



PROGNOSIS DETECTION SYSTEM

MINI PROJECT REPORT

Submitted by

GARRE SAI SARVAGNA SADVIK(1920110011)

MEDA VENKATA NARAYANA PRANATH(1920110025)

MOHAN KUMAR G(1920110026)

RAGUL S(1920110037)

in partial fulfilment for the award of the degree

of

BACHELOR OF TECHNOLOGY

IN

**ARTIFICIAL INTELLIGENCE
AND DATA SCIENCE**

**SONA COLLEGE OF TECHNOLOGY, SALEM-5
(Autonomous)**

NOVEMBER 2023

ANNA UNIVERSITY: CHENNAI 600 025

BONAFIDE CERTIFICATE

Certified that this project report “**Prognosis Detection System**” is the bona-fide work of “**GARRE SAI SARVAGNA SADVIK (1920110011),RAGUL S (1920110037),MEDA VENKATA NARAYANA PRANATH(1920110025), MOHAN KUMAR G(1920110026)**”who carried out the project work under my supervision.

SIGNATURE

Dr.J.Akilandeswari

Professor

HEAD OF THE DEPARTMENT

Department of Information Technology
InformationSona College of Technology,
Salem-636 005.

SIGNATURE

Mr.S.David Samuel Azariya

Assistant Professor

SUPERVISOR

Department of
Technology,
Sona College of
Technology,Salem-636
005.

INTERNAL EXAMINER

EXTERNAL EXAMINER

ABSTRACT

Brain tumor is a life-threatening disease that requires early detection for effective treatment. In recent years, the use of deep learning algorithms has become a popular approach for brain tumor detection. In this paper, we propose a novel approach that combines Multi-Class CNN algorithms for brain tumor detection. Our approach uses magnetic resonance imaging (MRI) data as input and extracts features using the Multi-Class CNN network. The extracted features are then fed into the Multi-Class CNN algorithm for classification. The proposed approach is evaluated on a publicly available brain tumor dataset, and the results show that our approach achieves high accuracy and outperforms other state-of-the-art methods. The Multi-Class CNN network is used to extract relevant temporal features from the MRI data, and the Multi-Class CNN algorithm is used for classification to improve the accuracy of the model. Multi-Class CNN is a machine learning algorithm that can be used to boost the performance of weak classifiers. The combination of these two algorithms results in a powerful model that can accurately detect brain tumors. In conclusion, our proposed approach provides a promising solution for brain tumor detection using deep learning algorithms. The combination of Multi-Class CNN algorithms offers a robust and accurate method for early detection of brain tumors, which can ultimately save lives.

ACKNOWLEDGEMENT

First and foremost, we thank to **power of almighty** for showing us inner peace and for all blessings. Special gratitude to our parents, for showing their support and love always.

We express our sincere thanks to Chairman **Sri.C.Valliappa** and Principal **Dr.S.R.R.Senthil Kumar** for providing adequate facilities to complete the project.

We are immensely grateful to Head of Information Technology, **Dr.J.Akilandeswari** for the continues encouragement to complete the project.

We express our heartfelt thanks to our project supervisor **Mr.S.David Samuel Azariya** for his valuable guidance and fruitful discussions throughout the course of the project work.

We feel proud in sharing this success with all our staff members and friends who helped directly or indirectly in completing this project successfully.

TABLE OF CONTENTS

CHAPTER NO.	TITLE	PAGE NO
	ABSTRACT	3
1.	INTRODUCTION	
	1.1 Introduction	6
	1.2 Aim of the Project	7
	1.3 Objective of the project	7
	1.4 Scope of the project	7
	1.5 Applications	8
	1.6 Literature Review	9
	1.7 Existing System	28
	1.8 Hardware and Software Requirements	29
2.	DESIGN AND IMPLEMENTATION	
	2.1 Proposed System	30
	2.2 Architecture Design	31
	2.3 Modules	32
	2.4 Modules Description	33
	2.5 Result	34
3.	CONCLUSION	
	3.1 Conclusion	38
	3.2 Future Enhancement	38
	REFERENCES	39

CHAPTER 1

1.1 Introduction

Brain is the most complex organ of the body. The tumor is defined as uncontrolled growth of cells on any part of the body and respectively brain tumor is uncontrolled growth of brain cells. The body is made up of many types of cells. Each type of cell has special functions. Most cells in the body grow and then divide in an orderly way to form new cells as they are needed to keep the body healthy and working properly. When cells lose the ability to control their growth, they divide too often and without any order. The extra cells form a mass of tissue called a tumor. Tumors are benign or malignant. Benign brain tumors do not contain cancer cells. Although they do not invade nearby tissue, they can press on sensitive areas of the brain and cause symptoms. Malignant brain tumors contain cancer cells. They interfere with vital functions and are life threatening. Malignant brain tumors are likely to grow rapidly and crowd or invade the tissue around them. Like a plant, these tumors may put out "roots" that grow into healthy brain tissue. If a malignant tumor remains compact and does not have roots, it is said to be encapsulated. When an otherwise benign tumor is located in a vital area of the brain and interferes with vital functions, it may be considered malignant (even though it contains no cancer cells). The Average life expectancy of HGG patient is 14 months. Brain tumors are scaled from grade I to IV and they are further classified in benign (class I II) and malignant (class III IV). Benign tumors are non-aggressive and mostly they don't move from their infected area. Whereas, malignant tumors are aggressive and more fatal than that of benign tumors. Benign tumors are treatable through chemotherapy and they can be reduced to a smaller size. Reducing it to an extent where it can be removed through operation.

On the other hand, malignant tumors are non- operable, but they can be reduced through chemotherapy to some extent. It may increase the life expectancy of the patient up to 2 or 3 months, but it is not completely curable.

1.2 Aim of the Project

The goal is to create a model that can identify brain cancers in medical imaging more reliably and accurately. This could have a big impact on how accurately brain tumours are identified and treated, which could improve patient outcomes.

1.3 Objective of the Project

The objective of brain tumor detection using Multi-Class CNN algorithm classifier is to develop an accurate and efficient system for detecting brain tumors in Magnetic Resonance Imaging (MRI) images. The proposed system aims to improve upon the accuracy and efficiency of existing methods for brain tumor detection. The ultimate goal of the proposed system is to provide clinicians and radiologists with an accurate and efficient tool for detecting brain tumors in MRI images, which can lead to earlier detection and better treatment outcomes for patients.

1.4 Scope of the Project

A project to identify brain tumours might cover the following areas: Assembling a dataset of medical pictures, such as MRI or CT scans, that contains both examples of brain cancers that are positive and those that are not ensuring that the data is prepared and cleaned so that machine learning algorithms may analyse it then creation of a machine learning model capable of precisely identifying brain cancers in medical photos utilising the dataset to train and validate the machine learning model assessing the machine learning model's performance, including its F1 score, recall, accuracy, and precision. performance optimization of the machine learning model by the use of cross-validation and the selection of hyperparameters and creating a user interface that makes it simple for medical professionals to enter and interpret medical pictures evaluating the model's performance on a different set of data to make sure it can generalise to fresh information to creating a report that summarises the project's findings, including the machine learning model's performance and potential therapeutic uses.

1.5 Applications

Brain tumor detection has a wide range of real-time applications, particularly in the field of medical imaging and neurology. Some of the applications are:

Early detection: Early detection of brain tumors is critical for effective treatment and improved patient outcomes. The use of machine learning algorithms for brain tumor detection can enable earlier detection and diagnosis of brain tumors, ultimately leading to better treatment outcomes.

