

**Abstract**

A brain tumor is a distorted tissue wherein cells replicate rapidly and indefinitely, with no control over tumor growth. Deep learning has been argued to have the potential to overcome the challenges associated with detecting and intervening in brain tumors. It is well established that the segmentation method can be used to remove abnormal tumor regions from the brain, as this is one of the advanced technological classification and detection tools. In the case of brain tumors, early disease detection can be achieved effectively using reliable advanced A.I. and Neural Network classification algorithms. This project aimed to critically analyze solutions for discovering brain tumors, implement a convolutional neural network (CNN) model framework, image pre-processing, and set parameters to train the model for desktop application.

The desktop application was developed an effective approach to detect brain tumors using MRI to aid in making quick, efficient, and precise decisions. For brain tumor classification and detection, image processing involves various steps such as pre-processing, segmentation, feature extraction, and classification. The prediction accuracy was used to assess performance. Our suggested methodology was evaluated on a data set for brain tumor diagnosis using MR images comprising 36000 MRI brain images. Our approach could identify brain tumors in MR images. In the testing data, the algorithm outperformed the current conventional approaches for detecting brain Tumors and achieved excellent accuracy.

**Chapter One: Introduction**

Brain Tumor

The source of brain tumors can be traced back to aberrant cells forming in the brain, some of which are precancerous, some of which are cancerous or damaging, and others which are innocuous or noncancerous.

Classification of brain tumors

Brain tumors can be classified into two main types, firstly there are Benign tumors which are not cancerous and secondly, and Malignant or harmful tumors that are cancerous.

1) Benign Tumor: Benign tumors in the brain are usually identified as groups of the same type of cells that have an abnormal cell division and growth process, and eventually transform into masses of cells that do not have a typical appearance of cancer.

2) Malignant Tumor: Malignant brain tumors are cancerous cells and often have boundaries and edges that are not easily visible or identified. With a highly rapid growth rate, Malignant tumors are the most life-threatening growths due thto eir tendency to aggressively spread and invade the surrounding tissues.

According to WHO standard, 700,000 humans are being with brain tumors and around 86,000 are diagnosed since 2019. While the total number of deaths due to brain tumors is 16,830 since 2019 and the average survival rate is 35%. Therefore, automated techniques are needed to grade brain tumors precisely from MRI scans. In this work, a new deep learning-based method is proposed for brain tumor detection and tumor type classification.

1.1 **Background of the project**

The application of information technology and machine learning in medicine has gained importance in today’s world. Artificial intelligence is a scientific field concerned with developing a machine that can learn on its own without human intervention to prepare itself for dealing with potential cases on its own. Application of this science finds high relevance in developing interventions for brain tumors, as the tumor cells show highly uncertain behavior that is too complex to be controlled through conventional medicine.

Due to the complexity of issues, brain tumors are extremely unstable and potentially fatal in the absence of intelligent solutions. To deal with such complex issues, humans can create machines behaving like living beings, capable of learning from experience and applying their experience to cater to the emerging issues due to the accumulation of tumor cells in the brain In this regard, in the field of medical imaging, AI and digital image processing a huge impact is made by a convolutional neural network (CNN)

Brain tumor segmentation is a process of separating tumors by isolating better and healthier tissues from affected areas. As a result, brain segmentation is the most challenging task in diagnostic techniques. Instead of being specialized in the brain tumor domain, many exclusionary techniques depend on general edge-based data. Due to their efficiency in detecting features of images, deep learning algorithms have lately been used for tumor segmentation tasks.

Several endeavors have been undertaken to investigate machine learning techniques for digitalizing this procedure in recent times. Deep learning methods have recently sparked an interest in more accurate and consistent detection of tumor cells.

The detection and tracking of tumors in Magnetic Resonance Imaging (MRI) is crucial because it offers details about abnormal tissues needed for therapeutic interventions. MRI brain tumor detection is a complicated task, due to the complexities and diverse forms of tumors. Collecting, organizing, and analyzing medical images has become digitized in today’s digital realm. Even with cutting-edge technology, thorough interpretation of medical images poses time and accuracy problems.

Considering the demand for advanced machine learning, this project intends to implement the CNN model in light of the current state of knowledge and propose the training of data to handle the complexities arising in detecting brain tumors while offering interventions.

**1.2 Statement of the problem**

Brain tumors are a major health concern, affecting thousands of people worldwide each year. They are caused by abnormal growths of cells in the brain and can have a range of negative effects on cognitive function, neurological health, and overall well-being. Brain tumors can be benign (non-cancerous) or malignant(cancerous), and the type and behavior of a brain tumor can vary depending on the location and type of abnormal cells.

Our study deals with automated brain tumor detection and classification. Normally the anatomy of the brain is analyzed by MRI scans or CT scans. The aim of the paper is tumor identification in brain MR images. The main reason for the detection of brain tumors is to provide aid to clinical diagnosis. The aim is to provide an algorithm that guarantees the presence of a tumor by combining several procedures to provide a foolproof method of tumor detection in MR brain images.

