used to help deal with the issue of class imbalance.

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3.4.3 Data Augmentation

It is extremely easy and straightforward to create false data and add it to the data set in the data augmentation phase. In the suggested approach certain altered images have been introduced to the original data set by random modifications to the existing data set. The IXI dataset includes over 600 images from normal and healthy photographs of the patient. When used in conjunction with a machine learning method, data augmentation may help to reduce the generalization error. As previously stated, one method of successfully improving the generalization capabilities of a machine learning model is to train it on additional data. In reality, however, obtaining a significant quantity of high-quality training data is virtually difficult, particularly in the medical sector. Data augmentation is a technique for increasing the amount of training data available by generating more synthetic data and adding (augmenting) it to the training set. It is possible to generally categorize data augmentation into two categories: the modification of existing data and the creation of new data from scratch. By applying various transformations to the original data, new data are generated. These transformations include affine transformations (which involve rotation, zooming, cropping, flipping, and translations), elastic transformations (which involve shape variations), and pixel-level transformations (which involve pixel-level transformations) (intensity variations). However, while these transformations are useful in mitigating the effects of insufficient data, they fundamentally produce highly correlated images, which results in very little performance improvement and occasionally generates anatomically incorrect examples (e.g., when rotation is used). Artificial data creation, on the other hand, makes use of Generative adversarial networks (GANs) to create realistic data that is indistinguishable from the actual data, and it also acts as an effective technique for data anonymization. Even though we are scaling down, the final term image size will be more than the original term image size. The crop is just taken as a random sample of a portion of the original image. Data augmentation involves different operations such as scaling, rotation, translation, flipping, resizing, adding noise, perspective transformation, etc. Details of data augmentation parameters used in this proposed approach with their values are tabulated in Table 2.

Table 2: Data Augmentation Parameters.

Parameter	Value
FillValue	0
RandXReflection	1
RandYReflection	0
RandZReflection	[0,1,0]
Rand XScale	[0,1,1]
Rand Yscale	[1,1,1]
Rand ZScale	[0,0,1]
Rand XShear	[0,0,0]
Rand YShear	[1,1,1]
Rand ZShear	[0,1,1]
RandXTranslation	[25,0,-25]
RandYTranslation	[0,25,-25]
RandZTranslation	[-25,0,25]