Treatment planning: Accurate detection and characterization of brain tumors can help clinicians and neurosurgeons to plan the most appropriate treatment strategy for patients. This can include determining the type of tumor, its size, location, and other characteristics that are essential for treatment planning.

Monitoring: After the diagnosis and treatment of brain tumors, monitoring is essential to ensure that the tumor has been fully treated and to detect any recurrence or progression of the tumor. Machine learning algorithms can help to automate this process by analyzing the MRI images and detecting any changes that may indicate recurrence or progression.

Research: Machine learning algorithms can also be used in research to study the characteristics and behavior of brain tumors. This can lead to a better understanding of the disease and its underlying mechanisms, ultimately leading to improved treatment strategies and better outcomes for patients. Overall, the real-time applications of brain tumor detection using machine learning algorithms are vast and can significantly improve patient outcomes and enhance the field of medical imaging and neurology.

1.6 Literature Review

Paper 1

Sunil Kumar, Renu Dhir, Nisha Chaurasia, Brain Tumor Detection Analysis Using CNN, International Conference on Artificial Intelligence and Smart Systems (ICAIS-2021)

A brain tumour is essentially an abnormal cell development that might or might not be malignant. The most fatal illness is a brain tumour, which may be quickly and accurately discovered on an MRI scan using automated tumour identification techniques. For the accurate diagnosis and segmentation of brain tumours, several researchers have put forth several methodologies. A detailed investigation reveals two serious issues with Image Restoration and Picture Enhancing. To ignore the dataset picture algorithm error, the unique method makes use of the CNN classification methodology. The findings also covered the strengths and weaknesses of the algorithms and approaches employed to address particular research issues. In order to forecast future research in the field with high accuracy and a low mistake rate, this study looks at the quantitative features of brain tumours, such as shape, texture, and signal intensity.

Paper 2

Shubhangi Solanki , Uday Pratap Singh , Siddharth Singh Chouhan, Sanjeev Jain, Brain Tumour Detection and Classification by using Deep Learning Classifier, (IJISAE2023).

One of the most important and challenging issues to be resolved is the classification of brain tumours. A model is created using a hybrid deep learning technique to identify brain tumours from 2D magnetic resonance scans of the brain. After that, this system is combined with both conventional classification methods and deep learning strategies.

The study used a Kaggle and BRaTS MICCAI dataset with a wide variety of tumours. When performing the traditional step of categorization, a total of six different classification methods, including SVM, KNN, MLP, LR, NB were applied. The SVM generated the most accurate results when compared to various traditional classification models. After that, CNN is deployed, showing a considerable improvement in overall performance when compared to the conventional classifiers. Several layers of CNN were assessed using various dataset split ratios. The experimental results show that utilising an 80:20 split ratio, a five-layered CNN can achieve the accuracy of 97.86%.

Paper 3

HASNAIN ALI SHAH ,FAISAL SAEED ,SANGSEOK YUN ,JUN-HYUN PARK ,ANAND PAUL ,JAE-MO KANG , A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet , National Research Foundation of Korea (NRF)-2022.

A brain tumour is a condition brought on by the expansion of unnatural brain cells. These tumours can be found using MRI Imaging, which are crucial for locating the tumour site. DL models are being utilised in medical imaging to detect brain malignancies using MRI images as AI technology progresses. In order to effectively categorise and detect brain tumour images, a CNN EfficientNet-B0 base model is customised with our suggested layers in this study.

To improve the quality of the photographs, several filters are applied using image enhancement techniques. The findings demonstrate that the proposed fine-tuned state-of-the-art EfficientNet-B0 outperforms other CNN models by obtaining the highest classification accuracy, precision, recall, and area under the curve values surpassing other state-of-the-art models, with an overall accuracy of 98.87% in terms of classification and detection. For comparative study, other DL algorithms including VGG16, InceptionV3, Xception, ResNet50, and InceptionResNetV2 are used.

Paper 4

Masoumeh Siar , Mohammad Teshnehlab ,Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm , International Conference on Computer and Knowledge Engineering (ICCKE 2019).

Early and prompt disease identification and treatment strategies increase the patients' quality of life and life expectancy. In order to build a CNN in this study, brain MRI images were used. The first to use visuals was CNN. The Softmax Fully Connected layer's classification accuracy was 98.67%. Also, the accuracy of the Radial Basis Function (RBF) classifier is 97.34%, compared to the Decision Tree (DT) classifier's accuracy of 94.24%.while the Radial Basis Function (RBF) classifier's accuracy is 97.34%.The network accuracy on the picture testing revealed that the Softmax classifier has the highest accuracy in CNN, according to the data from the categorizers. This is a novel strategy for tumour detection from brain imaging that combines feature extraction methods with CNN. The method's predicted accuracy for the test data was 99.12%.

Paper 5

Ayesha Younis ,Li Qiang ,Charles Okanda Nyatega ,Mohammed Jajere Adamu ,Halima Bello Kawuwa ,Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches , Appl. Sci - 2022.

In a brain tumour, cells multiply quickly and endlessly with no control over the tumor's rate of expansion. Using the Visual Geometry Group (VGG 16) to find brain tumours, implementing a convolutional neural network (CNN) model architecture, and setting parameters to train the model for this problem were the objectives of this study. Because of its effectiveness, VGG is one of the best CNN models employed.In addition, the study created a useful method for MRIbased brain tumour detection to help with making prompt, effective, and accurate decisions.

Convolutional feature maps were created by Faster CNN using the VGG 16 architecture as its primary network. These maps were subsequently categorised to produce recommendations for tumour regions.

The performance was evaluated using prediction accuracy. The system beat existing traditional methods for identifying brain tumours in the testing data (Precision = 96%, 98.15%, 98.41% and F1-score = 91.78%, 92.6% and 91.29% correspondingly) and achieved an excellent accuracy of CNN 96%, VGG 16 98.5%, and Ensemble Model 98.14.

Paper 6

Ali Mohammad Alqudah , Hiam Alquraan , Isam Abu Qasmieh , Amin Alqudah, Wafaa Al-Sharu , Brain Tumor Classification Using Deep Learning Technique - A Comparison between Cropped, Uncropped, and Segmented Lesion Images with Different Sizes, (IJATCSE-2019)

In general, brain tumours are among the most prevalent and severe malignant tumour disorders, and if they are identified at a higher stage, they might result in a very short predicted life. Thus, grading a brain tumour is a very important step to take after finding the tumour in order to develop a successful treatment strategy. In this study, we graded (classified) a dataset of 3064 T1 weighted contrast-enhanced brain MR images into three classes by using CNN, one of the most popular deep learning architectures. The suggested CNN classifier is an effective tool with an overall performance of 98.93% accuracy and 98.18% sensitivity for the cropped lesions, 99% accuracy and 98.52% .

Paper 7

Andronicus A. Akinyelu , Fulvio Zaccagna , James T. Grist , Mauro Castelli ,and Leonardo Rundo , Brain Tumor Diagnosis Using Machine Learning, Convolutional Neural Networks, Capsule Neural Networks and Vision Transformers, (J. Imaging – 2022)

The treatment for brain tumours is determined by the presumed grade and is based on clinical and radiological data. In order to select the most effective treatment strategy, a non-invasive assessment of tumour grade is of the utmost importance. One of the successful Deep Learning (DL)-based approaches that has been utilised to diagnose brain tumours is Convolutional Neural Networks (CNNs). They are unable to efficiently manage input revisions, though. In order to solve the shortcomings of CNNs, a novel sort of machine learning (ML) architecture known as capsule neural networks (CapsNets) was recently created.

