

PAPER NAME AUTHOR

OMAD Project Report Sem V.docx Abhay Mathur

WORD COUNT CHARACTER COUNT

6044 Words 34548 Characters

PAGE COUNT FILE SIZE

34 Pages 2.8MB

SUBMISSION DATE REPORT DATE

Dec 12, 2023 8:05 PM GMT+5:30 Dec 12, 2023 8:06 PM GMT+5:30

4% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

- 3% Internet database
- Crossref database
- 4% Submitted Works database

- 0% Publications database
- Crossref Posted Content database

Excluded from Similarity Report

- · Bibliographic material
- · Cited material
- · Manually excluded sources

- Quoted material
- Small Matches (Less then 10 words)
- · Manually excluded text blocks

OMAD – Brain Tumour Detection

Submitted in partial fulfillment of the requirements of the course Innovative Product Development under

T. Y. B. Tech. Artificial Intelligence and Machine Learning

By

Abhay Mathur - 60017210016

Mahir Madhani - 60017210019

Darsh Thakkar - 60017210040

Omar Shaikh - 60017210088

Guide

Nilesh Rathod

Assistant Professor

University of Mumbai 2022-2023

CERTIFICATE

This is to certify that the project entitled "OMAD – Brain Tumour Detection" is a bonafide work of Abhay Mathur (60017210016), Mahir Madhani (60017210019), Darsh Thakkar (60017210040) and Omar Shaikh (60017210088) submitted to the Department of Artificial Intelligence and Machine Learning in partial fulfillment of the requirement for the course of Innovative Product Development.

(Prof.)

(Prof.)

(Dr. Aruna Gawade)

Internal Guide

I/c. Head of the Department

(Dr. Hari Vasudevan) Principal

Project Report Approval for Innovative Product Development.

This project report entitled *OMAD – Brain Tumour Detection* by *Abhay Mathur (60017210016), Mahir Madhani (60017210019), Darsh Thakkar (60017210040) and Omar Shaikh (60017210088)* is approved for the course of Innovative Product Development.

	Examiners
	1
	2
Date:	
Place: Mumbai	

Declaration

I/We declare that this written submission represents my/our ideas in my/our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Student Name (Sap Ids)	
Student Name (Sap Ids)	

Date:

Acknowledgement

Our sincere appreciation extends for the invaluable guidance and support provided throughout the duration of our project. The expertise and mentorship from our mentors have played a pivotal role in shaping our understanding and approach, and we are sincerely grateful for the time and effort dedicated to our development.

The constructive feedback and insightful suggestions from our mentors have significantly contributed to the success of our project. Their commitment to excellence and willingness to share knowledge have not only enriched our skills but have also inspired us to strive for the highest standards in our work.

We genuinely thank our mentors for the opportunity to work under their mentorship. Their dedication to our success has been a driving force, and we are appreciative of the encouragement and motivation consistently provided. The mentorship has not only enhanced our project but has also left a lasting impact on our academic and professional growth.

Expressing our gratitude for being exceptional guides and mentors, we truly value the wisdom and support shared with us.

Abstract

Artificial Intelligence (AI) has emerged as a promising avenue for healthcare advancements. Its implementation in image recognition goes beyond the limitations of human vision, proving especially beneficial in medical imaging for automated diagnosis. Diagnostic radiology is being transformed from a subjective skill into an objective science, thanks to the integration of AI.

Brain tumours have become dangerously common in this day and age. In the United States, brain and nervous system tumors affect about 30 adults out of 100,000. Brain tumors are dangerous because they can put pressure on healthy parts of the brain or spread into those areas. Some brain tumors can also be cancerous or become cancerous. They can cause problems if they block the flow of fluid around the brain, which can lead to an increase in pressure inside the skull. Some types of tumors can spread through the spinal fluid to distant areas of the brain or the spine

Having researched in the application of Artificial Intelligence and Machine learning in the field of Medicine, our team has decided to work on methods to assist doctors and medical professionals in the early and accurate detection of brain tumours using Machine Learning algorithms.

Table of Contents

Chapter	Contents	Page No.
I	Introduction	8
	1.1 Aim of the Project	8
	1.2 Motivation	8
	1.3 Organization of Report	9
II	Literature Survey	10
III	Problem Description	19
	3.1 Problem Statement	19
	3.2 Scope of the Project	19
IV	Proposed Design	20
VI	Results and Discussions	22
VII	Conclusion	29
VIII	Publication	30
IX	References	31

List of Figures

Fig. No.	Figure Caption	Page No.
2.5.1	Structure of a CapsNet	15
4.1	Architecture diagram	21
5.1	Training Results	23
5.2	Validation Batch	23
5.3	Graphs of Training Results	24
5.4	Confusion Matrix	25
5.5	Precision and Recall Curves for Box	25
5.6	Precision and Recall Curves for Mask	26
5.7	Inference from Labels	27
5.8	Labels Correlogram	28
5.9	ViT Segmentation Results	28
5.10	Inference from ViT Segmentation Results	28

List of Abbreviations

Sr. No.	Abbreviation	Expanded form

1. Introduction

Artificial intelligence (AI) holds great potential for revolutionizing health innovation. Utilizing AI in image recognition expands our understanding beyond human capabilities, particularly in medical imaging for automatic diagnosis. With AI, diagnostic radiology is shifting from subjective interpretations to objective and scientific analysis.

Artificial Intelligence (AI) and Machine Learning (ML) have shown immense potential in the field of brain tumor detection, revolutionizing the way we approach this critical medical challenge. By utilizing advanced

Deep Learning algorithms and image recognition and segmentation techniques, AI can extend beyond human visual capabilities, aiding in the automatic diagnosis of brain tumors from medical images, particularly MRI scans. The importance of early and accurate brain tumor detection cannot be overstated, as timely identification allows for prompt intervention and improved treatment outcomes. Brain tumors can be highly dangerous and life-threatening, as they can exert pressure on vital brain structures, leading to various neurological symptoms and impairments. Early detection through AI and ML technologies can significantly enhance the chances of successful treatment, ultimately contributing to better patient care and improved survival rates. Additionally, AI's ability to analyze large datasets and identify patterns in medical images can facilitate research, enabling medical professionals to gain deeper insights into brain tumor development, progression, and potential personalized treatment strategies.

1.1 Aim of the Project

Our aim is to increase the accuracy of existing Brain Tumour Detection models by experimenting with more expansive datasets and newer and cutting edge image segmentation models along with deep learning algorithms. We also aim to work on identifying early symptoms of brain tumours and how we can detect them using Machine Learning.

