BRAIN TUMOR DETECTION USING RECURRENT NEURAL NETWORK

Dr S. Hemalatha[1], Dr A. Swaminathan[2], Jancy. A[3], Swetha. G. S[4]

[1]HOD department of CSBS, Panimalar Engineering College, Chennai-India

[2]Associate Professor department of CSBS, Panimalar Engineering College, Chennai-India

[3]Department of CSBS, Panimalar Institute of Technology, Chennai-India

[4]Department of CSBS, Panimalar institute of Technology,Chennai-India

ABSTRACT:

Another common and deadly condition is brain tumours, which often only have a few years to live in their most severe stages. Planning therapy is so essential to improving living conditions for a patient. The techniques include ultrasonic imaging, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI) that can be used to evaluate tumours in several human organs, including the breast, prostate, liver, brain, and lungs. Many different types of brain malignancies are specifically diagnosed via MRI imaging. On the other hand, tumour or non-tumour segregation is permanently disrupted by the enormous amount of data that MRI scans acquire. Yet there are many issues with it because there are so few photographs. To prevent death, a trustworthy automatic separation mechanism is necessary. Automated brain tumour differentiation is extremely challenging since it is difficult to distinguish big regions from the surrounding many various types of brain tumour shapes. CNN is one particular deep learning algorithm architecture that is used for operations like analyzing pixel data and picture recognition. In this study, we use RECURRENT NEURAL NETWORK that stimulates neuron activity in the human brain as it uses patterns to predict the next likely scenario. RNN saves the output of a particular layer and feeds this back to the input, so as to predict the output of the layer.

Keywords: LSTM, RNN, TUMOR, MRI, CT, CNN, Brain tumor detection, Brain tumor segmentation, neoplasm, Deep learning.

RELATED WORK

Aditya Miglani[1] Magnetic Resonance Imaging (MRI) images are used by neurosurgeons and other specialists to identify brain cancers. To work past these restrictions, several deep-learning approaches have been developed to identify brain tumours. This review article evaluates and summarises the most recent studies on the topic to provide a thorough overview of the field of brain tumour detection, paying particular attention to segmentation and classification.

Shahzad Akbar[2]The suggested CNN architecture is used to segment images of brain tumours, and the global threshold technique is applied in post-processing to remove small non-tumour regions that improved segmentation outcomes. The findings demonstrate that the proposed framework is efficient and successful because it outperformed the other two datasets on the BRATS2020 dataset. The experimentation's findings show that the suggested framework performs better than other recent investigations in the literature. Furthermore, this discovery will support medical professionals in their automatic diagnosis of brain tumour conditions.

Deepak Chaudhary [3] The binary thresholding and CNN segmentation methods were utilised next for precise cancer location detection. Accuracy, sensitivity, and specificity are just a few of the performance indicators that will be used to analyse the final results. It is hoped that the planned work will perform more admirably than its competitors.

Javaria Amin[4] This study aims to give researchers with a comprehensive literature assessment of magnetic resonance imaging's potential for brain cancer identification. This study database explored the anatomy of brain tumours that were made public, augmentation methods, segmentation, feature extraction, classification, deep learning, transfer learning, and quantum algorithms. The final section of this review includes a summary of all pertinent information for the diagnosis of brain cancers, including advantages, limitations, advances, and prospects.

AMRUTHA PRAMOD HEBLI[5] The function of the brain is restricted by the brain tumour and abnormal development of cells inside the brain skull. It is now possible to identify brain tumours early because of the progress of machine learning (ML) and image analysis. The stages of image analysis are covered in this study, and an overview of related publications is provided by examining many research papers. This article summarises the technologies that can be used to forecast brain tumours.

Venkatesh S Lotlikar[6] This review article's goal is to provide a thorough examination of the methods used in the last 15 years, including preprocessing, machine learning, and deep learning, and then, using that information, to give a thorough comparative analysis. The difficulties that researchers have had in the past when attempting to detect tumours have been explored, along with potential future research areas.