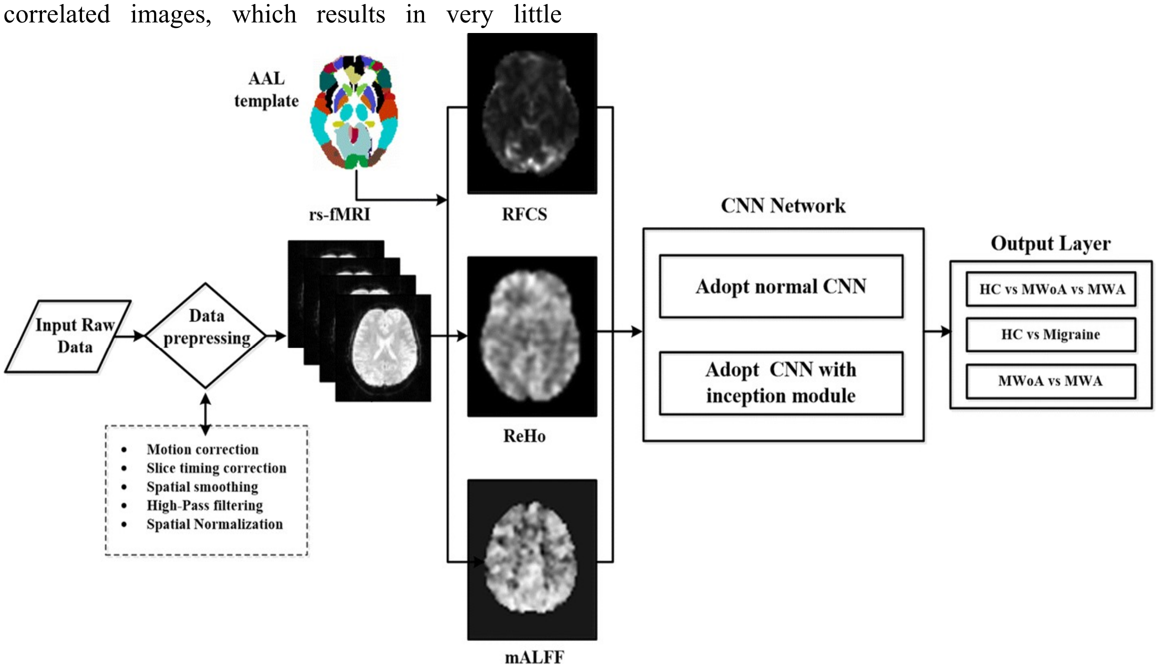

Figure 4: Proposed System Architecture

3.5 Convolution Neural Network Prediction Model

Figure 4 illustrates, that the term "Convolution Neural Network" refers to the network using a mathematical process known as convolution. A convolution neural network has an input and an output layer and many hidden layers. Typically, the hidden layers of a CNN consist of a sequence of convolution layers describing a multiplication or other dot product. The activation function is usually referred to as a RELU layer and is followed subsequently by additional convolutions known as hidden layers such as pooling layers, fully connected layers, and normalization layers because the activation function includes their inputs and outputs and the final convolution. In general, a convolution network design consists of three major layers that are combined and completely linked. The network utilizes multiple kernels in convolution layers to represent the input image to generate distinct function mappings. Each convolution neural network has two kinds of training: forward feed and backpropagation. The convolution process using a convolution filter is carried out in each layer and followed by a pooling action.

3.6 Initialization of weight

The primary aim of weight initialization is to avoid the disappearance in a deep neural network of activation layer outputs at the time of a forward pass. If this happens, loss gradients are either too little or too big to flow backward and if it can even converge, the network will take longer. The result of this layer multiplication may be the inputs of the next layer, etc.

3.7 Weight initialization

The main objective of weight initialization is to prevent a deep neural network with activation layer outputs from disappearing while passing forward. If this is true, the loss gradients are either too little or too large to flow backward and the network takes longer if it can even converge. The output of this layer multiplication may be the following layer inputs, etc.

3.8 Pooling

In general, a pooling layer follows a convolution layer that lowers the number of network parameters and the size of the maps which reduces computing costs. Max pooling is one of the commonly used methods of pooling.

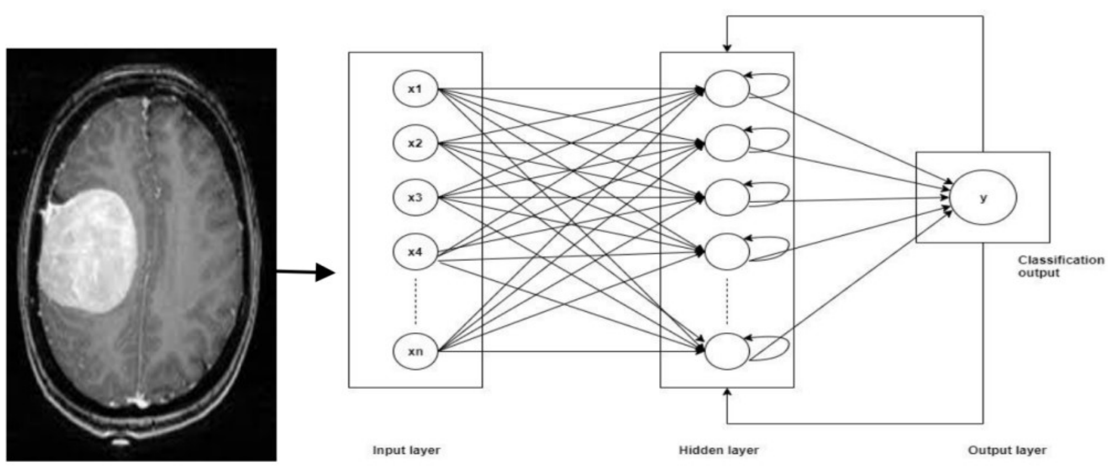

Figure 5: Recurrent Neural Network Architecture

3.9 Recurrent Neural Network Prediction Model

Recurrent Neural Networks (RNNs) are neural networks that can handle input data of time series. Speech recognition, sentiment analysis, machine translation, activity identification, etc are among the uses of this network. The Recurrent Neural Network model is shown in Figure 5. There is a link between nodes which form a directed diagram and a time sequence. This enables it to show dynamic temporal behavior. Based on feed-forward neural networks, RNNs can handle varied input lengths by using their internal state (memory). There are two main categories of networks with a general structure comparable, one of which is finite and one is endless. Both classes may show dynamic temporary behavior. A directed acyclic graph is a finite impulse recurrent network that may be unrolled and substituted by a pure feedback neural network. The recurrent network with infinite impulses is a cyclically directed graph that cannot be unrolled. The

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data may be scanned in a recurring neural network from left to right. The mistake is reported from the final step to the first step. The error is computed at each step and enables us to adjust weights. By giving equal weights and bias for all layers, RNN transforms independent activation into dependent activations decreasing the complexity of raising parameters and entering a concealed next layer by remembering each previous output. This enables all three layers to be linked together such that the distinctions and weights of all hidden levels are the same and may form one recurrent layer.