1.2 Motivation

Brain tumours are an extremely dangerous kind of ailment that is quite common. In the United States, brain and nervous system tumors affect about 30 adults out of 100,000. Tumours can also turn malignant and cancerous and cause pressure inside your skull to increase. This can cause brain damage and be lifethreatening. We chose to work on this problem since we think it is a crucial one that needs immediate

attention.

1.3 Objective

Our objective is to create a functioning machine learning model well-trained on large and extensive datasets validated by medical experts and producing accurate results in detecting brain tumours when the earliest symptoms of them start to manifest. We hope this model will be of assistance to medical professionals in immediate and accurate detection of brain tumours.

2. Literature Survey

A literature survey, also known as a literature review, is a comprehensive examination and evaluation of existing academic, scholarly, and relevant sources on a specific topic or research question. It involves systematically reviewing and summarizing the current state of knowledge, theories, and research findings related to the chosen subject. The primary objectives of a literature survey are to gain a deep understanding of existing research, identify gaps in the current knowledge, and establish a theoretical framework for a new study or research project. Researchers conducting a literature survey explore various sources such as books, academic journals, conference papers, and other scholarly publications to provide a well-rounded overview of the existing literature in their field of interest. The findings of a literature survey are crucial for informing the direction of new research and ensuring that it contributes meaningfully to the existing body of knowledge.

[1] Artificial Intelligence Approach for Early Detection of Brain Tumors Using MRI Images by Adham

Aleid, Khalid Alhussaini, Reem Alanazi, Meaad Altwaimi, Omar Altwijri and Ali S. Saad This research introduces a classical automated segmentation approach designed to detect early-stage brain tumors in MRI images. The method relies on a multilevel thresholding technique implemented through a harmony search algorithm (HSO), specially tailored for MRI brain segmentation. The parameters were optimized to suit this particular purpose. By employing multiple thresholds based on variance and entropy functions, the histogram is partitioned into distinct segments, each associated with different colors. Subsequently, morphological operations are applied to remove small areas that could be considered noise, and a connected component analysis is utilized to identify and detect brain tumors after the segmentation process.

The assessment of brain tumor detection performance relies on various performance parameters, including Accuracy, Dice Coefficient, and Jaccard index. These results are then compared to manual assessments conducted by domain experts. Additionally, a comparison is made with different CNN and DLA approaches using the "BraTS 2017 challenge" Brain Images dataset. For this comparison, the average Dice Index serves as the performance measure. The outcomes of the proposed approach exhibit competitive accuracy levels similar to those achieved by CNN and DLA methods. However, the proposed method outperforms these approaches significantly in terms of execution time, computational

complexity, and data management.

Future prospects entail investigating and incorporating pixel-based methods within the region of interest to refine the segmentation process. The primary objective is to enhance the accuracy and Dice index of brain tumor detection, leading to more precise diagnoses.

[2] Accurate brain tumor detection using deep convolutional neural network by Md. Saikat Islam Khan, Anichur Rahman, Tanoy Debnath, Md. Razaul Karim, Mostofa Kamal Nasir, Shahab S. Band, Amir Mosavi and Iman Dehzangig

This research introduces two deep learning models for identifying brain abnormalities as well as classifying different tumor grades, including meningioma, glioma, and pituitary. The "proposed 23-layer CNN" architecture is designed to work with a relatively large volume of image data, whereas the "Finetuned CNN with VGG16" architecture is designed for a limited amount of image data. A comprehensive data augmentation technique is also conducted to enhance the "Fine-tuned CNN with VGG16" model's performance.

The experimental results demonstrated that both models enhance the prediction performance of diagnosis of brain tumors. They achieved 97.8% and 100% prediction accuracy for dataset 1 and dataset 2, respectively outperforming previous studies found in the literature.

Future Scope:

In order to make a robust deep learning model, we would require a large dataset i.e. a substantial amount of annotated images collected by a qualified physician or radiologist.

Adopting zero-shot, few-shot, and deep reinforcement learning (DRL) techniques could help us to tackle this problem in the future. Zero-shot learning has the capacity to build a recognition model for unseen test samples that are not labeled for training. Zero-shot learning can thereby address the issue of the tumor classes' lack of training data. Additionally, a deep learning model can learn information from a small number of labeled instances per class using few-shot learning technique. On the other hand, DRL can reduce the need for precise annotations and high-quality images.

Another future direction is to use more layers or other regularization techniques to work with a small image dataset using CNN model.

[3] MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques by Soheila Saeedi, Sorayya Rezayi, Hamidreza Keshavarz & Sharareh R. Niakan Kalhori

A dataset containing 3264 Magnetic Resonance Imaging (MRI) brain images comprising images of glioma, meningioma, pituitary gland tumors, and healthy brains were used in this study. First, preprocessing and augmentation algorithms were applied to MRI brain images. Next, they developed a new 2D Convolutional Neural Network (CNN) and a convolutional auto-encoder network, both of which were already trained by our assigned hyperparameters. Then 2D CNN includes several convolution layers; all layers in this hierarchical network have a 2*2 kernel function. This network consists of eight convolutional and four pooling layers, and after all convolution layers, batch-normalization layers were applied. The modified auto-encoder network includes a convolutional auto-encoder network and a convolutional network for classification that uses the last output encoder layer of the first part. Furthermore, six machine-learning techniques that were applied to classify brain tumors were also compared in this study.

The training accuracy of the proposed 2D CNN and that of the proposed auto-encoder network were found to be 96.47% and 95.63%, respectively. The average recall values for the 2D CNN and auto-encoder networks were 95% and 94%, respectively. The areas under the ROC curve for both networks were 0.99 or 1. Among applied machine learning methods, Multilayer Perceptron (MLP) (28%) and K-Nearest Neighbors (KNN) (86%) achieved the lowest and highest accuracy rates, respectively. Statistical tests showed a significant difference between the means of the two methods developed in this study and several machine learning methods (p-value < 0.05).

Future Scope:

Considering the importance of rapid and accurate diagnosis of brain tumors without latency, the constructions of other robust deep neural networks for brain tumor classification with less execution time and more simplicity can be investigated.

Hence, full machine learning and deep learning algorithms can be implemented as future enhancements. Furthermore, the proposed techniques can be used to detect different forms of cancers in MRI or Computed Tomography (CT) scan.

[4] <u>Brain tumor detection from MRI images using deep learning techniques</u> by P Gokila Brindha, M Kavinraj, P Manivasakam and P Prasanth

In this paper ANN and CNN is used in the classification of normal and tumor brain. ANN(Artifical

Neural Network) works like a human brain nervous system, on this basis a digital computer is connected with large amount of interconnections and networking which makes neural network to train with the use of simple processing units applied on the training set and stores the experiential knowledge. It has different layers of neurons which is connected together. The neural network can acquire the knowledge by [3] using data set applied on learning process. There will be one input and output layer whereas there may be any number of hidden layers. In the learning process, the weight and bias is added to neurons of each layer depending upon the input features and on the previous layers(for hidden layers and output layers). A model is trained based on the activation function applied on the input features and on the hidden layers where more learning happens to achieve the expected output.