Currently, the most common method for diagnosing brain tumors is through the use of medical imaging techniques such as CT scans and MRI scans. These imaging modalities allow doctors to visualize the structure of the brain and identify potential areas of abnormal growth. However, interpreting medical images can be challenging, and the accuracy of brain tumor diagnosis using these methods is limited by the experience and expertise of the radiologist. In addition, medical imaging is costly and time-consuming and can be difficult to access in some regions. As a result, there is a high rate of misdiagnosis and delay in the diagnosis of brain tumors, leading to inadequate treatment and poor outcomes for patients.

There is therefore a need for improved methods for detecting brain tumors that are both accurate and efficient. Machine learning has the potential to address these limitations and enhance the diagnosis of brain tumors. By training a machine learning model on a large dataset of medical images and corresponding diagnosis labels, we can develop a system that can accurately identify the presence of brain tumors in medical images. However, the development of effective and reliable machine-learning algorithms for detecting brain tumors in medical images is a complex and challenging task, requiring a carefully designed and executed research plan.

The goal of this project is to develop a machine learning-based system for detecting brain tumors in medical images. Our system will be able to process images from a range of different imaging modalities, such as CT scans and MRI scans, and provide a diagnosis in near real-time. Additionally, our system will be designed to be highly sensitive and specific, minimizing the risk of false positives and false negatives. Through our research, we aim to contribute to the

development of effective and reliable methods for detecting brain tumors, and ultimately improve the diagnosis and treatment of this condition.

**1.3 Objective Of the project**

The main objective of this project is to develop a machine learning-based system for detecting brain tumors in medical images. This system will be able to process images from a range of different imaging modalities, such as CT scans and MRI scans, and provide a diagnosis in near real-time. Additionally, our system will be designed to be highly sensitive and specific, minimizing the risk of false positives and false negatives. Through our project, we aim to contribute to the development of effective and reliable methods for detecting brain tumors, and ultimately improve the diagnosis and treatment of this condition.

The focus of this project is MR brain image tumor extraction and its representation in a simpler form such that it is understandable by everyone. The objective of this project is to bring some useful information in simpler form in front of the users, especially for the medical staff treating the patient. This project aims to define an algorithm that will result in an extracted image of the tumor from the MR brain image. The resultant image will be able to provide information like size, dimension, and position of the tumor, and its boundary provides us with information related to the tumor that can prove useful for various cases, which will provide a better base for the staff to decide the curing procedure. Finally, we detect whether the given MR brain image has a tumor or not using Convolution Neural Network.

To achieve this objective, we will undertake the following specific tasks:

- Collect and compile a large dataset of medical images and corresponding diagnosis labels - Pre-process and augment the data to improve the quality and diversity of the data - Train and test machine learning models on the dataset to develop a system for detecting brain tumors in medical images - Evaluate the performance of our system using a range of metrics, such as accuracy, sensitivity, and specificity - Refine and improve the system based on the evaluation results - Develop a user-friendly interface for the system, allowing doctors and health care professionals to easily use our system to diagnose brain tumors.

In summary, our objective is to develop a machine learning-based system for detecting brain tumors in medical images that is both accurate and efficient and has the potential to significantly improve the diagnosis and treatment of this condition.

**1.4 Scope of the project**

The scope of this project is the development of a machine learning-based system for detecting brain tumors in medical images. Wewillfocusspecificallyonthedevelopmentofalgorithmsthat can process images from a range of different imaging modalities, including CT scans and MRI scans, and provide a diagnosisofthepresenceorabsenceofabraintumor. Our system will is designed to be highly sensitive and specific, minimizing the risk of false positives and false negatives. To develop and evaluate our system, we will require a large dataset of medical images and corresponding labels, which we will collect and process as part of this project.

The system can be used by neurosurgeons and healthcare specialists. The system incorporates image processing, pattern analysis, and computer vision techniques and is expected to improve the sensitivity, specificity, and efficiency of brain tumor screening. The primary goal of medical imaging projects is to extract meaningful and accurate information from these images with the least error possible. The proper combination and parameterization of the phases enable the development of adjunct tools that can help with the early diagnosis or the monitoring of tumor identification and locations.

We will begin by conducting a thorough view of the existing literature on medical imaging and machine learning, to gain a detailed understanding of the state of the artinthisfield. We will then design and implement our machine learning algorithms, and train and test the honor dataset of medical images. We will carefully evaluate the performance of our system, and make any necessary adjustments to improve its accuracy and reliability. Finally, we will conduct a series of experiments to compare the performance of our system to existing methods for detecting brain tumors in medical images.

Throughout this project, we will be guided by the following objectives:

- Develop and implement a machine learning-based system for detecting brain tumors in medical images. - Minimize the risk of false positives and false negatives in the diagnosis of brain tumors. - Achieve a high degree of accuracy, sensitivity, and specificity in the detection of brain tumors. - Conduct a thorough evaluation of the performance of our system, and make any necessary adjustments to improve its accuracy and reliability. - Compare the performance of our system to existing methods for detecting brain tumors in medical images.

We believe that achieving these objectives will significantly advance the field of medical imaging and machine learning, and could have a positive impact on the lives of people with a brain tumor.

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**1.5 Limitations of the project**

A major challenge for brain tumor detection arises from the variation in tumor lactation, size, and shape.we use many techniques to detect brain tumors from MRI images. These methods face challenges like finding the location and size of the tumor. Image segmentation is used to detect the tumor from the MRI image. It is the most important and difficult part of brain tumor detection.

owing to the small size of tumors compared to the rest of the brain, brain imaging data are imbalanced .due to this characterization, existing networks get too biased to words the one class that is overrepresented, and training a deep model often leads to low true positive rates.