CapsNets are advantageous for processing medical imaging datasets because they are robust to rotations and affine translations. Also, very recently have solutions based on Vision Transformers (ViT) been suggested to deal with the problem of long-range reliance in CNNs. This survey includes a thorough overview of CNN, CapsNet, ML, and ViT-based, as well as other, brain tumour classification and segmentation methods.

Paper 8

F. P. Polly , S. K. Shil , M. A. Hossain , A. Ayman , and Y. M. Jang , Detection and Classification of HGG and LGG Brain Tumor Using Machine Learning , (ICOIN 2018)

Brain cancers called gliomas begin in the glial cells. Low grade (slow growing) or high grade gliomas are both possible (fast growing). The grade of a brain tumour based on gliomas is used by doctors to determine the patient's need for therapy.

The tumor's state is crucial to the course of treatment. In this study, we propose a computerised system to categorise abnormal brain cancers into HGG or LGG tumours and to further classify the abnormal brain tumours in the MRI images into normal brain and abnormal brain with tumour. The suggested computerised system combines discrete wavelet transform (DWT) and principal component analysis (PCA) as the primary components of the feature extraction and feature reduction methods, respectively. K-means is used as the segmentation methodology for clustering. The key component of our proposed system that classifies the abnormal brain tumours in the LGG and HGG after feature extraction and reduction is the support vector machine (SVM).

Paper 9

Dr.A Chandrashekhar, Gangu Rama Naidu, Dr.Santosh Kumar, Dr.Sampada Gulavani, Dr.Manoj Sharma , Dr.Dhirendra Kumar Shukla , Automated Classification and Detection of Brain Tumor using Wavelet Transform and Machine Learning , (ISSN -2021)

A brain tumour is the name given to the abnormal growth of brain tissue that impairs brain function. One crucial aspect of diagnosis is the proper detection of brain tumours. The suggested work may categorise the provided MRI image as either having a tumour present or not. The provided MRI picture is prepossessed first to eliminate noise using a variety of filters, followed by OTSU segmentation, and the characteristics of the segmented MRI image are recovered using Discrete Wavelet Transform. the most useful characteristics within a collection of features discovered using principle component analysis. Support Vector Machine with Radial Basis Function training and testing both employ these features. Throughout literature, the outcomes of the suggested tumour detection approach are effective.

Paper 10

Ameer Hussian Morad and Hadeel Moutaz Al-Dabbas , Classification of Brain Tumor Area for MRI images (ISCPS-2020)

The employment of numerous techniques that are integrated into each processing phase of filtering, segmentation, and features is the technological strength of the recommended solution. Choosing the appropriate implementation strategy based on particular parameters is the creative aspect. The current approach, which utilises MATLAB, includes smoothing, segmentation, feature extraction, and classification with the goal of improving an example MRI of a patient from AlKindy Hospital as a case study to present an effective diagnosis procedure. The technique uses the Median and Slantlet filters, the K-mean cluster and the Morphology operation segmentation methods, as well as area-size-aware feature extraction.

The classification of the experimental results shows that 50% of the employed photos represent medium cases of brain tumour, 10% represent low stage cases, and both can be treated, while 40% represent high cases of brain tumour, reflecting that the treatment is challenging.

Paper 11

Hein Tun Zaw , Noppadol Maneerat , Khin Yadanar Win , Brain tumor detectionbased on Naïve Bayes Classification (IEEE – 2019)

The brain's population of aberrant cells known as glial cells is what causes brain cancer. The goal of this study is to provide a technique for identifying brain tissues that have been impacted by cancer, especially grade-4 tumours like glioblastoma multiforme (GBM).

Since they develop quickly and have a higher propensity to spread to other sections of the brain, GBMs are among the most dangerous cancerous brain tumours. In this study, Naive Bayes classification is used to precisely identify the tumour region that comprises all metastatic malignant tissues.

This study uses a brain MRI database, together with preprocessing, morphological procedures, pixel removal, maximum entropy threshold, statistical feature extraction, and a Naive Bayes classifier-based prediction algorithm. Using various brain MRI images, the method's objective is to identify tumor-bearing regions and determine whether they are tumours or not. The key benefit of this method is ,when compared to other methods, it can accurately identify tumours that are situated in various parts of the brain, including the central area .

This method achieves an overall accuracy of 94% when tested on 50 MRI images, with a tumour identification rate of 81.25% and a non-tumor detection rate of 100%.

Paper 12

Miss. Priyanka Aiwale and Dr. Saniya Ansari , Brain Tumor Detection Using KNN ,International Journal of Scientific & Engineering Research (IJSER – 2019)

The correct study of the brain tumor's structure is actually a challenging work, and as a result, an automatic method for tumour detection is currently in use. In comparison to manual detection, this unquestionably saves time and produces results that are more precise. The suggested strategy is a novel one for both tumour detection and the estimation of the percentage of total brain cells that the tumour will take up. The first step is to segregate tumour areas from an MR image using the OSTU Algorithm. For both detecting and separating tumor - affected tissues from unaffected tissues, KNN& LLOYED are employed.

By applying the "wavelet transform on the transformed grey scale image," 12 features are recovered, including correlation, contrast, energy, homogeneity, etc. Use of the DB5 wavelet transform is for feature extraction.

Paper 13

Hayder Saad Abdulbaqi , Ahmad Fairuz Omar , Mohd Zubir Mat Jafri , Iskandar Shahrim Bin Mustafa , Loay Kadom Abood , Detecting Brain Tumor in Magnetic Resonance Images Using Hidden Markov Random Fields and Threshold Techniques (IEEE – 2014)

The aberrant and uncontrolled cell division that occurs inside the brain is what causes brain tumours. One difficult task in medical image processing is brain tumour detection. In this study, we describe a strategy based on Hidden Markov Random Fields (HMRF) and threshold methods for enhanced brain tumour identification. The proposed method has been developed in this research in order to construct hybrid method. The aim of this paper is to introduce a scheme for tumor detection in Magnetic Resonance Imaging (MRI) images using (HMRF) and Threshold techniques. These methods have been applied on 3 different patient data sets. They have the property of organizing their soothing effect on the final segment of brain tumor homogeneous tissue regions, while the edges between different tissues constituents are better kept.

Paper 14

Annisa Wulandari, Riyanto Sigit, Mochamad Mobed Bachtiar, Brain Tumor Segmentation to calculate Percentage Tumor Using MRI (IESKCIC-2018)

One condition that affects the brain by forming clots is a brain tumour. Using an MRI scan is one approach to see a brain tumour in great detail.

Because of their similar colours, normal tissue and brain tumour tissue are difficult to identify from one another. Accurate analysis of brain tumour is necessary.

Segmentation is the answer to the problem of analysing brain tumours. To get around this problem, brain tumour segmentation is used to separate brain tumour tissue from other tissues such as fat, edema, normal brain tissue, and cerebrospinal fluid.

The median filtering technique must be used to maintain the MRI image's edge. Thresholding is then needed for the tumour segmentation procedure, and the largest area is selected after each iteration.

By employing the watershed approach to designate the parts of the brain and those outside of the brain, followed by cleaning the skull, the brain is segmented. Through cropping. 14 MRI scans of brain tumours were used in this investigation. Brain tumours and brain tissues are contrasted in the segmentation results. The average error in the tumour area calculation made by this approach is 10%.