As ANN works with the fully connected layers, where it involves more processing and as in this paper the image is used as the input it focuses on applying CNN also. [10] In CNN (convolutional neural network) convolutional is name of mathematical linear operation. The dimension of the image is reduced at each layers of CNN without the loss of information needed for training. Different processing like convolve, [1] maxpooling, droupout, flatten and dense are applied for creating the model. This paper focuses on creating an self defined architecture of ANN and CNN model and finally the performance of ANN and CNN is compared when applied on brain tumor MRI dataset.

When ANN model is applied on the training data for fifty epochs training accuracy obtained is 97.13% and a validation accuracy of 71.51 %. The same when applied on the testing data gives 80.77% accuracy. The maximum validation accuracy obtained when the model is applied on the training dataset for 200 epochs is 94.00%.

CNN is considered as one of the best technique in analyzing the image dataset. The CNN makes the prediction by reducing the size the image without losing the information needed for making predictions. ANN model generated here produces 65.21% of testing accuracy and this can be increased by providing more image data. The same can be done by applying the image augmentation techniques and the analyzing the performance of the ANN and CNN can be done.

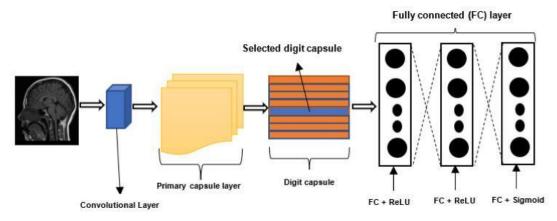
Future Scope:

In future, optimization techniques can be applied so as to decide the number of layers and filters that can used in a model. As of now for the given dataset the CNN proves to be the better technique in predicting the presence of brain tumor.

[5] <u>Brain Tumor Diagnosis Using Machine Learning, Convolutional Neural Networks, Capsule Neural Networks and Vision Transformers, Applied to MRI: A Survey</u> by Andronicus A. Akinyelu, Fulvio Zaccagna, James T. Grist, Mauro Castelli, and Leonardo Rundo

Convolutional Neural Networks (CNNs) represent one of the effective Deep Learning (DL)-based techniques that have been used for brain tumor diagnosis. However, they are unable to handle input modifications effectively. Capsule neural networks (CapsNets) are a novel type of machine learning (ML) architecture that was recently developed to address the drawbacks of CNNs. CapsNets are resistant to rotations and affine translations, which is beneficial when processing medical imaging datasets. Moreover, Vision Transformers (ViT)-based solutions have been very recently proposed to address the issue of long-range dependency in CNNs. This survey provides a comprehensive overview of brain tumor classification and segmentation techniques, with a focus on ML-based, CNN-based, CapsNet-based, and ViT-based techniques.

Despite the remarkable success of CNNs, there are some drawbacks associated with them. First, CNNs require vast datasets for training. Second, CNNs are typically not robust to affine rotations and transformations. Additionally, the routing mechanism employed by CNN's pooling layers is distinct from that employed by the human visual system. The CNN pooling layer routes all the information extracted from the image to all the neurons in the subsequent layer, neglecting essential details or little objects in the image. Capsnet was designed to address the drawbacks of CNN.



Fig, no. 2.5.1 Structure of a CapsNet

A CapsNet is a three-layer network composed of convolutional, primary capsule, and class capsule layers. The primary capsule layer is typically the first one, followed by an undetermined number of capsule layers. The capsule layer is followed by the class capsule layer. The convolutional layer is used to extract features, which are then transmitted to the primary capsule layer. The primary capsule performs a series of operations and transmits the resulting feature map to the digit capsule. Typically, the digit capsule is composed of a $n \times m$ weight matrix, where n denotes the number of classes and m the size of each digit capsule. The digit capsule is used to classify the input image before it is fed into the decoder. The decoder consists of three fully connected layers that are used to reconstruct or decode the selected digit capsule into an image.

CapsNet can recognize spatial and hierarchical relationships among objects in images. They are resistant to rotation and image transformations. Additionally, as shown in, CapsNet requires substantially less training data than CNN. Moreover, results reported in the literature show that CapsNet has the potential to improve the accuracy of CNN-based brain tumor diagnosis using a very small number of network parameters.

CNNs have demonstrated state-of-the-art performance in computer vision tasks, such as brain tumor segmentation and classification over the last few years. However, CNNs cannot efficiently capture long-range information or dependencies due to their small kernel size. These long-range dependencies can be effectively handled by techniques that can process sequence relations. A self-attention mechanism in ViTs has the capacity to model long-range dependencies which is very important for precise brain tumor segmentation. They achieve this by modeling pairwise interactions between token embeddings, thus

Future Scope:

Most of the current research is devoted to brain tumor detection, segmentation, or grade estimation. Most studies did not develop frameworks that can perform these three tasks simultaneously. Moreover, most studies focused on binary-grade classification with less attention paid to multi-grade classification. Designing a framework that can handle brain tumor segmentation, tumor classification (benign versus malignant), and multi-grade estimation would be valuable in improving the decisions and accuracy of medical practitioners when diagnosing brain tumors.

Most of the existing DL brain tumor techniques are based on CNNs. However, these architectures require a huge quantity of data for training. They are also incapable of correctly distinguishing between inputs of different rotations. In addition, obtaining and labelling large-scale datasets is a demanding task [9]. Unfortunately, most publicly available brain cancer datasets are small and imbalanced. The accuracy and generalization performance of a CNN model will be affected if it is trained on small-scale or imbalanced datasets. CapsNet is a recently developed network architecture that has been proposed to address the above-mentioned shortcomings of CNNs. CapsNet are particularly appealing because of their robustness to rotation and affine transformation. CapsNets require significantly less training data than CNN, which is the case for medical imaging datasets such as brain MRI images. CapsNets have the potential to improve the accuracy of CNN-based brain tumor diagnosis using a very small number of network parameters. Most studies did not explore the use of CapsNet for brain cancer diagnosis.