Maryam Naseri &
Malika Bendechache [7] To mine both local and global properties, this C-CNN model employs two different strategies. In addition, the segmentation accuracy of brain tumours is demonstrated to be enhanced by a novel Distance-Wise Attention (DWA) mechanism compared to cutting-edge models. Comprehensive tests on the BRATS 2018 dataset are performed to demonstrate that the suggested model generates competitive results. Mean dice scores of 0.9203, 0.9113, and 0.8726 are obtained using the suggested technique for the tumour core, augmenting tumour, and overall tumour, respectively.

Kavita Bathe[8] The depth-wise separable Convolution Neural Network used in this paper employs deep learning to detect the tumour based on Brain MRI. Experiments are run on the open dataset made accessible by Kaggle. According to testing data, Depth-wise Separable Convolution Neural Network outperforms Support Vector Machine, K Nearest Neighbor, and Convolution Neural Network in terms of accuracy.

Aryan Methil[9]This study suggests a novel technique for identifying brain cancers from distinct brain pictures by doing multiple image analyses first. The effect of other photo preprocessing techniques, outside those that have been selected for training, on our dataset is also explored in the paper. The classification problem was solved using a neural network using convolutions technology. CNN had an impressive recall of 98.6% on the training set and 99.73% on the validation set at the time of our study.

P Gokila Brindha[10] Brain cancers can be found using deep learning and machine learning techniques. When these algorithms are applied to MRI images, it takes a relatively short time to forecast a tumour, and more accuracy assists the patient’s treatment. These projections enable the radiologist to take prompt action. The proposed study uses two different kinds of artificial neural networks to detect brain cancers and assesses the performance of self-defined neural networks which are artificial and convolution neural networks.

INTRODUCTION

Several non-invasive techniques for examining the inside of the body are referred to as "medical imaging". Medical imaging is primarily used in the human body for therapeutic and diagnostic purposes. So, it has a big impact on how well people are treated and how healthy they are. The success of image processing at a higher level is determined by the image segmentation process, which is a vital stage. In this instance, our primary attention has been on segmenting the brain tumour from the MRI scans. It makes it simple for medical personnel to locate the tumour in the brain. Medical image processing (MRI) involves using and examining 3D datasets of the physical body that are typically obtained via CT or the use of magnetic resonance imaging (MRI). Using medical image processing The anatomy of individuals as well as communities is well-understood by radiologists, engineers, and clinical practitioners. Measurement, statistical analysis, and the creation of simulation models with accurate anatomical geometry can all help us get a deeper knowledge of how human anatomy and medical equipment interact. The term "tumour" is a synonym for "neoplasm," which is a proliferation of cells that is abnormal. Cancer and tumours are very distinct from one another. Every state-of-the-art language modelling task, including machine translation, uses recurrent neural networks. Machine translation, document detection, sentiment analysis, and information extraction are just a few of the modern language modelling applications that make using recurrent neural networks.

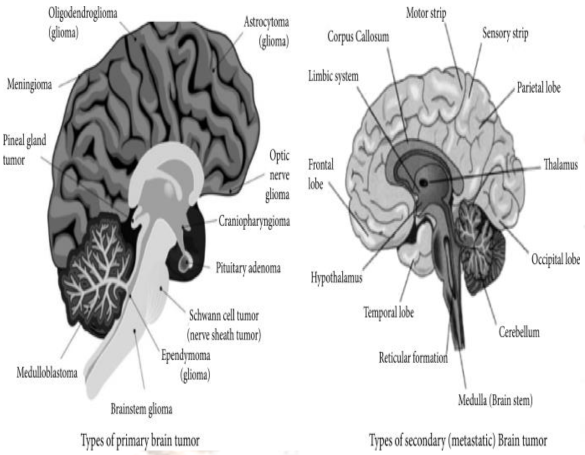


Figure 1

Recurrent neural networks (RNNs) are a type of neural network in which the result of one phase is utilised also as inputs for the following one. Conventional neural networks have separate inputs and outputs, but in circumstances where it is necessary to recall the words that came before to predict the following word in a phrase. As a result, RNN with a Hidden Layer has been established to address this problem. The Hidden state, which preserves certain data about just a sequence, would be the key or most significant characteristic of RNNs. All this data used in calculations are stored in the "memory" of RNNs. It employs similar settings for each input and executes the same operation on each input or hidden layer to create the output. In contrast to other neural networks, the parameters' complexity is lower.