Paper 15

M.Kadkhidai, S. Samavi, N. Karimi, H. Mohaghegh, S.M.R. Soroushmehr, K. Ward, A. All, K. Najarian, Automatic Segmentation of Multimodal Brain Tumor Images Based on Classification of Super-Voxels (IEEE-2016)

Despite the increasing expansion of technologies for segmenting brain tumours, there are still several obstacles in this field. The load of manual labelling is lessened and the accuracy of diagnosing brain tumours is increased thanks to the automatic segmentation of brain pictures. Using 3D super-voxels, the improved images are then segmented according to their intensities. Typically, a tumour zone might be considered a conspicuous object in a picture. This observation led us to develop a novel feature that makes use of a saliency detecting technique. The edges of the original image are aligned with the saliency map using an edge-aware filtering technique, which improves the tumor's borderlines.

Paper 16

Padma Ganasala, Durga Srinivas Kommana, Bhargav Gurrapu, Semiautomatic and Automatic Brain Tumor Segmentation Methods: Performance Comparison, (INDISCON-2020).

If the cells are grown in brain uncontrolled manner, then it develops a tumor in the brain. If the brain tumor occurs in any hemisphere then it leads to disfunction of body parts. Brain tumor can be categorized as benign tumor (noncancerous) and malignant tumors (cancerous). So, it is crucial to sense a brain tumor as early as possible to save the life of a patient. Today, medical imaging takes a vital part in identifying abnormalities in different organs. They are several medical imaging techniques like X-ray computed tomography (CT) scan, positron emission computed tomography (PET) scan, magnetic resonance imaging (MRI) scan, and ultrasound scan etc... Out of all, MRI scan is the most suitable technique to display the abnormalities in the brain. The specificity value for different segmentation methods varies between 76.18% to 95.56%. Specificity is least for K-means and highest for U-net based method. This implies that segmented tumor area is less than the U-net based method.

Paper 17

Mina Ghaffari, Arcot Sowmya, Ruth Olive, Multimodal brain tumour segmentation using densely connected 3D convolutional neural network, (IEEE-2019).

Reliable brain tumour segmentation methods from brain scans are essential for accurate diagnosis and treatment planning. We propose a semantic segmentation method based on CNN for brain tumour segmentation using multimodal brain scans. The proposed model is a modified version of the well-known Unet architecture. It gains from DenseNet blocks between the encoder and decoder parts of the U-net to transfer more semantic information from the input to the output.

In addition, to speed up the training process, we employed deepsupervision by adding segmentation blocks at the end of the decoder layers and summing up their outputs to generate the final output of the network. We trained and evaluated our model using the BraTS 2018 dataset. a new CNN architecture for segmenting a brain tumour into three regions of interest, namely whole tumour, tumour core and enhancing tumour.

Paper 18

Vishvesh Pathak, B. Uma Maheswari, Sridhar Iyer, Modified CNN for Multi-classBrain Tumor Classification in MR Images with Blurred Edges, (MysuruCon-2022).

Brain tumors are caused by the hyperproduction of specific cells. Only early stages of the cancer can be successfully treated with these approaches, making early cancer detection crucial. However, the doctors with exceptional domain knowledge need not be occupied with this task as it is linear enough to program computers to achieve adequate success in predictions, and hence, the doctors can be involved only when there is an uncertainty in the computer predictions. In order to determine the type of tumor on Magnetic Resonance Images (MRI), this article suggests a novel strategy that combines deep learning and image transformation techniques using Fourier transformation, and classifies brain tumors into four categories, including gliomas, meningiomas, pituitary tumors and no-tumor.

The results show that, in comparison to the existing deep learning models, proposed strategy yields a 5% gain in accuracy simultaneously classifying and providing results more quickly.

Paper 19

Peng Zequan, Fang Yanhong, Brain Tumor MRI Image Segmentation Via Combining Pyramid Convolution and Attention Gate, (PRAI-2022).

Gliomas are the most common primary brain malignancies. In this regard, this paper proposes a brain tumor segmentation algorithm based on the improved U-Net model to achieve accurate segmentation of brain tumors. By adding a pyramid residual module to the encoding end of U-Net, the receptive field and feature extraction capability of the model is increased, and an improved attention gate is used to enhance the feature mapping capability of skip connections. We evaluated the performance of our model on the BraTS 2018 and BraTS 2019 validation datasets, where the Dice scores for the whole tumor, core tumor, and enhancement tumor were 0.885, 0.801, and 0.748, respectively, on the BraTS 2018 validation set. In the validation set of BraTS 2019, the Dice scores of the whole tumor, core tumor, and enhancing tumor were 0.883, 0.758, and 0.684 respectively. The experimental results demonstrate the effectiveness of our model for the task of brain tumor segmentation.

Paper 20

Shashank Bhardwaj, Niraj Singhal, Neeraj Gupta, Adaptive Neurofuzzy System for Brain Tumor, (CIPECH-2014).

It emphasizes on brain tumor detection and hereby minimizing the deviation of target value and actual value using back-propagation algorithm. In this paper, a structure of adaptive system is proposed with the help of Adaptive neurofuzzy inference system (ANFIS) for diagnosis of brain tumor.

Investigation of brain tumor is performed based on predefined rules. Investigation of brain tumor by the proposed system is illustrated and good performance is achieved.

In this paper, the prototype consisting of six symptoms of brain tumor and using different rules have been explained. The behavioral pattern of EEG with normal and abnormal activities has also been shown. Fuzzy Logic (FL) has appeared as one of the active area of research activity especially in control system application. FL is a powerful way of reasoning that is used when there is no mathematical model and input data are not precise. The process of converting the scalar value into fuzzy value is known as Fuzzification. Triangular fuzzifiers, Gaussian fuzzifiers, Trapezoidal fuzzifiers and singleton fuzzifier are four type of fuzzifiers used for the process of fuzzification.

Literature survey table

Sr. No	Paper Name	Publication Year	Methods	Advantages	Disadvantages
1	Brain Tumor Detection Analysis Using CNN	ICAIS-2021	CNN classification	High accuracy, Automated analysis	Limited generalizability, Limited data availability
2	Brain Tumour Detection and Classification by using Deep Learning Classifier	IJISAE-2023	CNN & SVM classification	Segmentation and less time, significantly improvement for multi-class classification	Algorithm is not optimized, The gradient is vanishingly small and consequently prevent
3	A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet	National Research Foundation of Korea (NRF) - 2022	CNN EfficientNet-B0 Model, VGG16, InceptionV3	Robustness, Transfer learning, Efficient	Technical expertise required, Limited flexibility
4	Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm	ICCKE - 2019	CNN, Softmax classifier, RBF, DT	Provides a clear and intuitive way to interpret the output of the model.	May be sensitive to outliers or noisy data

5	Brain Tumor Analysis Using Deep Learning and VGG- 16 Ensembling Learning Approaches	Appl. Sci - 2022	CNN – VGG16	Good trade-off between accuracy and complexity	Limited architecture flexibility, Computationally expensive
6	Brain Tumor Classification Using Deep Learning Technique - A Comparison between Cropped, Uncropped, and Segmented Lesion Images with Different Sizes	IJATC SE- 2019	CNN	It can reduce the size of the image, which can lead to faster processing and training times	Cropping the lesion may result in a loss of information from the surrounding areas, which can negatively impact the accuracy of the model
7	Brain Tumor Diagnosis Using Machine Learning, Convolutional Neural Networks	J. Imaging – 2022	CNN, CapsNet , ViT	Improved accuracy, Non-invasive	Reliance on data quality, Limited interpretability