Another limitation of this project can be the quality of the MRI image result and it can change the result of the detection if it is not clear and net. This shows the accuracy of the image processing is not always correct. And depending on the economical background of our country most of the MRIs we are using don’t have the best image qualities and this can be a huge limitation for our project.

**1.6 Feasibility study**

A feasibility study is an analysis that takes all of the project’s relevant factors into account –including economic, technical, l,egal and scheduling considerations. It is essential to evaluate the cost and benefits of the new system. Based on the feasibility study decision is taken on whether to proceed or cancel the project.

**1.6.1 Technical feasibility**

In technical feasibility, the following issues are taken into consideration: Whether the required technology is available or not and Whether the required resources are available like Manpower, programmers, testers & debuggers, Software, and hardware. From a technical point of view, the feasibility of this project is high because the proposed system is designed to be built on existing well-known and well-tested technologies . The team also can develop this project without any difficulty since the team has studied the required methodologies and tools.

**1.6.2 Economic**

Economic feasibility is a kind of cost-benefit analysis of an examined project, which assesses whether it is possible to implement it. It consists of market analysis, economic analysis, and technical and strategic analysis. For any system if the expected benefits equal or exceed the expected costs, the system can be judged to be economically feasible. Our project will be used only in hospitals. It means that we won’t have to think the economic feasibility in ordinary people’s perspective. Our project will reduce the use of man power and extra exhaustion for the translation of the MRI results and the time and resource of both doctors and patients.

**1.6.3 Operational feasibility**

Operational feasibility is mainly concerned with issues like whether the system will be used if it is developed and implemented. Whether there will be resistance from users that will affect the possible website benefits We will perform a series of steps to solve problems and user requirements. The project will have a positive impact in users as most hospitals in Ethiopia have short comings in case of time, knowledge to properly diagnose, and awareness about the use of automated systems to aid them in their work. As we have understood from most researches, hospitals have provided their opinion about the use of this work because they understood how it will help and support their day to day operations.

**1.7 Significance of the project**

Image processing plays an important role in medical field and medical imaging is growing and challenging field.Now a day’s tumor is second leading cause of cancer,and due to that,that large numbers of patients are in danger .if proper detection of tumor is possible that doctors can keep a patient out of danger.

Brain tumor detection at early stage can increase the chance of the patients recovery after treatment.there is substantial development in the medical image technologies, and they are now becoming an integral part in the diagnosis and treatment processes. In image processing various algorithms are developed for image segmentation.When these algorithms are applied on the MRI images the prediction of brain tumor is done very fast and a higher accuracy helps in providing the treatment to the patients also helps the radiologist in making quick decisions.

The manual process of evaluation many image obtained in a clinic is complicated and inefficient to understand the behaviour of different tumor. In order to understand and intervene in this complex phenomenon, more precise computer based tumor detection/diagnosis technologies are required.

**1.8 The beneficiary of the project**

Computer Vision plays a significant role, which reduces the human judgment that gives accurate results. CT scans, X-Ray, and MRI scans are the common imaging methods among magnetic resonance imaging (MRI) that are the most reliable and secure. MRI detects every minute object.

These beneficiaries could benefit from a project that uses machine learning to detect brain tumors:

- Patients who are at risk of or have been diagnosed with brain tumors: The ability to detect brain tumors earlier, using machine learning, could be very beneficial for patients. Earlier diagnosis can lead to earlier treatment, which can often improve the chances of successful treatment and a positive outcome. In addition, using machine learning to detect brain tumors can be more accurate and efficient than traditional methods, which can reduce the risk of misdiagnosis and unnecessary treatments.

One of the potential beneficiaries of a project that uses machine learning to detect brain tumors is the broader healthcare industry. The use of machine learning-based methods for detecting brain tumors can have a positive impact on the healthcare industry as a whole, by providing more accurate and efficient methods for detecting these tumors. This can help to improve the quality of care provided to patients with brain tumors, which can ultimately lead to better outcomes for individuals and the healthcare system.

- Healthcare providers, such as doctors, nurses, and other medical professionals: Machine learning-based methods for detecting brain tumors can help healthcare providers make more accurate and efficient diagnoses. This can be particularly important for medical professionals who are specialized in diagnosing and treating brain tumors, as it can help them to provide the best possible care to their patients. In addition, using machine learning to detect brain tumors can free up time and resources that healthcare providers can use to focus on other aspects of patient care.

- Hospitals and other healthcare facilities that provide care to patients with brain tumors can benefit from the use of machine learning to detect these tumors. Machine learning-based methods for detecting brain tumors are often more accurate and efficient than traditional methods, which can help to improve the quality of care provided by these facilities. In addition, using machine learning to detect brain tumors can help hospitals and other facilities to reduce the risk of misdiagnosis and unnecessary treatments, which can save time, money, and other resources.