A special kind of artificial neural network called an RNN employs a special looping architecture to provide continuous knowledge about earlier experiences. They can be used to predict the next word in a series, among other situations involving data with sequences.

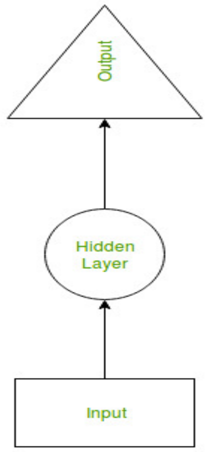


Figure 2

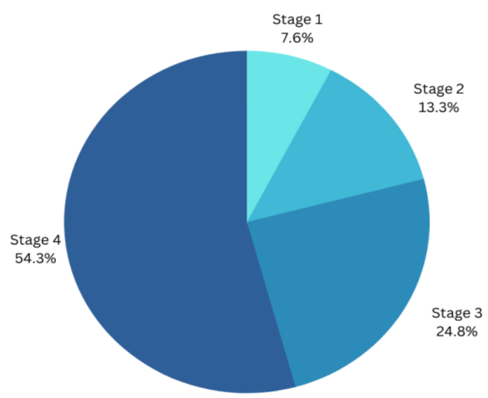
CLASSIFICATION OF TUMOR

Benign Tumor: Unlike cancer, it might not spread to other areas of the body or infect surrounding tissue. Although it can be catastrophic if it pushes on vital systems like blood vessels or nerves, the prognosis for benign tumours is normally not too poor.

Precancerous tumour: These tumours do not contain cancerous cells. However, they must have the potential to become cancerous. The cells will grow and spread to generate various bodily components.

Malignant Tumors: They occur when cells multiply uncontrolled. The sickness will become hazardous if the cells continue to grow and unfold. Malignant tumours grow quickly and metastasize, or spread to different regions of the body regions.

Figure 3



STAGES OF TUMOR	VIGOROUSNESS OF TUMOR
Stage 1	7.6%
Stage 2	13.3%
Stage 3	24.8%
Stage 4	54.3%

Table 1

RESEARCH METHODOLOGY

Module for an RNN

The existence of facial characteristics in a picture is commonly accepted. The image's pixels have a temporal link at the pixel level. Each image's pixel row may be conceived of as having a temporal connection if the image's height and width are viewed as the time step and the eigenvalue, respectively. As a result, both the geographical relationship of the picture and the temporal relationship between the pixels were taken into account when building the model. We may extract time sequence properties from the pixel using the RNN component termed stacked LSTM. Arbitrary input and output values can be handled by RNN. Working with sequential or time series data, It is a form of synthetic neural network. RNN predicts the expected future condition based on trends. RNNs are employed in deep learning and in the development of models that replicate the activity of neurons in the human brain. RNN operates under the tenet that it can forecast a layer's output by saving that layer's output and retransmitting it via the network. A RECURRENT NEURAL NETWORK is composed of nodes from all of the neural network's layers compressed into a single layer.

LSTM:

RNN can remember input over a long period thanks to LSTM (LONG SHORT-TERM MEMORY). Because LSTM keeps data in memory, akin to a computer's memory, this is the case. The LSTM's memory can be used to read, write to, and remove data. It is the most effective RNN since it addresses the issues with recurrent network training and is utilised in a variety of applications.

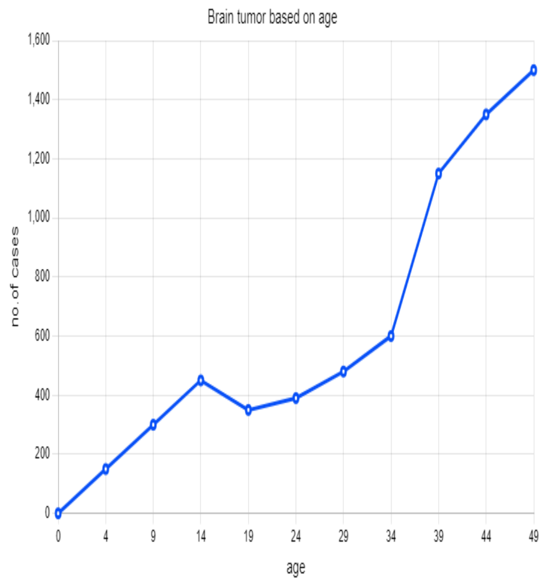


Figure 4

Age at Diagnosis	No. of cases
0	0
4	150
9	300
14	450
19	380
24	400
29	490
34	600
39	1150
44	1380
49	1500

Table 2

From the above graph, we infer that the number of active cases has a steady increase until teen. There is a gradual slope in the later twenties and early thirties. There is a gradual increase after the later thirties.