3.10 RNN Classification algorithm

1. Apply a filter in the first layer
2. Filter sensitivity is decreased by smoothing the filter (i.e.)
3. The signal transmission is regulated by the activation layer from one layer to another.
4. Set the training period using the linear unit rectified (RELU). In the processing, layer neurons are linked to all neurons in the layer.
5. During the training loss layer at the end is added to provide the neural network feedback.

4. RESULT AND DISCUSSION

Our data collection includes images of MRI tumors and non-tumors obtained from various sources. Radiopedia13 includes actual instances in patients, Brain Tumor images were acquired from the original test dataset. This study uses a recurrent neural network to efficiently identify brain tumors automatically. The simulation is done using Python. The precision is calculated and compared with all other techniques of art. The accuracy of training, validation, and validation losses are computed to determine the effectiveness of the proposed brain tumor classification scheme.

Deep Learning Algorithm is being used for training:

In recent years, DL has become more popular for categorization. RNN is the most used deep learning algorithm for the categorization of medical images, and it is also the most recent. Using a hierarchical learning approach, the RNN learns the spatial connection between the pixels. This is accomplished via the use of feature maps to convolve the image. Then, using the max-pooling layer, decrease the size of the features, and lastly flatten the features before feeding them into the dense layer.

The 'DenseNet' CNN network, which has been pre-trained, is being utilized in this proposed study. DenseNet is a well-known design that consists of five convolutional layers, three max-pooling layers, and three fully-connected layers. It is one of the most often used architectures. [25] This architecture is taught to classify 1000 distinct objects in a single session. Additionally, some layers of the network may be retrained to detect objects that do not appear in the original dataset.

The proposed work introduces several advancements compared to prior research in brain tumor classification. Unlike traditional studies that primarily rely on 3D CNNs or hybrid models, this work leverages Recurrent Neural Networks (RNNs) to process 3D MRI data, effectively capturing sequential and spatial dependencies. Prior approaches often focus on static slices, whereas this method utilizes volumetric data, providing a more comprehensive representation of tumor structures. Additionally, the RNN model achieves a significantly higher AUC (0.9992), outperforming previously reported results. Furthermore, the study emphasizes generalization by testing on diverse datasets, a step often overlooked in earlier works, ensuring broader applicability.

4.1 Analysis of Performance

In this part, we described how the model may be created by adjusting and comparing parameters between the CNN model and the RNN model.

4.2 Metrics Performance

In this study, we have used loss and precision to analyze the system's performance.

4.3 Accuracy

Precision is one measure for classification models to be assessed. By utilizing the following formula, we can simply determine accuracy via the confusion matrix.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

4.4 Loss

The loss functions are used to update the weight vector with a labeled output and a computer model output. This study utilizes two widely used loss methods, "Gradient Descent" and "Medium-Square-Error." Mathematical decision and optimization theory indicate that a loss feature or cost function is a feature that translates an event with one or more variables to a real number intuitively reflecting some "cost" connected with the occurrence. Middle Squared Error (MSE) using the following formula is calculated:

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$$L(0) = \frac{1}{N}\sum_{i=0}^{N}(y_i - y_1) \times 100 \quad (2)$$

In the following formula N, the numbers of samples are represented and provide the basis real value and the forecast value of the sample.

4.5 Training

Training a model simply involves learning values from labeled instances for all weights. Builds a model in supervised learning by analyzing numerous example images and trying to find a model that minimizes loss. This approach is referred to as empirical risk reduction. A model aims to identify a set of weights and biases that lead to a loss reduction in all instances on average. We have evaluated the model with various learning rates, number of hidden layers, number of layers, different optimizers, and numbers of epochs to get an effective prediction model. The model is assessed by its precision and loss.

4.6 Analysis of results

Figure 6 and Figure 7 show the performance measurements such as training accuracy, training losses, test accuracy, and test loss when applying CNN architecture and RNN architecture. By comparing the architecture of CNN and RNN, RNN provides better precision concerning CNN; however, training time on a model based on RNN is more than that on a CNN model shown below in Table 3.

Table 3: Comparison of CNN and RNN Architectures Based on Precision and Training Time.