- Medical researchers: Machine learning-based methods for detecting brain tumors can be a valuable tool for medical researchers who are looking to further their understanding of these conditions and develop new treatments. By providing more accurate and efficient methods for detecting brain tumors, machine learning can help researchers to better study the underlying mechanisms of these tumors and identify new potential avenues for treatment. In addition, the results of the project could be used by medical researchers to develop new machine-learning models that are even more accurate and efficient at detecting brain tumors.

Some of the specific ways that the broader healthcare industry could benefit from using machine learning to detect brain tumors include:

- Improved accuracy and efficiency in the detection of brain tumors, which can help to reduce the risk of misdiagnosis and unnecessary treatments. This can save time, money, and other resources, and can ultimately lead to better outcomes for patients.

- Advanced knowledge and expertise in the field of brain tumor detection and treatment, as the results of the project can be shared with the broader medical community. This can help to promote innovation and collaboration in the field, and can ultimately lead to the development of even better methods for detecting and treating brain tumors.

- The reduced burden of brain tumors on individuals, families, and society as a whole, as the use of machine learning to detect brain tumors can lead to earlier and more accurate diagnoses. This can help to improve the chances of successful treatment and a positive outcome for patients, and can ultimately help to alleviate the physical, emotional, and financial burden of brain tumors.

Overall, the broader healthcare industry can benefit from using machine learning to detect brain tumors in many ways, including improved accuracy and efficiency, advanced knowledge and expertise, and reduced burden on individuals and society. These benefits can ultimately help to improve the quality of care provided to patients with brain tumors and can contribute to the overall advancement of the healthcare industry.

- Society as a whole, as improved methods for detecting and treating brain tumors can help reduce the burden of this condition on individuals and the healthcare system.

**1.9 Proposed methodology**

Brain tumor diagnosis is a very crucial task. To minimize fatal consequences, an accurate tumor detection of brain is crucial for a treatment plan. In diagnosing brain tumors imaging plays a very important role. Accurate results can be obtained only through computer aided automated systems. Even though several automated methods are available with the desirable performance measures, there is no clear differentiation between these techniques about the suitability for various applications. Anyone with tumor symptoms should see a doctor as soon as possible. Only a doctor can diagnose and treat the problem. If a person has symptoms that suggest a brain tumor, the doctor may perform one or more of the following procedures: Physical exam, Neurological exam, CT scan, MRI scan, Biopsy, etc. Among these magnetic resonance imaging (MRI) and computed tomography (CT) scans are used most often to look for brain diseases. During this project, we will use MRI based image data because MRIs shows more particular views than CT scans and are the favorable way to diagnose a brain tumor.

**Magnetic Resonance Image (MRI)**

Magnetic Resonance Imagining (MRI) is a medical imagining technique employed in radiology to capture images of anatomy and physiological process of the human body. MRI scans use radio waves and strong magnets to make pictures. Automated brain tumor detection from MRI images will play a vital role by reducing the requirement for manual processing of huge amount pf data.

**Data collection methods**

This project will make use of a publicly accessible augmented brain tumor data set. The datasets will be obtained from the free-source Kaggle database named Brain TumorAugmentedDataset[https://www.kaggle.com/datasets/mohammedredaomramn/brain-tumor-augmented-dataset]. This collection includes pictures of brain MRI from healthy and brain tumor patients. We might use additional datasets from different sources to enhance the accuracy if needed or we will use a pre-trained model. That is an efficient model which will use the weights from ImageNet dataset.

**Preprocessing**

Pre-processing is important in order to create a seamless training experience because the MRI scans differ in intensity, contrast, and size. Because the photographs in the data set are of varying sizes, the image will be reshaped to the proper size. Normalization will be employed if necessary to scale pixel values which will be beneficial to the training process.Firstly, the MRI brain image is given to the framework as an input. Then Pre-processing provides improvement to the MRI images that enhances some of the image features that are important for further processing. Classification can be defined as the process of predicting a class or category from observation values or given data points. The classification of a biomedical image is a very important step for an automated Computer Aided Design (CAD) system. At the end of detection process, decision will be been taken whether that MRI image consists of any tumor or not and the normal or the abnormal state will be checked.

**Data augmentation**

These process is done as necessary if the datasets are not augmented. Data augmentation is the process of creating images artificially and expanding the training data set.This is done so that the model learns multiple other variations of images along with the ones actually fed. This is important especially when datasets are small, but should be done in the case of large datasets also. Data augmentation is only done to the training datasets. We will not augment our test datasets. This is mandatory so as to make the model predict on non-augmented images, which have as low variation as possible.

**CNN Model**

A classic use case of CNNs is to perform image classification, e.g. looking at an image of a pet and deciding whether it’s a cat or a dog. The reason why we are not using Neural networks is that: Images are big and our network would be *huge* and nearly impossible to train.The other reason is that : Positions can change, If we train a network to detect dogs, we’d want it to be able to detect a dog regardless of where it appears in the image. If we feed it a slightly shifted version of the same dog image, the dog would not activate the same neurons, so the network would react completely different.

In this work, we will mainly target the tumor diagnosing and in line that approach have collected many of MRI images of brain and detecting the tumor in it by applying CNN (convolution Neural Networks) machine learning techniques. Post processing of the image of noise, we will next proceed with the CNN machine learning techniques using Keras and TensorFlow. The convolution neural network is used for automatic brain tumor classification. The data preprocessing is done on both the training and testing data set. Following that, the CNN will be built with different CNN layers such as convolution layer, maxpool layer, flatten layer, connection layer, dense layer and the output layer.