FEATURES OF RNN:

One of the most crucial aspects of RNNs is the hidden state, which retains some details about a sequence. RNNs have a memory where they keep track of all the calculations' details. In an LSTM cell, there are three separate gates.

1. AVOID gate

2. INTAKE gate

3. OPEN the gate

Types of RNN:

Traditional neural networks are poor at processing sequential data because they have separate input and output layers. The Recurrent Neural Network, a brand-new neural network, was created as a result to store the results of earlier outputs in internal memory. These outcomes are then used as inputs by the network. It may be used to detect patterns, differentiate sounds and voices, examine conversations, and forecast time-series data.

In RNN, hidden layers serve as memory spaces for storing the results of a layer in a loop.

The four most typical varieties of RECURRENT NEURAL networks are as follows:

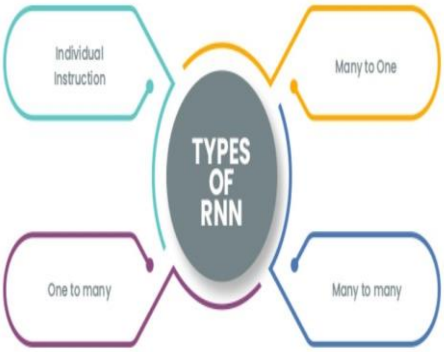


Figure 5

1. Individualized instruction:
One-to-One RNNs are the most basic, with a single input and a single output, and behave like a standard neural network with fixed input and output sizes.

2. Many-to-One:

With just one input, a one-to-many RNN may provide several results. It accepts a fixed input size and returns a data string. It may be used to create audio and captions for images.

3. one-to-many

When numerous input units or a series of them must produce a single output, many-to-one is utilised. Several inputs are required for a given output. An illustration of this kind of recurrent neural network is sentiment analysis.

4. Many-to-many:
A technique called "Many-to-Many" creates a stream of data from a sequence of input units. There are additional subdivisions within this RNN type:

Equal Unit Size:

In this instance, there are equal input and output units. Name-Entity Recognition is a widely used software.

Unequal Unit Size:

The inputs' and outputs' unit counts are different. Machine translation is one area where it is used.

ARCHITECTURAL CLASSIFICATION OF RNN:

• Fundamental classification based on input and output quantities

• Not all RNNs have input and output sequences of equal length.

• Machine translation is a multi-tiered architecture.

• A deep learning approach is used to model sequential data. NEURAL NETWORK CURRENT

• A conventional LSTM RNN design has three layers: an input layer, a recurrent LSTM layer, and an output layer.

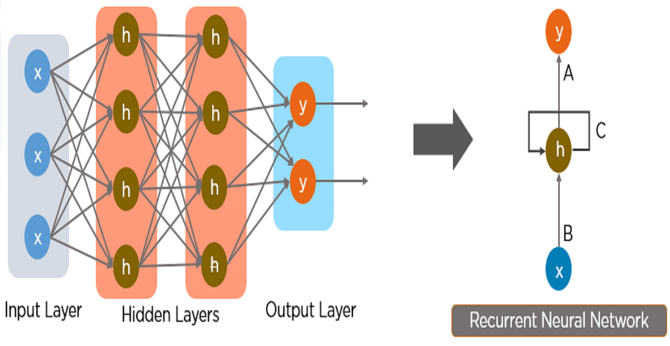


Figure 6

RNN'S PRIMARY STRUCTURE:

Every RNN has been made up of a series of reiterated neural network modules. Standard RNNs will have a relatively basic structure for this recurring module, such as one tanh layer. The recurrent module in LSTMs also has a chain-like structure, although it is a little bit different.