Parameter	Value
Network	'DenseNet'
Gradient Decay Factor	0.9000
Squared Gradient Decay Factor	0.9900
Epsilon	1.0000e=08
Initial Learn Rate	3.0000e-04
L2 Regularization	1.0000e-04
Gradient Threshold Method	'12norm'
Gradient Threshold	Inf
Max Epochs	100
Verbose	64
Verbose Frequency	0
Validation Data	50
Validation Frequency	Augmented Image Datastore
Validation Patience	3
Shuffle	5
Execution Environment	'auto'
Plots	'training-progress'
Sequence Length	'longest'
Sequence Padding Value	0

However, rather than a significant increase in the number of trained pictures, the current size of the dataset is insufficient to train a deep-learning model from the ground up. The transfer learning method is used in two distinct ways to solve this issue on the pertained DenseNet architecture to overcome it. First, the classification layer of the DenseNet is replaced with the softmax layer, which has two classifications, one of which is benign and the other of which is malignant. First and foremost, the weight is fine-tuned and back-propagated, preparing it for training with fresh weights. As a result, the learning rate is set to a low value to ensure that the weights of the convolution layer do not change much, while the weights of the dense layer are initialized at random. The stochastic gradient descent (SGD) method was used to update the weight of the network based on the input-enhanced dataset of brain MRI images collected during the training phase. The optimum weights of the extremely accurate network model are determined by this procedure.

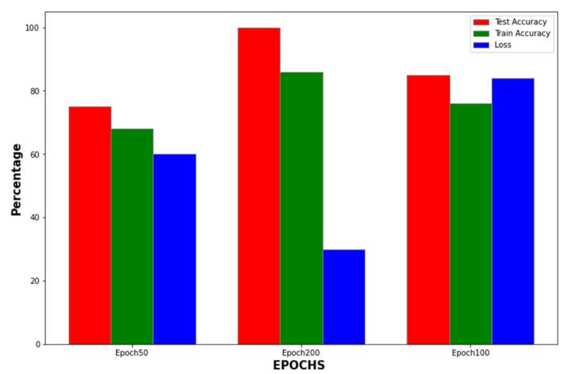

Figure 6: Recurrent Neural Network Test and Train Model

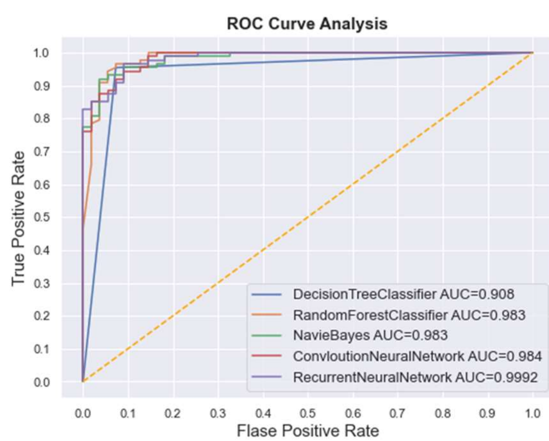

Figure 7: Comparison of Test and Train Model other Machine Learning Algorithms

The graph displays an ROC (Receiver Operating Characteristic) curve analysis comparing the performance of various classifiers in brain tumor classification. The x-axis represents the False Positive Rate (FPR), while the y-axis shows the True Positive Rate (TPR). The Area Under the Curve (AUC) is a key metric, indicating the model's ability to distinguish between classes. Among the classifiers, the Recurrent Neural Network (RNN) achieves the highest AUC (0.9992), signifying superior performance. Convolutional Neural Networks (CNN) also perform well (AUC = 0.984), followed by Naive Bayes and Random Forest (AUC = 0.983), with Decision Tree performing the least (AUC = 0.908).

5. CONCLUSION

Instead of employing 3D brain tumor detection 3D MRI image machine-learning methods, deep learning approaches are recommended to automate function extraction. The suggested approach improves precision and lowers losses in comparison to the current system. The network with the best accuracy throughout the testing was chosen and utilized as a classifier for the identification of brain tumors. To enhance the accuracy and decrease the calculation time, the suggested method introduces a convolution neural network classification. The findings are also shown as tumor or normal brain images. CNN is one of the techniques of deep learning that includes a series of feed layers. For implementation, python language is also utilized. A real image database for categorization is utilized. It's one of the models pre-trained. Thus, the training is done for the last layer alone. CNN extracts also raw pixel data with depth, width, and height characteristic values. Finally, the reasonable loss-based gradient function is used for high precision. The accuracy of training, validation precision, and loss of validation are determined. The accuracy of training is 99.92%. Likewise, the accuracy of validation is excellent and the loss of validation is extremely low.

In conclusion, this study validates the hypothesis that Recurrent Neural Networks (RNNs) are highly effective for brain tumor classification using 3D MRI data. The RNN's superior AUC (0.9992) demonstrates its ability to capture sequential and spatial dependencies, outperforming traditional methods like CNNs and Decision Trees. The initial question of whether RNNs can enhance classification accuracy is answered affirmatively, with the model addressing key limitations in existing approaches, such as static slice-based analysis. This work underscores the potential of RNNs in advancing diagnostic precision and sets a benchmark for future research in AI-driven medical imaging, bridging innovation with clinical relevance.

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