**Transfer learning**

Deep convolutional neural network models may take days or even weeks to train on very large datasets. Not only that but due to hardware limitations involved in training CNN, transfer learning must be adopted. A way to short-cut this process is to re-use the model weights from pre-trained models that were developed for standard computer vision benchmark datasets, such as the ImageNet image recognition tasks. ImageNet is a one of the pre-trained model. If we want to train from the starting layer, we have to train the entire layer (i.e) up to ending layer. So time consumption is very high. It will affect the performance. In the proposed CNN, If the datasets are too small or we don’t have the time and resource to train our big dataset, we will train only last layer in python implementation. So computation time is low meanwhile the performance is high in the proposed automatic brain tumor classification scheme. Top performing models can be downloaded and used directly, or integrated into a new model for our own computer vision problems.

**1.10 Development tools**

The software tool we are planning to use is Python. Python is a general-purpose high level programming language that is widely used in data science and for producing deep learning algorithms. Python has an excellent collection of in-built libraries. It claims a huge number of in-built libraries for data mining, data manipulation, and machine learning which makes it an appropriate tool for data processing especially when dealing with deep learning algorithms. Here we will train a model to specifically identify aberrations from MRIs and predict presence of a tumor with high accuracy. To dot that, several Python-based packages will be investigated to implement our algorithms. We proposed that CNN is one of the most effective techniques for the problem statement. Thus using image preprocessing and deep learning using keras and tensorflow, we will build a highly reliant and robust model to solve problems.

**1.11 Project Deliverable**

In this section we are going to talk about the project or service deliverable at the end of this year we are going to make a difference with a better and a more sophisticated version of a human mind in a piece of mobile app. This project have a tangible result which is to scan an MRI of a brain and tell us if the scanned MRI have a brain tumor . In addition to that our project is going to be a very big help to radiographers and/or doctors . For the future we are thinking about classifying the tumor to its type for example there is a person with tumor then after the website says yes to the tumor then at that time there will be a classification of the tumor to Glioblastoma, Glioma and Meningioma as detailed as possible. If the above become a success we also are thinking to build a hardware that have an MRI in it and with a quick scan it will distinguish if the person have a brain tumor or not .

**1.12 Cost Breakdown**

|  |  |  |
| --- | --- | --- |
| Material name | No. Material | Price in birr |
| paper | 1 pack | 700 |
| Pen/pencil | - | 120-300 |
| Computer/ laptop | - | - |
| Flash 16gb | - | 250 |
| print | - | 500 |
| GPU | 1 | 40,000 |
| Total price |  |  |

**1.4 Task and Schedule**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Time  Activity | DEC 13-20 | Dec21-jan21 | Jan22- Apr22 | Apr 23-May28 | May29-jun 4 |
| Requirement  gathering  and Analysis |  |  |  |  |  |
| Design/Documentation |  |  |  |  |  |
| implementation |  |  |  |  |  |
| Testing |  |  |  |  |  |
| Maintenance |  |  |  |  |  |

**Chapter Two: Literature Review**

**2.1 Brain Tumour Detection Using CNN**

**Sri lekha Jagannadham 1\*, K. Lakshmi Nadh 2@,M. Sireesha 3#**

Department of CSE, Narasaraopeta Engineering College, Narasaraopet, Andhra Pradesh

this research work will apply augmentation techniques to increase the training set and apply different Convolution Neural Network [CNN] techniques to grab out the best details from the image. In order to enhance the details from the image, the outer portion of the image cut out from all 4 sides.

In this system they have 5 stages to completely achieve the final result: skull stripping, segmentation, tumour contouring, feature extraction, applying to models. 1) Skull Stripping: The major step for medical image processing and it is introduced to eliminate the non-brain tissues from MR images of brain and it also increases the time of processing the image. We have removed the outer portion which is skull in the image by using the open-cv library.2.Augmentation:they perform this by making the images rotated and changed to a different mode. Some models are created to be suitable for grayscale mode and they are also using the predefined models which supports the RGB mode of images.

1. Tumour Contouring: contoured the tumour based on the intensity and the image is highlighted with the dark background as an output of this step. 4) Feature Extraction: identifying the part by contouring the image and the process goes on for all the images and extract the part of the image and extract the required part with the images. 5) Applying to the model: they have created 3 different models use the images which are augmented to these models and train the models.

Analysis for this custom CNN Model: Using CNN model with the layers as: Input layer, Zero Padding layer, Convolution2D layer, Batch Normalization Layer and an Activation function called ‘relu’ followed by 2 MaxPooling2D layers.the model has given accuracy of 98. 067023%.

**2.2 Brain Tumor Classification using CNN**

**Aditi Kanwar1, Nakshita Khokhar2, Pawanneet Kaur3, Dr Sanjay Pawar4 1B.Tech,**

Department of Information Technology, Usha Mittal Institute of Technology, SNDT Women’s University, Maharashtra, India

the authors have described their own model and compared it with the existing ones. Within the model, the authors have proposed a feature selection algorithm that will evaluate the importance of new feature sets by comparing them with the existing ones. Through this method, the most appropriate feature can be found. For this paper, the processing time and memory consumption of the presented model were high. In addition to that, the dataset that was used also limits the accuracy of the overall model.