RULE USED IN RNN:

Essentially, applying the chain rule to the unfolded graph is what results in X, Y, Z, r and s parameters, as well as the sequence of nodes indexed by u for b(u), g(u), p(u), and m(u). The sources are based on the basic RNN form.

INVENTOR OF RNN:

The ISING MODEL (1925) by Wilhelm Lenz and Ernst Ising was the first non-learning RNN architecture. In 1972, Shun'ichi Amari made it adaptable. This was also known as the Hopfield network (1982).

An artificial neural network called an RNN can analyse sequential input, identify patterns, and

forecast the outcome. Because it may repeatedly carry out the same action or operation on a series

of inputs, it is known as recurrent.

STEPS IN AN RNN:

• STEP 1: Get Started. We must first determine the size of the multiple variables before we can start creating the basic neural network cell X, Y, Z, r, and s.

• STEP 2: Make a forward pass

• STEP 3: Calculate Loss

• STEP 4: Reverse pass

• STEP 5: Recalculate weights

• STEP 6: Repetition of steps 2-5

ASSESSMENT RESULTS:

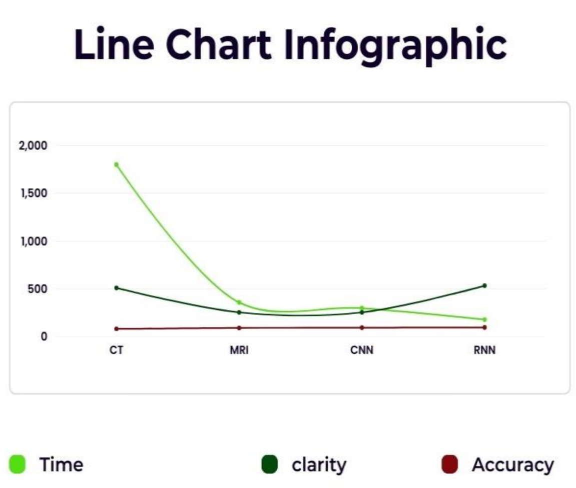


Figure 7

The above chart depicts the accuracy, time and clarity concerning the methodologies used.

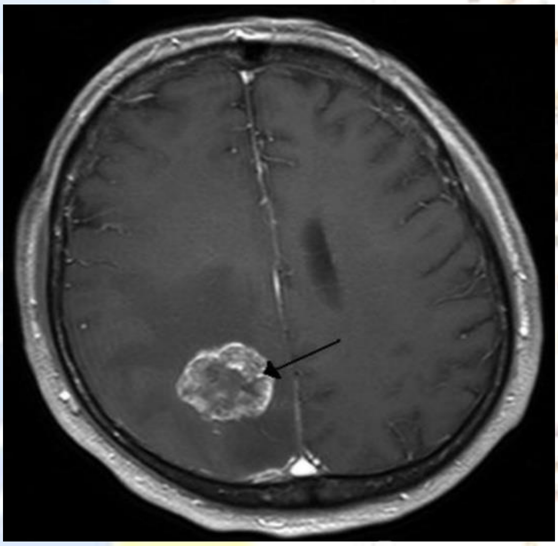
PROBABILITY DATA SET:

To analyse our experimental data, we employ the RNN module. RNN should have three dimensions

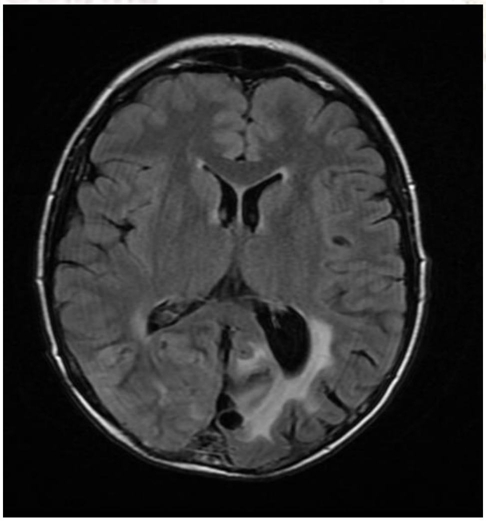
for its input data (batch size, sequence length, and input dimension). The number of samples we

submit to the model in a single batch.