8	Detection and Classification of HGG and LGG Brain Tumor Using Machine Learning	ICOIN 2018	DWT , PCA , K-means , SVM	data reduction, feature extraction, signal processing	K-means can struggle with non-linearly separable data, SVM can be prone to overfitting
9	Automated Classification and Detection of Brain Tumor using Wavelet Transform and Machine Learning	ISSN -2021	DWT , PVA , SVM	Wavelet transform can extract features that are not visible in raw images	Data quality , Overfitting
10	Classification of Brain Tumor Area for MRI images	ISCPS-2020	K-mean cluster, segmentation methods,	Simple and fast , Preserves object boundaries	Lack of flexibility , Limited applicability
11	Brain tumor detection based on Naïve Bayes Classification	IEEE – 2019	Naive Bayes classification	Naive Bayes classification is easy to interpret	Naive Bayes classification may not perform well when the training data is imbalanced
12	Brain Tumor Detection Using KNN	IJSER – 2019	KNN & LLOYD, Ostu Algorithm	KNN is a simple and fast algorithm, Lloyd's algorithm is Computed.	KNN is sensitive to noise, Lloyd's algorithm may not scale well to large images ,

13	Detecting Brain Tumor in Magnetic Resonance Images Using Hidden Markov Random Fields and Threshold Techniques	IEEE – 2014	Hidden Markov Random Fields (HMRF) and threshold methods	Can handle multimodal images	May not work well with uneven illumination
14	Brain Tumor Segmentation to Calculate Percentage Tumor Using MRI	IESKCI C -2018	median filtering technique	Noise reduction, Edge preservation	May blur small structure, May not remove all noise
15	Automatic Segmentation of Multimodal Brain Tumor Images Based on Classification of Super-Voxels	IEEE - 2016	saliency detecting technique, edge-aware filtering technique	Super-voxel-based segmentation can be combined with machine learning algorithms	Super-voxel-based segmentation may not be effective in detecting small tumors
16	Automatic Brain Tumor Segmentation Methods: Performance Comparison	INDISC ON-2020	K-means and highest for U-net based method	Accurate Diagnosis, Adaptive System	limited data, expert knowledge bias

17	Multimodal brain tumour segmentation using densely connected 3D convolutional neural network	IEEE-2019	CNN , Unet architecture	it can handle multiple types of brain scans	DenseNet blocks and deep supervision can increase the computational complexity
18	Modified CNN for Multi-class Brain Tumor Classification in MR Images with Blurred Edges	MysuruCon-2022	CNN	improve survival rates by allowing for timely intervention and treatment	ethical and privacy concerns regarding the handling and use of patient data
19	Brain Tumor MRI Image Segmentation Via Combining Pyramid Convolution & Attention Gate	PRAI-2022	Pyramid Convolution and Attention Gate	model achieves high accuracy in the segmentation of brain tumors	require a large amount of computational resources and time for training
20	Adaptive Neurofuzzy System for Brain Tumor	CIPE CH-2014.	Adaptive neurofuzzy inference system (ANFIS)	Magnetic resonance imaging (MRI) provides non-invasive and high-quality images of brain lesions.	limited by the quality and resolution of the MRI images, as well as the variability and heterogeneity of brain tumors

1.8 Existing System

- LSTM and Adaboost: LSTM and Adaboost are well-suited for image classification tasks, as they can learn to extract spatial features from images.
- Recurrent neural networks (RNNs): RNNs can be used to model sequential data, such as the time-series data from MRI scans.
- Transformer models: Transformer models have recently been shown to achieve state-of-the-art results on a variety of image classification tasks, including brain tumor detection.

Existing deep learning systems for brain tumor detection have been shown to achieve high accuracy in clinical trials. For example, a recent study showed that a deep learning system was able to detect brain tumors with an accuracy of 99.5%, which is significantly higher than the accuracy of human radiologists.

However, there are still some challenges that need to be addressed before deep learning systems can be widely adopted for clinical use. One challenge is the need for large datasets to train deep learning models. Another challenge is the need to develop deep learning systems that are robust to variations in MRI images, such as different scanner types and imaging protocols.

1.9 Hardware and Software Requirements:

HARDWARE REQUIREMENTS

Processor : Intel Core i3-4590

RAM : 4GB

SSD : 128 GB

Graphics Card : GPU with CUDA-enabled cores can significantly speed up the training process

SOFTWARE REQUIREMENTS

Operating system : Windows 7, Mac OS 10.15

Programming language : Python 3.7

TOOLS : Google Colaboratory, Jupyter, Kaggle.

CHAPTER 2

DESIGN AND IMPLEMENTATION

2.1 PROPOSED SYSTEM

Data Preprocessing:

- Collect a dataset of brain MRI images, labeled with the type of tumor (or no tumor).
- Preprocess the images by normalizing the intensity values, resizing them to a consistent size, and cropping them to focus on the brain region of interest.

Model architecture:

- Choose a CNN architecture that has been shown to be effective for image classification tasks. Some popular options include ResNet, VGGNet, and DenseNet.
- Modify the architecture to accommodate the number of classes in your dataset. For example, if you are classifying images into four classes (no tumor, glioma, meningioma, and pituitary tumor), you will need to add a fourth output layer to the CNN.

Model training:

- Split the preprocessed dataset into training and validation sets.
- Train the CNN model on the training set using a suitable loss function and optimizer.
- Evaluate the model's performance on the progress during training.

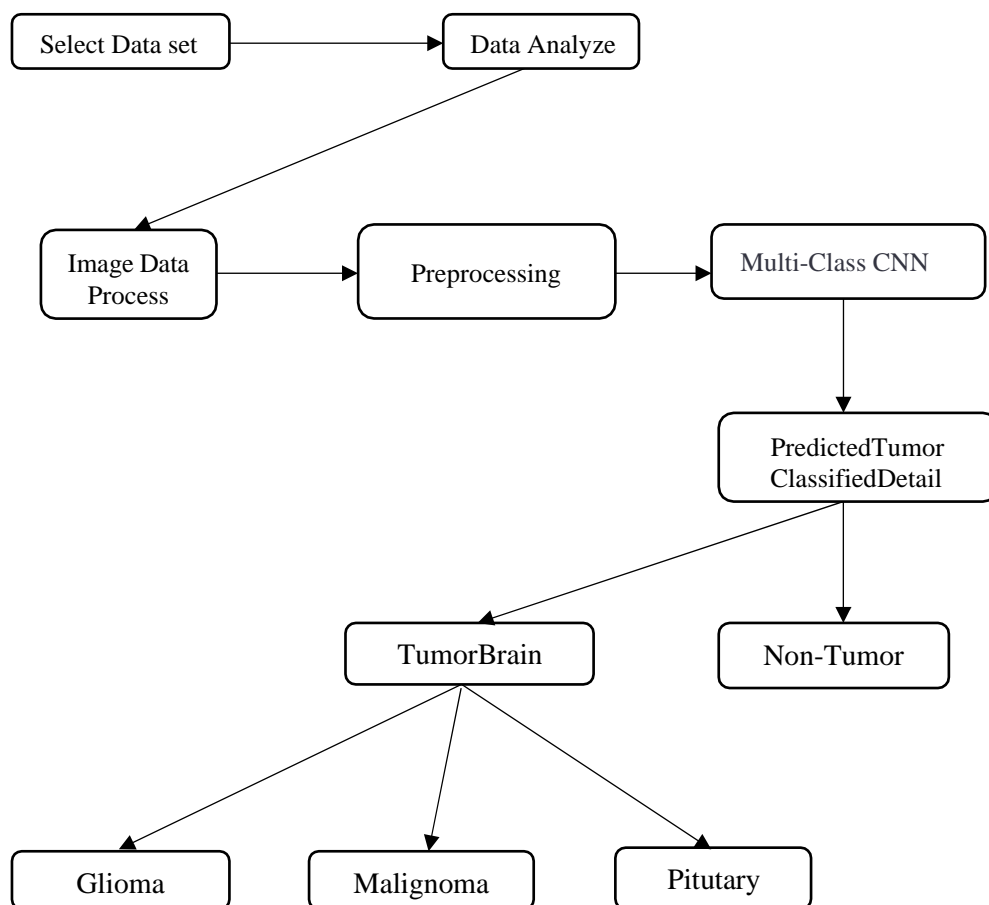
Model evaluation:

Once the model is trained, evaluate its performance on a held-out test set that was not used for training or validation. This will give you a more realistic estimate of the model's generalization ability.

Model deployment:

Once the model is trained and evaluated, it can be deployed to a production environment to be used for real-world brain tumor detection.

2.2 Architect Design



2.3 Modules

The specific modules used in a multiclass CNN for brain tumor detection will depend on the specific task and the available data. However, the core modules of feature extraction and classification are essential for all multiclass CNNs.

Here are some examples of how the different modules of a multiclass CNN can be used for brain tumor detection:

- The feature extraction module can be used to extract features from the MRI images that are relevant for distinguishing between different types of brain tumors and healthy tissue. For example, the feature extraction module could be designed to extract features such as the tumor shape, size, and texture.
- The classification module can be used to take the extracted features as input and predict the class of the MRI image (e.g., normal, tumor, or tumor type). For example, the classification module could be designed to output four probabilities, corresponding to the probability of the MRI image being normal, having a glioma tumor, having a meningioma tumor, or having a pituitary tumor.
- The attention module can be used to focus on the most important features in the MRI images for classification. For example, the attention module could be designed to focus on the tumor region of the MRI image, while ignoring the surrounding healthy tissue.
- The SPP module can be used to extract features from the MRI images at different scales. This helps to improve robustness to variations in image size and resolution. For example, the SPP module could be designed to extract features from the entire MRI image, as well as from smaller patches of the MRI image.

- The residual block module can be used to add shortcut connections between layers of the network. This helps to improve training performance and prevent overfitting. For example, the residual block module could be used to add shortcut connections between the convolution and pooling layers of the network.
- By combining these different modules, multiclass CNNs can be used to develop highly accurate and robust systems for brain tumor detection.

2.4 Modules Description

- Feature extraction module: Extracts spatial features from MRI images using convolution, pooling, and activation functions.
- Classification module: Predicts the class of the MRI image using a fully connected layer with a softmax activation function.
- Attention module: Focuses on the most important features in the MRI images using a weighted attention map.
- Spatial pyramid pooling (SPP) module: Extracts features from the MRI images at different scales to improve robustness to variations in image size and resolution.
- Residual block module: Adds shortcut connections between layers of the network to improve accuracy and prevent overfitting.