PROPOSED ARCHITECTURE

1. Data Acquisition The dataset contains several MRI scans from various patients which are categorized into training and testing. Adding on, these are further labeled into the four types of tumors which are glioma, meningioma, pituitary and no tumor; containing approximately 1000 images per class for training and approximately 100 images per class for testing. The diversity of this dataset helped in giving more accurate and reliable predictions.
2. Image Pre-processing
3. Conversion to grayscale: To make the operations less complicated and easier to process, the input image is converted to its gray scale. 2) Image Resizing: To make all the images of the same size i.e.150×150 pixels they have used image resizing.

4 .Data Augmentation =A small data set does not contain enough examples to train the neural network. Therefore, data augmentation was done on the training set to add validation data set which helped in avoiding the under fitting or over fitting of the CNN model.

5.CNN- There are two specific ways to build a Keras model i.e. sequential and functional. In this research a sequential model has been implemented. The sequential API allows the user to create models one layer after another. .

Conclusion

In this research the proposed system used MRI scan image as an input to a multi-layered CNN model. We investigated the capabilities of CNN architectures by building them with small kernels, as opposed to standard deep CNN implementations that use shallow architectures with big filtering algorithms. We also discovered that shallow architectures performed worse even when employing a larger number of feature maps. The system apart from just classifying the brain tumor into yes or no categories, further classifies the tumor into four classes i.e. Glioma, Meningioma, Pituitary and No Tumor. The average accuracy reached by the proposed methodology was 96.26%. Accuracy of 96.26% was accomplished with the help of wide and diverse range of dataset containing more than 4500 images. The multi-layered CNN architecture containing convolution, max pool, dropout, fully connected and SoftMax layer

**2.3 BRAIN TUMOUR IDENTIFICATION USING CONVOLUTIONAL NEURAL NETWORK**

**J. G. SIVA SAI and his team member**

This paper aims to focus on the use of different techniques for the discovery of brain cancer using brain MRI. their paper provides the architecture of the system that developed by their hands. It consists of six steps where the execution starts from taking an input image from the data set followed by the image pre-processing, image enhancement, Image segmentation using binary thresholding, and brain tumor classification using a Convolutional Neural Network. Finally, the output is observed after all the abovementioned steps are completed. They used Pandas for data analysis, anaconda for scientific computing that aims to simplify package management and deployment, NumPy for a high-performance multidimensional array object, tensor flow, and Keras for writing deep neural network code, and OpenCV for programming functions mainly aimed at real-time computer vision.

The project used the Sobel filter for edge detection. It also used the cv2.threshold() function for Thresholding which is the simplest method of image segmentation and 256 feature detectors for CNN's. Among all the images, the proposed Convolutional Neural Network (CNN) based approach seems too much better in terms of the quality of the output in 128 \*128 images when compared to its other sized images. The proposed model obtained an accuracy of 84% and yielded promising results without any errors and much less computational time.

**2.3 AUTOMATIC BRAIN TUMOR DETECTION AND CLASSIFICATION ON MRI IMAGES USING MACHINE LEARNING TECHNIQUES**

**SHREYAS GHOSH, Sayeri Biswas, and Jitsona De**

In this project, They attempted at detecting and classify the brain tumor and compare the results of binary and multi-class classification of brain tumors using Convolutional Neural Networks (CNN) architecture. The project's brain tumor images are composed of 128 by 128 pixels which make up 16,384 pixels. Each pixel is fed as input to each neuron of the first layer.

They sometimes have a classification task in one domain of interest, but they only have sufficient training data in another domain of interest, where the latter data may be in a different feature space or follow a different data distribution. in this case they used transfer learning. Transfer learning allows neural networks to use significantly less data. With transfer learning, they are in effect transferring the knowledge that a model has learned from a previous task to our current one.

This project used Sthe igmoid function ranges from 0 to 1 to predict probability as an output in case of binary classification whthe ile Softmax function is used for multi-class classification. Their pre-processing includes rescaling, noise removal to enhance the image, applying Binary Thresholding and morphological operations like erosion and dilation, contour forming (edge-based methodology). To identify the tumor region from the brain image, Binary Thresholding can be used (via the Region Growing method), which converts a grayscale image to a binary image based on the selected threshold values. The problems associated with such approach are that binary image results in loss of texture and the threshold value come out to be different for different images. Hence, they were looking for a more advanced segmentation algorithm, the watershed algorithm by using Otsu Binarisation. Without the pre-trained Keras model, the training accuracy is 97.5% and the validation accuracy is 90.0%. The validation result had the best figure of 91.09% accuracy. It is observed that without using the pre-trained Keras model, although the training accuracy is >90%, the overall accuracy is low unlike where the pre-trained model is used. Also, when they trained their dataset without Transfer learning, the computation time was 40 min whereas when they used Transfer Learning, the computation time was 20min. Hence, training and computation time with the pre-trained Keras model was 50% lesser than without.