While ViT has demonstrated outstanding performance in NLP, its potential has not been fully explored for medical imaging analysis, such as brain tumor segmentation. Additionally, future research could further investigate the use of Swin transformers, as they seem to perform better than standard ViTs

[6] <u>A Lightweight Deep Learning Based Microwave Brain Image Network Model for Brain Tumor</u> Classification Using Reconstructed Microwave Brain (RMB) Images

The article titled "Enhancing Brain Tumor Classification through a Lightweight Deep Learning Model Utilizing Reconstructed Microwave Brain (RMB) Images" introduces an innovative deep learning model tailored for the categorization of brain tumors leveraging reconstructed microwave brain (RMB) images. This model stands out for its efficiency and low computational footprint, rendering it particularly apt for deployment in settings with limited resources. The research team amassed a comprehensive collection of RMB images featuring both single and double tumors, employing this

dataset to both train and assess the model's performance. The outcomes of the study underscore the remarkable accuracy achieved by the proposed model in effectively classifying diverse brain tumors. In essence, the paper not only offers a fresh perspective on brain tumor classification via RMB images but also underscores the potential provess of deep learning in revolutionizing this domain.

The study titled "Innovative Brain Tumor Segmentation and Classification via Lightweight Deep Learning Models in Sensor-Based Portable Microwave Brain Imaging System" introduces a novel framework tailored to the tasks of brain tumor segmentation and classification by harnessing advanced deep learning methodologies. Within this research, the authors unveil two groundbreaking components: MicrowaveSegNet (MSegNet), a nimble segmentation model, proficient in demarcating brain tumors, and BrainImageNet (BINet), an ingenious classifier adept at categorizing the segmented images into distinct brain tumor types. Through meticulous evaluation on a dataset of images sourced from a sensor-based portable microwave brain imaging system (PMBIS), the findings underscore the remarkable accuracy achieved by these novel models across both segmentation and classification endeavors. Furthermore, the paper delves into the shortcomings of existing brain tumor segmentation and classification techniques while accentuating the strengths inherent in the proposed framework. In summation, the paper unfurls a promising avenue for the realm of brain tumor segmentation and classification, capitalizing on the efficacy of lightweight deep learning models.

[7] SDResU-Net: Separable and Dilated Residual U-Net for MRI Brain Tumor Segmentation by Jianxin Zhang, Xiaogang Lv, Qiule Sun, Qiang Zhang, Xiaopeng Wei and Bin Liu
In this work, the authors propose a novel FCN based network called SDResU-Net for brain tumor segmentation, which simultaneously embeds dilated convolution and separable convolution into residual U-Net architecture.

SDResU-Net introduces dilated block into a residual U-Net architecture, which largely expends the receptive field and gains better local and global feature descriptions capacity.

To fully utilize the channel and region information of MRI brain images, they separate the internal and inter-slice structures of the improved residual U-Net by employing separable convolution operator.

The proposed SDResU-Net captures more pixel-level details and spatial information, which provides a considerable alternative for the automatic and accurate segmentation of brain tumors.

Results and conclusion: The proposed SDResU-Net is extensively evaluated on two public MRI brain image datasets, i.e., BraTS 2017 and BraTS 2018. Compared with its counterparts and stateof- the-arts,

SDResU-Net gains superior performance on both datasets, showing its effectiveness.

[8] An early detection and segmentation of Brain Tumor using Deep Neural Network by Mukul Aggarwal, Amod Kumar Tiwari, M Partha Sarathi, Anchit Bijalwan

Magnetic resonance image (MRI) brain tumor segmentation is crucial and important in the medical field, which can help in diagnosis and prognosis, overall growth predictions, Tumor density measures, and care plans needed for patients.

The difficulty in segmenting brain Tumors is primarily because of the wide range of structures, shapes, frequency, position, and visual appeal of Tumors, like intensity, contrast, and visual variation. With recent advancements in Deep Neural Networks (DNN) for image classification tasks, intelligent medical image segmentation is an exciting direction for Brain Tumor research.

DNN requires a lot of time & processing capabilities to train because of only some gradient diffusion difficulty and its complication.

To overcome the gradient issue of DNN, this research work provides an efficient method for brain Tumor segmentation based on the Improved Residual Network (ResNet). Existing ResNet can be improved by maintaining the details of all the available connection links or by improving projection shortcuts. These details are fed to later phases, due to which improved ResNet achieves higher precision and can speed up the learning process.

<u>Results:</u> The proposed improved Resnet address all three main components of existing ResNet: the flow of information through the network layers, the residual building block, and the projection shortcut. This approach minimizes computational costs and speeds up the process.

An experimental analysis of the BRATS 2020 MRI sample data reveals that the proposed methodology achieves competitive performance over the traditional methods like CNN and Fully Convolution Neural Network (FCN) in more than 10% improved accuracy, recall, and f-measure.

Outcome of Survey

Most importantly we have understood that we need to find larger datasets validated by medical professinoals in with expertise in the field of brain tumours and their early detection. We have also found out that there are some new algorithms and models that have not been explored as much in this field such as CapsNet and Vision Transformers. We intend to find more such models and apply them to the task of brain tmour detection while also attempting to improve accuracy in the models published by previous researchers.

3. Project Description

"OMAD – Brain Tumour Detection" involves the use of machine learning and deep learning models to detect brain tumors in MRI/CT scan images with improved accuracy. The project also aims to identify and detect possible symptoms of brain tumors at an early stage. The scope of the project includes the application of the newest unexplored machine learning models for semantic segmentation and object detection in MRI/CT scan images of brain tumors. This involves training these models with professionally validated expansive datasets of such scans. Additionally, the project involves conducting research on the early symptoms of brain tumors and how their detection can be automated

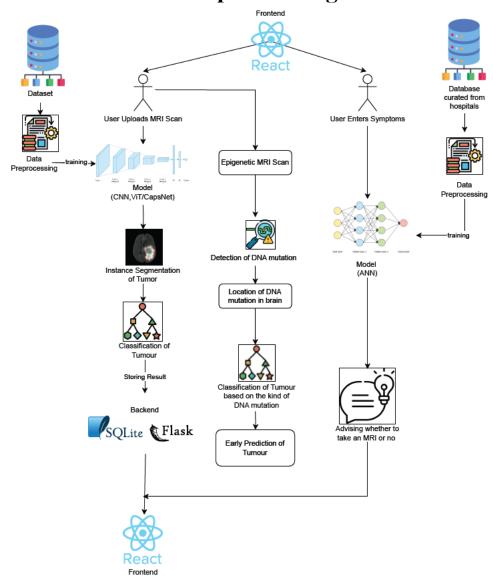
3.1 Problem Statement

Use Machine Learning and Deep Learning models to detect brain tumours in MRI/CT scan images with improved accuracy and also to identify and detect possible symptoms of brain tumours very early.

3.2 Scope of the Project

Applying the newest unexplored Machine Learning models for semantic segmentation and object detection in images to MRI/CT scan images of brain tumours after training those models with professionally validated expansive datasets of such scans. Also conducting research in the early symptoms of brain tumours and how their detection can be automated.