TIME COMPLEXITY: For simple single-layer recurrent networks, such as plain RNNs, LSTMs, or GRUs, the computational complexity with the supplied sequence's size in a sequence that is linear both during training and during inference, or O(n), where n is the size of the supplied sequence.



IMAGES WITH TUMOR
Figure 8



IMAGES WITH NON-TUMORS
Figure 9

CORRELATION COEFFICIENT:

The parameters	Value
Correlation index (r) for Pearson	**0.989**
the significance level	0.001391
The covariance coefficient	1055
(n) size of sample	5
Statistic data	11.5581

Table 3

r = 0.989

Table 4

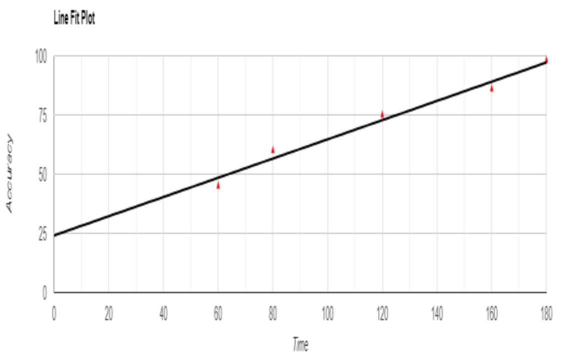


Figure 10

CONCLUSION:

Recurrent neural networks, also called neural networks, are adaptable devices that may be used to tackle a variety of issues. Recurrent neural networks are still a hot topic in automated tumour segmentation research.

When paired with Convolutional Neural Networks, this sort of neural network is used to produce labels for untagged illustrations. This mixture is effective.

When anticipating words, for instance, we may require more context than just the single previous word. This is referred to as the vanishing gradient problem, and Long-Short Term Memory Networks (LSTM), a subtype of Recurrent Neural Networks (RNN), are used to resolve it.

Recurrent Neural Network	Convolutional Neural Network
98%	96.47%

Table 5

ACCURACY TABLE

REFERENCES:

Time	60	80	120	160	180
Accuracy	45	60	75	86	98

[1]A Literature Review on Brain Tumor Detection and Segmentation
Aditya Miglani; Hrithik Madan; Saurabh Kumar; Sanjay Kumar. 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)

[2]Automated Detection of Brain Tumor through Magnetic Resonance Images Using Convolutional Neural Network Sahar Gull, Shahzad Akbar, and Habib Ullah Khan

[3] Deepak Chaudhary

UNIVERSITY SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY GAUTAM BUDDHA UNIVERSITY

[4] Brain tumour detection and classification using machine learning: a comprehensive survey Javaria Amin,

Muhammad Sharif,
Anandakumar Haldorai,
Mussarat Yasmin &
Ramesh Sundar Nayak
Complex & Intelligent Systems volume 8, pages3161–3183 (2022)

[5] BRAIN TUMOR DETECTION USING IMAGE PROCESSING: A SURVEY November 2016 Conference: 64th IRF International Conference Pune India
Authors: Amruta Pramod Hebli

[6]Brain Tumor Detection Using Machine Learning and Deep Learning: A Review
Venkatesh S Lotlikar An Efficient Multi-Scale Convolutional Neural Network Based Multi-Class Brain MRI Classification for SaMD.

[7] Brain tumour segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images Ramin Ranjbarzadeh, Abbas Bagherian Kasgari, Saeid Jafarzadeh Ghoushchi, Shokofeh Anari, Maryam Naseri & Malika Bendechache

[8] Brain Tumor Detection Using Deep Learning Techniques Proceedings of the 4th International Conference on Advances in Science & Technology (ICAST2021) Brain tumour detection from MRI images using deep learning techniques

[9]Brain Tumor Detection Using Deep Learning and Image Processing March 2021
DOI:10.1109/ICAIS50930.2021.9395823Conference: 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)
Authors:
Aryan Methil Narsee Monjee Institute of Management Studies

[10] P Gokila Brindha1, M Kavinraj2, P Manivasakam2 and P Prasanth2 Published under licence by IOP Publishing Ltd IOP Conference Series: Materials Science and Engineering, Volume 1055, International Virtual Conference on Robotics, Automation, Intelligent Systems and Energy (IVC RAISE 2020) 15th December 2020, Erode, India