2.5 Results:

Figure 1

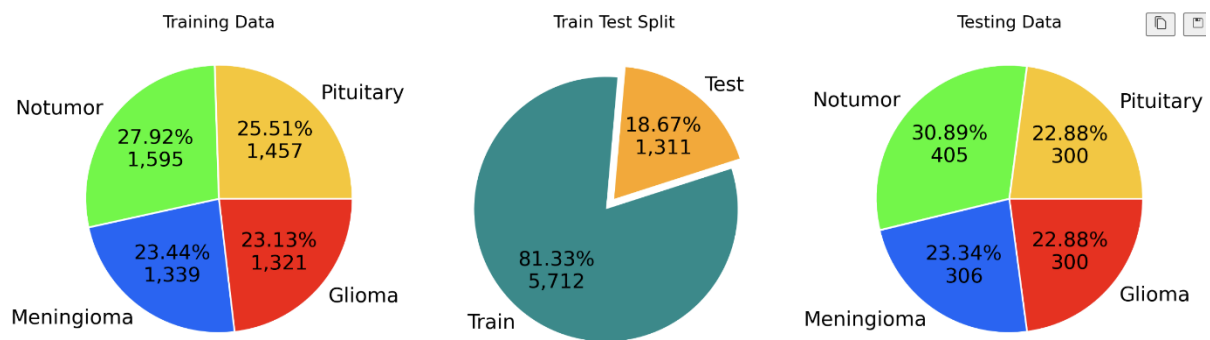


Figure 2

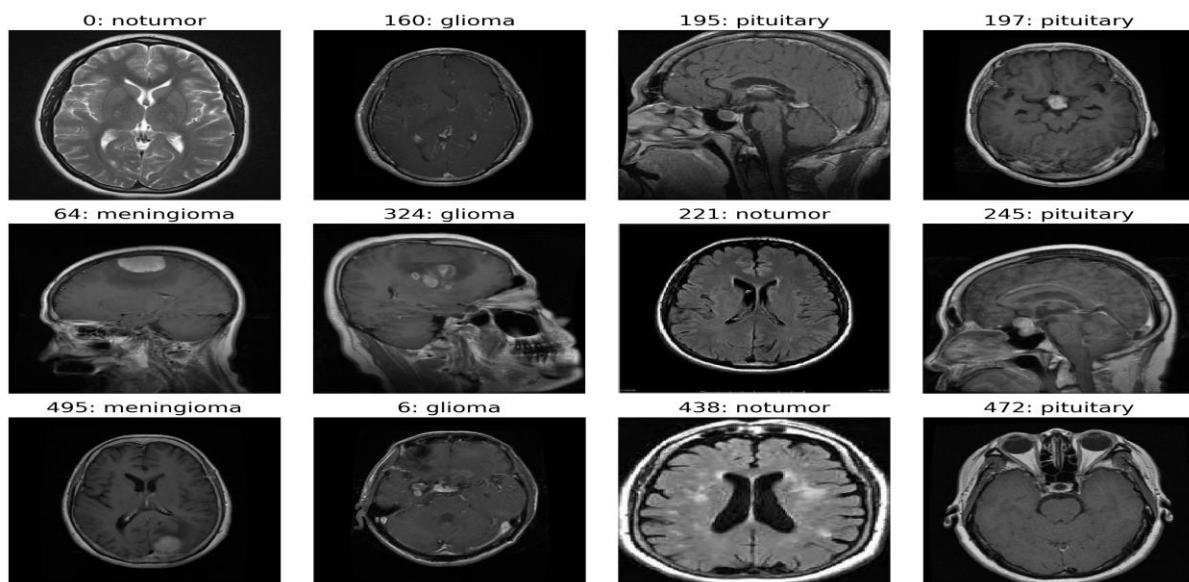


Figure 3

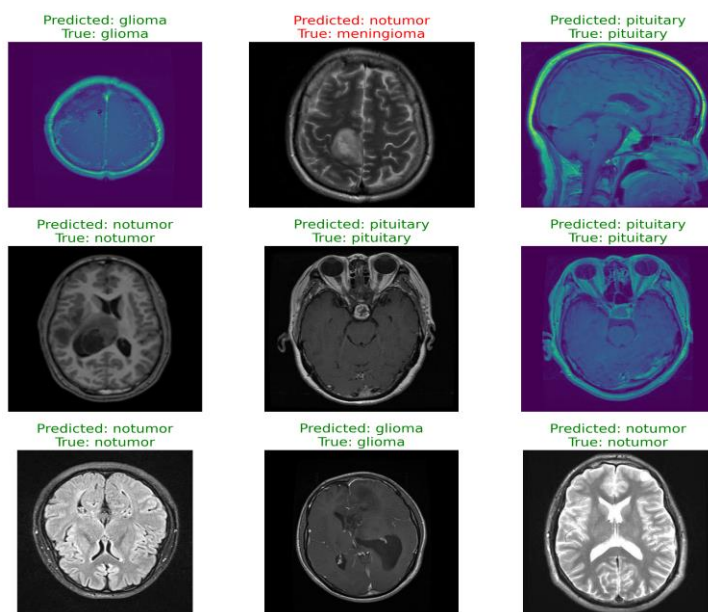
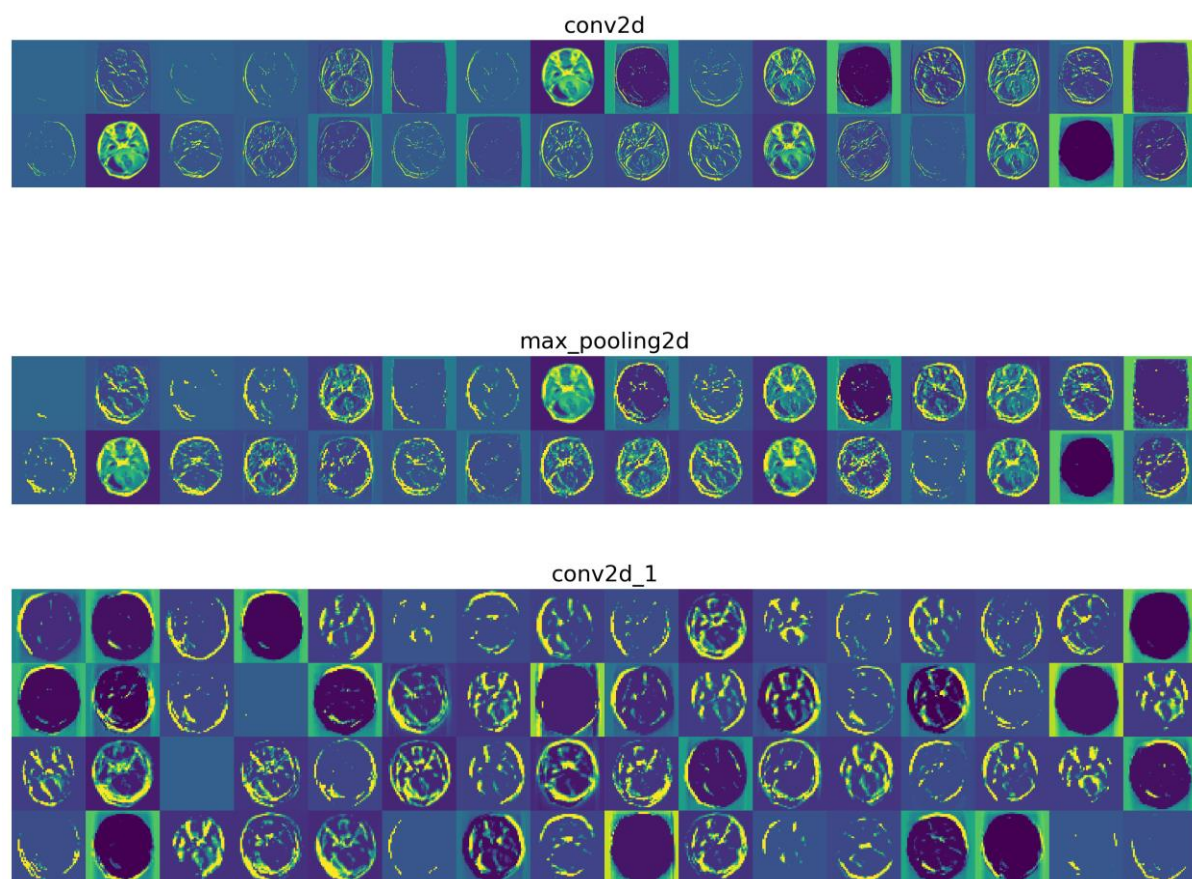