4. Proposed Design



Fig, no. 4.1 Architecture diagram

We have done extensive research about the various different deep learning model structures that can be used for instance segmentation and have come to the conclusion that the best options for that are CNN (YOLOv8), CapsNet and ViT. We intend to contrast and compare our results using all 3 models and then choose the best one going forward.

We are currently learning how to use and manipulate the BraTS 2020 dataset in order to train our selected model on it.

We intend to curate many such other datasets from medical professionals and train our models on them to improve accuracy and make our model capable of dealing with all kinds of image formats and tumor types.

As part of our detection of early signs of brain tumors feature, we intend to implement two things. Firstly, using eMRI (Epigenetic MRI) technology we can detect DNA methylation in the brain noninvasively. DNA methylation is one of the major causes of Brain Tumors. Thus, we can detect the tumor causing abnormal mutation in the DNA even before the tumor is formed. Secondly, analyzing symptoms of the patient using a neural network well trained on a personally constructed dataset of brain tumor symptoms with the help of medical professionals and hospitals to predict whether the patient should immediately get an MRI scan or consult a doctor first.

We plan to host the Brain Tumor Detection model on a web application for doctors. We also plan to host the need of MRI scan prediction model on the basis of symptoms on a web application.

5. Results and Discussion

We trained YOLOv8seg, ViT and SAM models on a brain tumour detection dataset 'celebal-p3kbm' from Roboflow and got the following results:

YOLOv8seg (CNN):

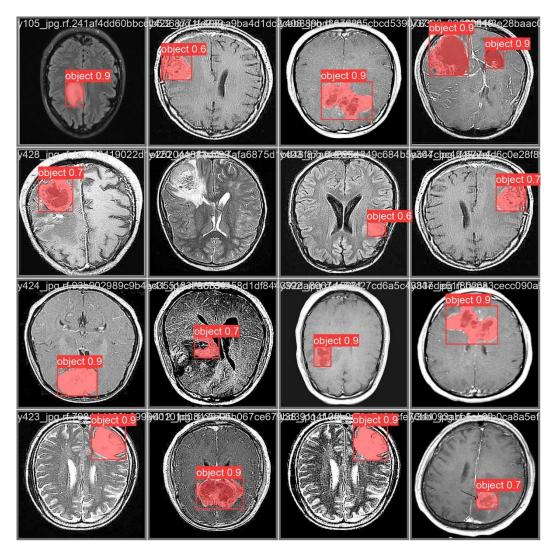
We have achieved 93.5% with a CNN-based YOLOv8 segmentation model so far.

```
YOLOv8n-seg summary (fused): 195 layers, 3258259 parameters, 0 gradients, 12.0 GFLOPs

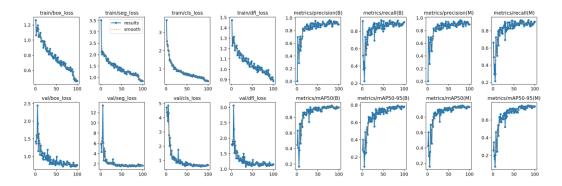
Class Images Instances Box(P R mAP50 mAP50-95) Mask(P all 100 98 0.866 0.923 0.935 0.796 0.866

Speed: 0.4ms preprocess, 6.4ms inference, 0.0ms loss, 7.1ms postprocess per image
```

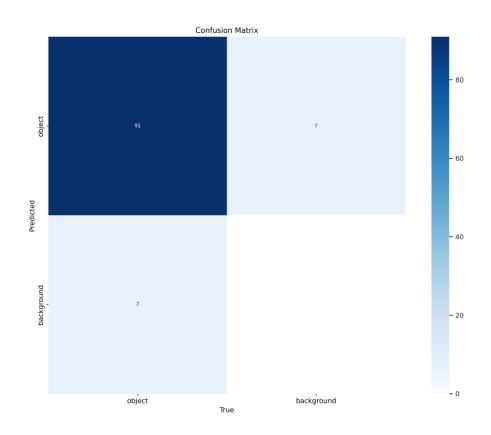
Fig, no. 5.1 Training Results



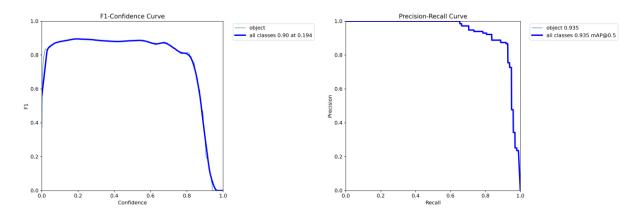
Fig, no. 5.2 Validation Batch



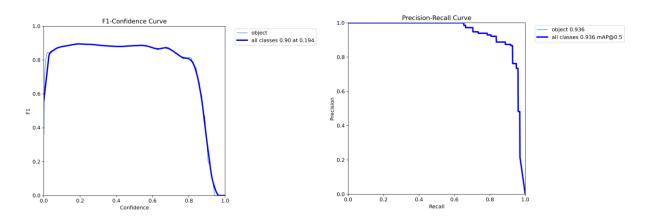
Fig, no. 5.3 Graphs of Training Results



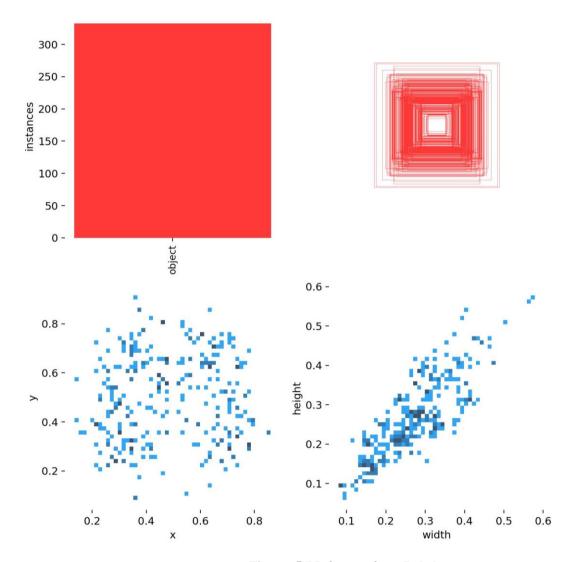
Fig, no. 5.4 Confusion Matrix



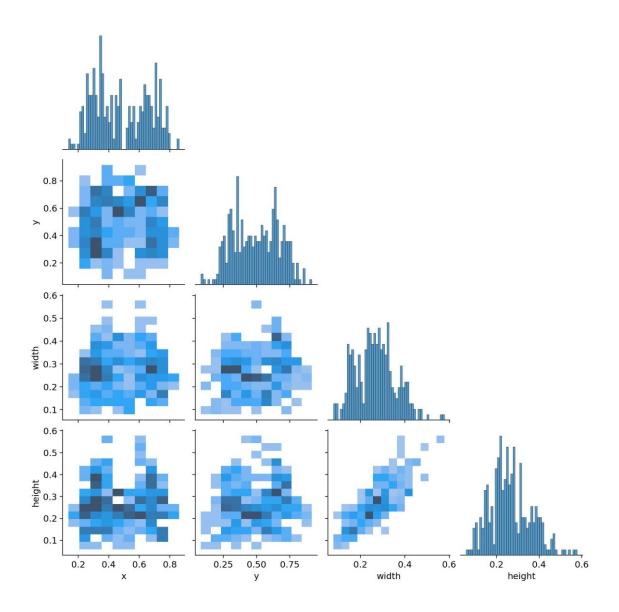
Fig, no. 5.5 Precision and Recall Curves for Box