**Chapter Three: Functional requirement and Non funtional requirement**

**3.1 Working theory of our project**

**Artificial intelligence:**

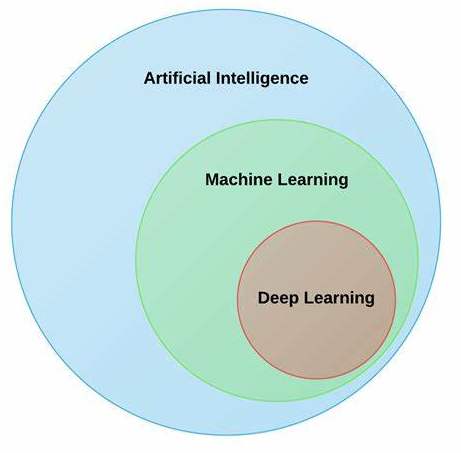
Artificial intelligence (AI) is the simulation of human intelligence processes by

machines, especially computer systems enabling it to even mimic human behaviour. Its applications lie in fields of Computer Vision, Natural Language Processing, Robotics, Speech Recognition, etc. Advantages of using AI are improved customer experience, accelerate speed to market, develop sophisticated products, enable cost optimisation, enhance employee productivity and improve operational efficiency.

**Machine Learning** is a subset of Artificial Intelligence which aims at providing machines with the ability to learn without explicitly programming. The idea is that such machines (or computer programs) once built will be able to evolve and adapt when they are exposed to new data.The main idea behind Machine Learning is the ability of a learner to generalize from its experience. The learner (or the program), once given a set of training cases, must be able to build a generalized model upon them, which would allow it to decide upon new cases with sufficient accuracy.

**Deep Learning** is a subset of Machine Learning which focuses on an area of algorithms which was inspired by our understanding of how the brain works in order to obtain knowledge. It’s also referred to as ***Deep Structured Learning*** or ***Hierarchical Learning***. Although training time via Deep

Learning (DL) methods is more than Machine Learning methods, it is compensated by higher accuracy in the former case. Also, DL being automatic, large domain knowledge is not required for obtaining desired results unlike in ML



**Brain tumor:**

In medical science, an anomalous and uncontrollable cell growth inside the brain is

recognised as tumor. Human brain is the most receptive part of the body. It controls muscle movements and interpretation of sensory information like sight, sound, touch, taste, pain, etc.

The human brain consists of Grey Matter (GM), White Matter (WM) and Cerebrospinal Fluid (CSF) and on the basis of factors like quantification of tissues, location of abnormalities, malfunctions & pathologies and diagnostic radiology, a presence of tumor is identified. A tumor in the brain can affect such sensory information and muscle movements or even results in more dangerous situation which includes death. Depending upon the place of commencing, tumor can be categorised into primary tumors and secondary tumors. If the tumor is originated inside the

skull, then the tumor is known as primary brain tumor otherwise if the tumor‘s initiation place is somewhere else in the body and moved towards the brain, then such tumors are called secondary tumors.

**MRI scans:**

Magnetic Resonance Imaging (MRI) has become the standard non-invasive technique for brain tumor diagnosis over the last few decades, due to its improved soft tissue contrast that does not use harmful radiations unlike other methods like CT(Computed Tomography), X-ray, PET (Position Emission Tomography) scans etc. The MRI image is basically a matrix of pixels having characteristic features.

Basic operation of Neural Network

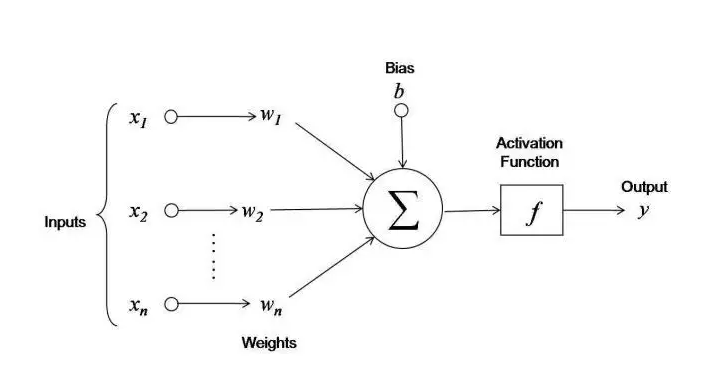
Neural Networks (NN) form the base of deep learning, a subfield of machine learning

where the algorithms are inspired by the structure of the human brain. NN take in data, train themselves to recognize the patterns in this data and then predict the outputs for a new set of similar data. NN are made up of layers of neurons. These neurons are the core processing units of the network. First we have the input layer which receives the input; the output layer predicts our final output. In between, exist the hidden layers which perform most of the computations required by our network.

What does a neuron do?

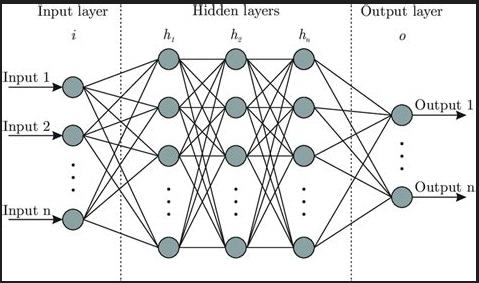
The operations done by each neuron is : First, it adds up the value of every neurons from the previous column it is connected to. This value is multiplied, before being added, by another variable called “weight” (w1, w2, w3) which determines the connection between the two neurons. Each connection of neurons has its own weight, and those are the only values that will be modified during the learning process.