Figure 4



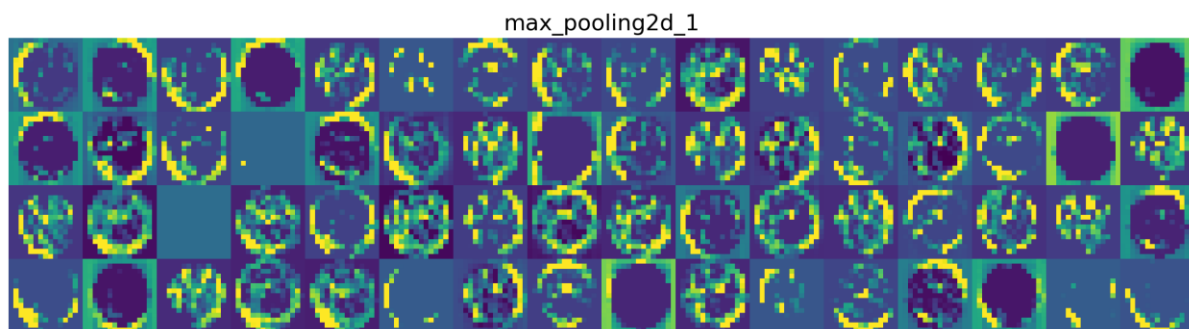


Figure 5

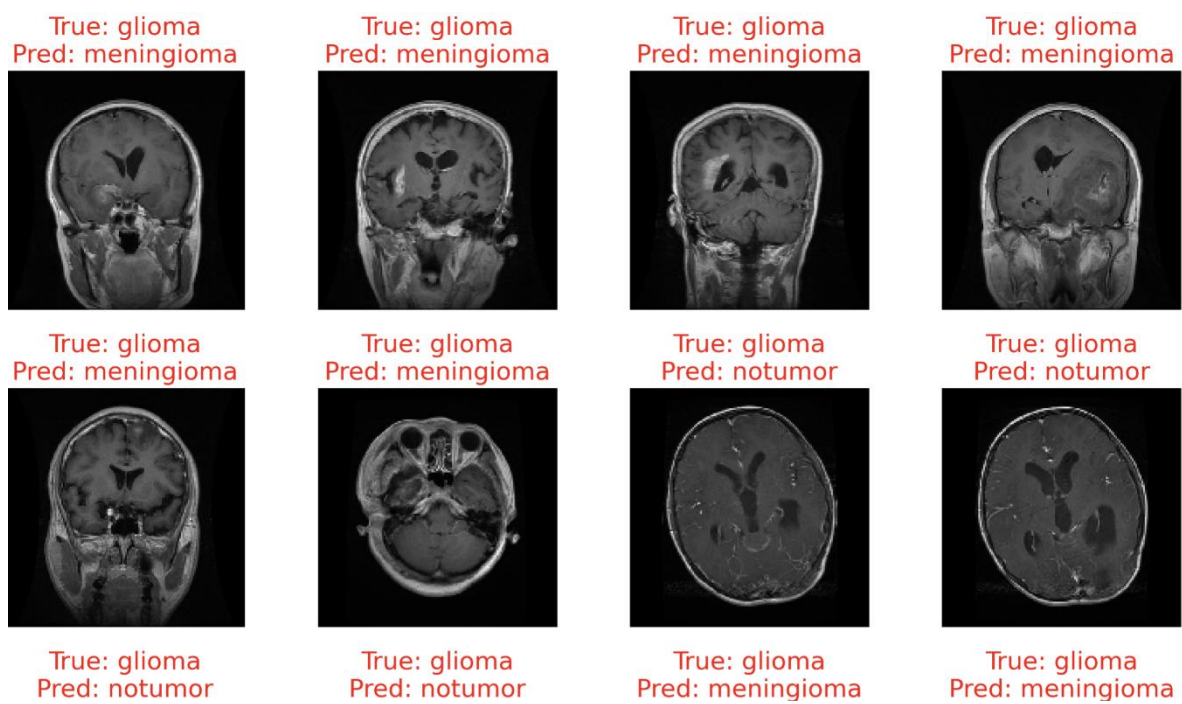


Figure 6

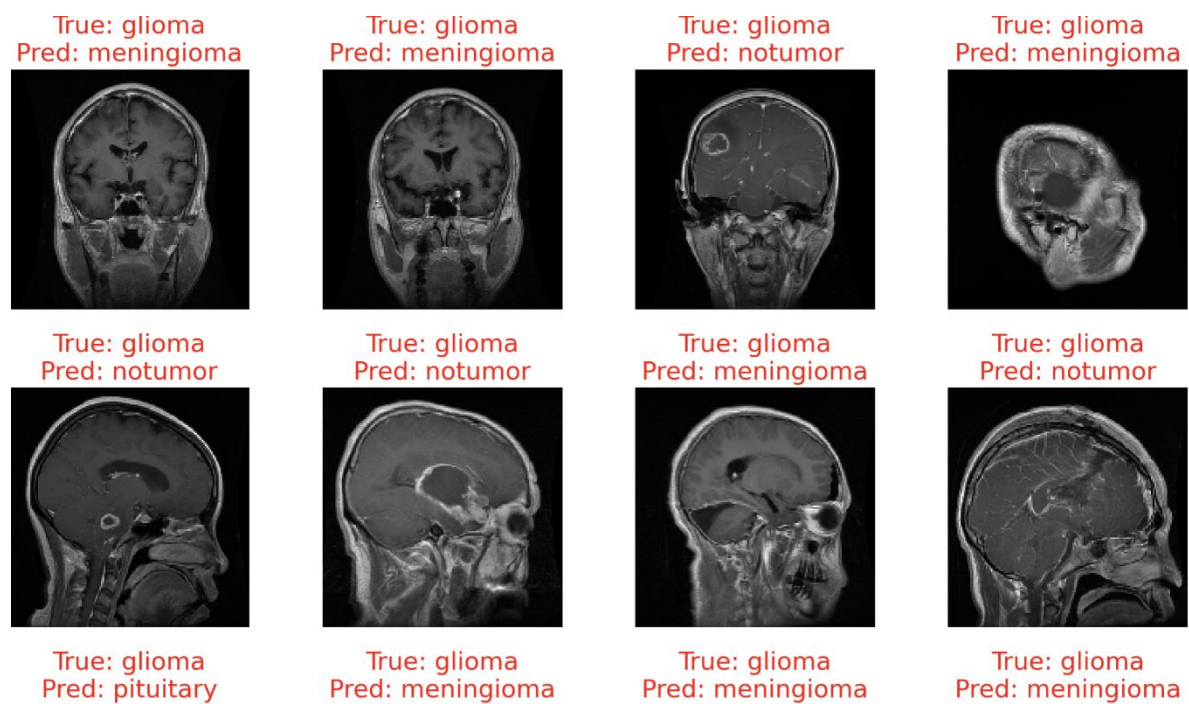


Figure 7

```
40/40 [=====] - 4s 98ms/step - loss: 0.3663 - accuracy: 0.8836
Test Loss: 0.36628
Test Accuracy: 0.88359
```

CHAPTER 3

CONCLUSION

3.1 Conclusion

- The provided code demonstrates the implementation of an Multi-Class CNN model for brain tumor classification using image data.
- It showcases various steps including data loading, preprocessing, augmentation, model training, evaluation, and visualization.
- The code can serve as a starting point for further experimentation and refinement of the brain tumor classification task.

3.2 Future Enhancement

- Incorporate prior knowledge and multi-modal data to improve accuracy and robustness.
- Use unsupervised learning to learn features from unlabeled data to improve tumor segmentation and anomaly detection.
- Use explainable AI to make the networks more transparent and interpretable for clinical use.

REFERENCES

1. Sunil Kumar, Renu Dhir, Nisha Chaurasia, “Brain Tumor Detection Analysis Using CNN”,Published in International Conference on Artificial Intelligence and Smart Systems (ICAIS-2021)
2. Shubhangi Solanki , Uday Pratap Singh , Siddharth Singh Chouhan, Sanjeev Jain, “Brain Tumour Detection and Classification by using Deep Learning Classifier”,Published in (IJISAE-2023).
3. Hasnain Ali Shah ,Faisal Saeed ,Sangseok Yun ,Jun-Hyun Park ,Anand Paul ,Jae- Mo Kang, “A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned” , Published in National Research Foundation of Korea (NRF)-2022.
4. Masoumeh Siar , Mohammad Teshnehlal , “Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm” , Published in International Conference on Computer and Knowledge Engineering (ICCCKE 2019).
5. Ayesha Younis ,Li Qiang ,Charles Okanda Nyatega ,Mohammed Jajere Adamu ,Halima BelloKawuwa , “Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches” , Published in (Appl. Sci 2022).
6. Ali Mohammad Alqudah , Hiam Alquraan , Isam Abu Qasmieh , Amin Alqudah, Wafaa Al- Sharu , “Brain Tumor Classification Using Deep Learning Technique” - A Comparison between Cropped, Uncropped, and Segmented Lesion Images with Different Sizes, Published in (IJATCSE-2019).
7. Andronicus A. Akinyelu , Fulvio Zaccagna , James T. Grist , Mauro Castelli ,and Leonardo Rundo , “Brain Tumor Diagnosis Using Machine Learning, Convolutional Neural Networks, Capsule Neural Networks and Vision Transformers”,Published in (J. Imaging 2022).
8. Ameer Hussian Morad and Hadeel Moutaz Al-Dabbas , “Classification of Brain Tumor Areafor MRI images”, Published in (ISCPS 2020).

9. Hein Tun Zaw , Noppadol Maneerat , Khin Yadanar Win , “Brain tumor detection based on Naïve Bayes Classification”, Published in (IEEE 2019).
10. Miss. Priyanka Aiwale and Dr. Saniya Ansari , “Brain Tumor Detection Using KNN , International Journal of Scientific & Engineering Research”, Published in (IJSER 2019).
11. Hayder Saad Abdulbaqi , Ahmad Fairuz Omar , Mohd Zubir Mat Jafri , Iskandar Shahrin Bin Mustafa , Loay Kadom Abood ,” Detecting Brain Tumor in Magnetic Resonance Images Using Hidden Markov Random Fields and Threshold Techniques” , Published in (IEEE 2014).
12. Annisa Wulandari , Riyanto Sigit , Mochamad Mobed Bachtiar , “Brain Tumor Segmentation to Calculate Percentage Tumor Using MRI”, Published in (IESKCIC 2018).