Fig, no. 5.6 Precision and Recall Curves for Mask

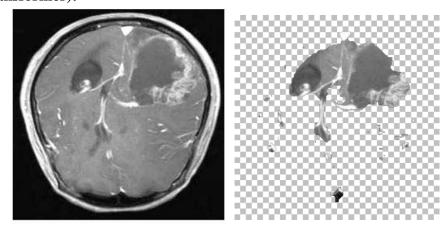


Fig, no. 5.7 Inference from Labels

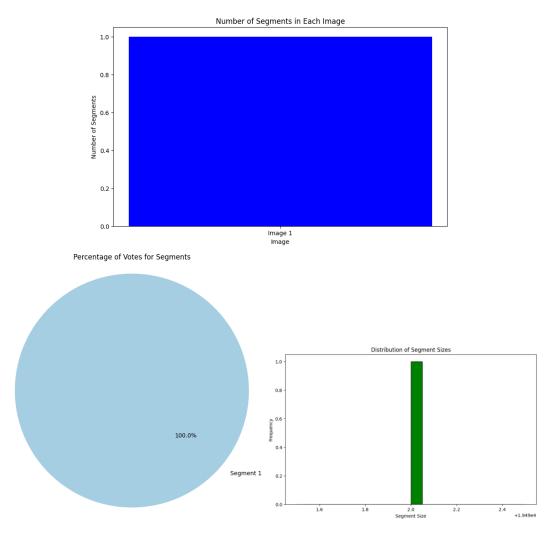


Fig, no. 5.8 Labels Correlogram

ViT (Vision Transformer):



Fig, no. 5.9 ViT Segmentation Results



Fig, no. 5.10 Inference from ViT Segmentation Results

6. Conclusion

Brain Tumours are an ever-increasing medical problem and this field has an immense scope of research work in terms of detection automation.

After conducting thorough research and surveying multiple articles and papers about brain tumour detection we have come to the conclusion that the most optimal way to do this is by trying to implement various cutting edge methods and models of semantic segmentation (for eg: YOLOv8 from ultralytics) and various new and unexplored Deep Learning models based on the base architecture of Convolutional Neural Networks (CNNs) such as CapsNet. ViT, etc.

We can also address detection of early signs of brain tumours by detecting changes in the DNA of brain cells such as DNA methylation which can be a cause of Brain tumours using Epigenetic MRI scans.

7. Publication

8. References

- [1] Aleid, A.; Alhussaini, K.; Alanazi, R.; Altwaimi, M.; Altwijri, O.; Saad, A.S. Artificial Intelligence Approach for Early Detection of Brain Tumors Using MRI Images. *Appl. Sci.* **2023**, *13*, 3808. https://doi.org/10.3390/app13063808
- [2] Khan, M. S. I., Rahman, A., Debnath, T., Karim, M. R., Nasir, M. K., Band, S. S., Mosavi, A., & Dehzangi, I. (2022). Accurate brain tumor detection using deep convolutional neural network. *Computational and structural biotechnology journal*, 20, 4733–4745. https://doi.org/10.1016/j.csbj.2022.08.039
- [3] Saeedi, S., Rezayi, S., Keshavarz, H. *et al.* MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. *BMC Med Inform Decis Mak* **23**, 16 (2023). https://doi.org/10.1186/s12911-023-02114-6
- [4] P Gokila Brindha *et al* 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1055** 012115 **DOI** 10.1088/1757-899X/1055/1/012115 (https://iopscience.iop.org/article/10.1088/1757-899X/1055/1/012115)
- [5] Akinyelu, A. A., Zaccagna, F., Grist, J. T., Castelli, M., & Rundo, L. (2022). Brain Tumor Diagnosis Using Machine Learning, Convolutional Neural Networks, Capsule Neural Networks and Vision Transformers, Applied to MRI: A Survey. *Journal of imaging*, 8(8), 205. https://doi.org/10.3390/jimaging8080205.
 - [6] Behin A, Hoang-Xuan K, Carpentier AF, Delattre J-Y. Primary brain tumours in adults. Lancet 2003;361(9354):323–31.
 - [7] Louis DN, Perry A, Reifenberger G, Von Deimling A, Figarella-Branger D, Cavenee WK, Ohgaki H, Wiestler OD, Kleihues P, Ellison DW. The 2016 world health organization classification of tumors of the central nervous system: a summary. Acta Neuropathol 2016;131(6):803–20.
 - [8] Dasgupta A, Gupta T, Jalali R. Indian data on central nervous tumors: A summary of published work. South Asian J Cancer 2016;5(3):147.
 - [9] C.R. UK, Published on may, 2019; 2019. URL: https://www.cancerresearchuk.org.
 - [10] Hollon TC, Pandian B, Adapa AR, Urias E, Save AV, Khalsa SSS, Eichberg DG, D'Amico RS, Farooq ZU, Lewis S, et al. Near real-time intraoperative brain tumor diagnosis using stimulated raman histology and deep neural networks. Nat Med 2020;26(1):52–8.

- [11] Prabukumar M, Agilandeeswari L, Ganesan K. An intelligent lung cancer diagnosis system using cuckoo search optimization and support vector machine classifer. J Ambient Intell Humaniz Comput. 2019;10(1):267–93
- [12] El-Dahshan ESA, Mohsen HM, Revett K, Salem ABM. Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm. Expert Syst Appl. 2014;41(11):5526–45.
- [13] Meng Y, Tang C, Yu J, Meng S, Zhang W. Exposure to lead increases the risk of meningioma and brain cancer: a meta-analysis. J Trace Elem Med Biol. 2020;60:126474.
- [14] McFaline-Figueroa JR, Lee EQ. Brain tumors. Am J Med. 2018;131(8):874–82.
- [15] Shen D, Wu G, Suk H-I. Deep learning in medical image analysis. Annu Rev Biomed Eng. 2017;19(1):221–48
- [16] Raheleh Hashemzehi Seyyed Javad Seyyed Mahdavi Maryam Kheirabadi Seyed Reza Kamel 2020 Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE Elsevier B.V. on behalf of Nalecz Institute of Biocybernetics and Biomedical Engineering of the Polish Academy of Sciences Online Publication.
- [17] Javeria Amin Muhammad Sharif Mudassar Raza Mussarat Yasmin 2018 Detection of Brain Tumor based on Features Fusion and Machine Learning Journal of Ambient Intelligence and Humanized Computing Online Publication.
- [18] Rajeshwar Nalbalwar Umakant Majhi Raj Patil Prof.Sudhanshu Gonge 2014 Detection of Brain Tumor by using ANN International Journal of Research in Advent Technology 2.
- [19] Fatih Özyurt Eser Sert Engin Avci Esin Dogantekin 2019 Brain tumor detection based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy Elsevier Ltd 147.
- [20] Fausto Milletari Seyed-Ahmad Ahmadi Christine Kroll Annika Plate Verena Rozanski Juliana Maiostre Johannes Levin Olaf Dietrich Birgit Ertl-Wagner Kai Bötzel, Nassir Navab 2016 Hough-CNN: Deep learning for segmentation of deep brain regions in MRI and ultrasound Elsevier Inc 164 92-102.
- [21] Louis, D.N.; Perry, A.; Wesseling, P.; Brat, D.J.; Cree, I.A.; Figarella-Branger, D.; Hawkins, C.; Ng, H.K.; Pfister, S.M.; Reifenberger, G. The 2021 WHO classification of tumors of the central nervous system: A summary. Neuro-Oncology 2021, 23, 1231–1251. [CrossRef] [PubMed]
- [22] The Brain Tumor Charity. Brain Tumor Basics. Available online: https://www.thebraintumourcharity.org/(accessed on 1 June 2022)
- [23] Tandel, G.S.; Biswas, M.; Kakde, O.G.; Tiwari, A.; Suri, H.S.; Turk, M.; Laird, J.R.; Asare, C.K.; Ankrah, A.A.; Khanna, N.N. A review on a deep learning perspective in brain cancer classification. Cancers 2019, 11, 111.

[CrossRef] [PubMed]

- [24] Overcast, W.B.; Davis, K.M.; Ho, C.Y.; Hutchins, G.D.; Green, M.A.; Graner, B.D.; Veronesi, M.C. Advanced imaging techniques for neuro-oncologic tumor diagnosis, with an emphasis on PET-MRI imaging of malignant brain tumors. Curr. Oncol. Rep. 2021, 23, 34. [CrossRef]
- [25] Zaccagna, F.; Grist, J.T.; Quartuccio, N.; Riemer, F.; Fraioli, F.; Caracò, C.; Halsey, R.; Aldalilah, Y.; Cunningham, C.H.; Massoud, T.F. Imaging and treatment of brain tumors through molecular targeting: Recent clinical advances. Eur. J. Radiol. 2021, 142, 109842. [CrossRef]
- [26] Biratu, E.S.; Schwenker, F.; Ayano, Y.M.; Debelee, T.G. A survey of brain tumor segmentation and classification algorithms. J. Imaging 2021, 7, 179. [CrossRef]
- [27] Nalbalwar R, Majhi U, Patil R, Gonge S. Detection of brain tumor by using ANN. Image. 2014;2(3):7.
- [28] Grist, J.T.; Miller, J.J.; Zaccagna, F.; McLean, M.A.; Riemer, F.; Matys, T.; Tyler, D.J.; Laustsen, C.; Coles, A.J.; Gallagher, F.A. Hyperpolarized 13C MRI: A novel approach for probing cerebral metabolism in health and neurological disease. J. Cereb. Blood Flow Metab. 2020, 40, 1137–1147. [CrossRef]
- [29] Havaei, M.; Davy, A.; Warde-Farley, D.; Biard, A.; Courville, A.; Bengio, Y.; Pal, C.; Jodoin, P.M.; Larochelle, H. Brain tumor segmentation with deep neural networks. Med. Image Anal. 2017, 35, 18–31. [CrossRef]
- [30] Deepak, S.; Ameer, P.M. Automated categorization of brain tumor from mri using cnn features and svm. J. Ambient Intell. Humaniz. Comput. 2021, 12, 8357–8369. [CrossRef]
- [31] Malathi M, Sinthia P. Brain tumour segmentation using convolutional neural network with tensor fow. Asian Pac J Cancer Prevent APJCP. 2019;20(7):2095.
- [32] Hussain S, Anwar SM, Majid M. Segmentation of glioma tumors in brain using deep convolutional neural network. Neurocomputing. 2018;282:248–61



4% Overall Similarity

Top sources found in the following databases:

- 3% Internet database
- Crossref database
- 4% Submitted Works database

- 0% Publications database
- Crossref Posted Content database

TOP SOURCES

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	Colorado Technical University on 2022-09-08 Submitted works	1%
2	Indian Institute of Technology, Bombay on 2023-07-26 Submitted works	<1%
3	28b15.budzianowski.eu Internet	<1%
4	University of Central Lancashire on 2022-11-07 Submitted works	<1%
5	Augusta State University on 2023-04-18 Submitted works	<1%
6	coursehero.com Internet	<1%
7	University of North Carolina, Greensboro on 2023-11-13 Submitted works	<1%
8	Farhana Khan, Shahnawaz Ayoub, Yonis Gulzar, Muneer Majid et al. "M Crossref	· <1%



9	Liverpool John Moores University on 2023-03-15 Submitted works	<1%
10	Canton College of Technology, SUNY on 2013-11-05 Submitted works	<1%
11	Queen Mary and Westfield College on 2023-08-23 Submitted works	<1%
12	Ramin Ranjbarzadeh, Annalina Caputo, Erfan Babaee Tirkolaee, Saeid Crossref	J <1%



Excluded from Similarity Report

- Bibliographic material
- Cited material
- Manually excluded sources

- Quoted material
- Small Matches (Less then 10 words)
- Manually excluded text blocks

EXCLUDED SOURCES

ncbi.nlm.nih.gov Internet	16%
mdpi.com Internet	11%
mdpi-res.com Internet	11%
Andronicus A. Akinyelu, Fulvio Zaccagna, James T. Grist, Mauro Cas	telli, Leon _{10%}
doi.org Internet	9%
researchgate.net Internet	7%
internationaljournalssrg.org Internet	6%
doaj.org Internet	6%
bmcmedinformdecismak.biomedcentral.com	6%



pubmed.ncbi.nlm.nih.gov Internet	5%
P Gokila Brindha, M Kavinraj, P Manivasakam, P Prasanth. "Brain tumor detect Crossref	4%
Soheila Saeedi, Sorayya Rezayi, Hamidreza Keshavarz, Sharareh R. Niakan Kal	3%
Mukul Aggarwal, Amod Kumar Tiwari, M Partha Sarathi, Anchit Bijalwan. "An e Crossref	2%
ijircce.com Internet	2%
Md. Saikat Islam Khan, Anichur Rahman, Tanoy Debnath, Md. Razaul Karim et Crossref	2%
Md. Saikat Islam Khan, Anichur Rahman, Tanoy Debnath, Md. Razaul Karim et Crossref	2%
Chapman University on 2023-03-12 Submitted works	2%
hopkinsmedicine.org Internet	2%
drsharafeddeen.com Internet	2%
Geethanjali N, V. Pushpalatha, Ramya C, Sandhiya L, Subhashri S. "Brain Tum Crossref	2%
scholarcommons.sc.edu Internet	2%



hmh-writable on 2023-03-21 Submitted works	1%
hmh-writable on 2023-03-21 Submitted works	1%
Sekolah Ciiputra High School on 2022-03-14 Submitted works	1%
Brisbane Catholic Education on 2023-06-05 Submitted works	1%
irjmets.com Internet	<1%
Higher Education Commission Pakistan on 2022-09-26 Submitted works	<1%
Higher Education Commission Pakistan on 2022-09-26 Submitted works	<1%
Adham Aleid, Khalid Alhussaini, Reem Alanazi, Meaad Altwaimi, Omar Altwijri Crossref	' […] <1%
www2.mdpi.com Internet	<1%
faculty.ksu.edu.sa Internet	<1%
EXCLUDED TEXT BLOCKS	
1	



Introduction81.1 Aim of the Project81.2

aaltodoc.aalto.fi

Artificial Intelligence Approach for Early Detection of Brain Tumors Using MRI Ima...

www2.mdpi.com

on a multilevel thresholding technique

Career Networks Institute on 2023-06-12

Accurate brain tumor detection using deep convolutional neural network by Md. Sa...

elibrary.stipram.ac.id

97.8% and 100% prediction accuracy for dataset 1 and dataset 2,respectively outp...

Liberty University on 2022-12-17

Adopting zero-shot, few-shot, and deep reinforcement learning (DRL) techniques c...

www.nature.com

Additionally, a deep

www.nature.com

layers or other regularization

University of Moratuwa on 2022-11-24

MRI-based brain tumor detection using convolutional deep learning methods and c...

University of Hertfordshire on 2023-08-21

A dataset containing 3264 Magnetic Resonance Imaging (MRI) brain images comp...

Coventry University on 2023-08-05

developed anew 2D Convolutional Neural Network (CNN) and a convolutional auto-...

IUBH - Internationale Hochschule Bad Honnef-Bonn on 2023-07-18

in this

Higher Education Commission Pakistan on 2022-10-04



aconvolutional network for classification that uses the last output encoder layer of...

Higher Education Commission Pakistan on 2022-10-04

six machine-learning techniques

Higher Education Commission Pakistan on 2022-10-04

The training accuracy of the

Coventry University on 2023-08-08

for the 2D CNN and auto-encoder

Middlesex University on 2023-04-14

Considering the importance of rapid and accurate

Higher Education Commission Pakistan on 2022-10-04

Brain tumor detection from MRI images using deep learning techniques

iopscience.iop.org

human brain nervous system

Nottingham Trent University on 2022-05-09

There will be

www.medrxiv.org

In CNN (convolutional neuralnetwork

www.ijnrd.org

flatten and dense are applied for creating the model. This

www.ijnrd.org

is applied on the training data for fifty epochs training accuracy obtained is 97.13...

Gitam University on 2022-07-13

obtained when the model

Manchester Metropolitan University on 2023-06-22



by reducing the size

"Proceedings of Trends in Electronics and Health Informatics", Springer Science and Business Media LLC, ...

accuracy and this can be increased by providingmore image data. The same can b...

www.medrxiv.org

In future, optimization techniques can be applied so as to decide the number

Fatma Taher, Mohamed R. Shoaib, Heba M. Emara, Khaled M. Abdelwahab, Fathi E. Abd El-Samie, Mohamm...

of layers and filters that canused in a model

VIT University on 2021-12-14

Brain Tumor Diagnosis Using Machine Learning, Convolutional Neural Networks, C... scholar.archive.org

Convolutional Neural Networks (CNNs) represent one of the effective Deep Learni... run.unl.pt

the human visual system

The British College on 2023-06-11

where n

Dat Tien Nguyen, Se Hyun Nam, Ganbayar Batchuluun, Muhammad Owais, Kang Ryoung Park. "An Ensembl...

has the potentialto

Ayesha Jabbar, Shahid Naseem, Tariq Mahmood, Tanzila Saba, Faten S. Alamri, Amjad Rehman. "Brain Tum...

CNNs have demonstrated state-of-the-art performance in computer vision tasks

huntercmd.github.io

A self-attention mechanism in

Mohammed Aloraini, Asma Khan, Suliman Aladhadh, Shabana Habib, Mohammed F. Alsharekh, Muhammad...

Moststudies did not

Surajit Das, Rajat Subhra Goswami. "Review, Limitations, and future prospects of neural network approache...



a framework that can

The British College on 2023-06-11

Most of the existing DL brain tumor techniques are based on CNNs. However, these

Universiteit van Amsterdam on 2022-12-19

less training data than

The British College on 2023-06-11

toimprove the accuracy of

Signal Mountain Middle High School on 2023-11-27

the use of CapsNet for brain

The British College on 2023-06-11

A Lightweight Deep Learning Based Microwave Brain Image Network Model for Br...

qspace.qu.edu.qa

of brain tumor segmentation and classification

www.slideshare.net

SDResU-Net: Separable and Dilated Residual U-Net for MRI Brain Tumor Segmenta...

eurekaselect.com

In this work

eurekaselect.com

An early detection and segmentation of Brain Tumor using Deep Neural Network

researchr.org

Magnetic resonance image (MRI) brain tumor segmentation is crucial and importa...

www.biomedcentral.com

because of the wide range of structures, shapes, frequency, position, and visual ap...

University of Florida on 2023-12-04



address all three main components of

www.semanticscholar.org

An experimental analysis of the BRATS 2020 MRI sample data reveals that the pro...

www.unboundmedicine.com

bymaintaining the details of

Pandit Deendayal Petroleum University on 2023-11-26