Moreover, a bias value may be added to the total value calculated. It is not a value coming from a specific neuron and is chosen before the learning phase, but can be useful for the network. After all those summations, the neuron finally applies a function called “activation function” to the obtained value.



Our brain tumor images are composed of 512 by 512 pixels which make up for 262,144 pixels. Each pixel is fed as input to each neuron of the first layer. At last value is then passed through a threshold function called the ‗activation function‘. The result of the activation function determines if the particular neuron will get activated or not. An activated neuron transmits data to the neurons of the next layer over the channels. In this manner the data is propagated through the network this is called ‗forward propagation‘. In the output layer the neuron with the highest value fires and determines the output. The values are basically a probable. The predicted output

is compared against the actual output to realize the ‗error‘ in prediction. The magnitude of the error gives an indication of the direction and magnitude of change to reduce the error. This information is then transferred backward through our network. This is known as ‗back propagation‘. Now based on this information the weights are adjusted. This cycle of forward propagation and back propagation is iteratively performed with multiple inputs. This process continues until our weights are assigned such that the network can predict the type of tumor correctly in most of the cases. This brings our training process to an end. NN may take hours or even months to train but time is a reasonable trade-off when compared to its scope.



**3.2 Advantage and disadvantages of CNN**

Convolutional Neural Networks (CNNs) are Artificial Intelligence algorithms based on multi-layer neural networks that learns relevant features from images, being capable of performing several tasks like object classification, detection, and segmentation.  
A CNN is topically composed by four types of layers:  
•Convolutional

•Pooling

•Relu

•Fully Connected

**3.2.1 Advantage**

The number of parameters in a neural network grows rapidly with the increase in the number of layers. This can make training for a model computationally heavy (and sometimes not feasible). Tuning so many of parameters can be a very huge task. The time taken for tuning these parameters is diminished by CNNs.

CNNs are fully connected feed forward neural networks. CNNs are very effective in reducing the number of parameters without losing on the quality of models. Images have high dimensionality (as each pixel is considered as a feature) which suits the above described abilities of CNNs. Also, CNNs were developed keeping images into consideration but have achieved benchmarks in text processing too. CNNs are trained to identify the edges of objects in any image.

•The advantage of CNNs over others classification algorithms (SVM,K-NN, Random-Forest, and others) is that the CNNs learns the best features to represent the objects in the images and has a high generalization capacity, being able to precisely classify new examples with just a few examples in the training set.

•CNNs do not require human supervision for the task of identifying important features. They are very accurate at image recognition and classification. Weight sharing is another major advantage of CNNs. Convolutional neural networks also minimize computation in comparison with a regular neural network.

•Dimensionality reduction is achieved using a sliding window with a size less than that of the input matrix. Intuitively thinking, we consider a small patch of the complete image at once. This square patch is the window which keeps shifting left to right and top to bottom to cover the complete image.CNN's are really effective for image classification as the concept of dimensionality reduction suits the huge number of parameters in an image.

Small regression models are trained to detect specific objects in an image  
•The learning rate is the most important neural network hyperparameter. It can decide many things when training the network. In most optimizers in Keras, the default learning rate value is 0.001. It is the recommended value for getting started with training.The amount that the weights are updated during training is referred to as the step size or the “learning rate.” Specifically, the learning rate is a configurable hyperparameter used in the training of neural networks that has a small positive value, often in the range between 0.0 and 1.0.

•Results are more accurate than typical machine learning techniques Results are more accurate than typical machine learning techniques. For a completely new task / problem CNNs are very good feature extractors. This means that you can extract useful attributes from an already trained CNN with its trained weights by feeding your data on each level and tune the CNN a bit for the specific task.

•Learning of accurate pattern and insights from the provided data.(Depends on how well structured, clean or feature engineered the data is)

**3.2.2 Disadvantage**

Nonetheless, CNN algorithms have their limits and they have fundamental drawbacks and sometimes it’s quite easy to fool a network.

•CNN do not encode the position and orientation of object

The main component of a CNN is a convolutional layer. Its job is to detect important features in the image pixels. Layers that are deeper (closer to the input) will learn to detect simple features such as edges and color gradients, whereas higher layers will combine simple features into more complex features. Finally, dense layers at the top of the network will combine very high level features and produce classification predictions.

In a CNN, all low-level details are sent to all the higher level neurons. These neurons then perform further convolutions to check whether certain features are present. This is done by striding the receptive field and then replicating the knowledge across all the different neurons

CNN do not encode the position and orientation of the object into their predictions. They completely lose all their internal data about the pose and the orientation of the object and they route all the information to the same neurons that may not be able to deal with this kind of information. A CNN makes predictions by looking at an image and then checking to see if certain components are present in that image or not. If they are, then it classifies that image accordingly.

•Lack of ability to be spatially invariant to the input data

Artificial neurons output a single scalar. In addition, CNNs use convolutional layers that, for each kernel, replicate that same kernel’s weights across the entire input volume and then output a 2D matrix, where each number is the output of that kernel’s convolution with a portion of the input volume. So we can look at that 2D matrix as output of replicated feature detector. Then all kernel’s 2D matrices are stacked on top of each other to produce output of a convolutional layer.

Then, we try to achieve viewpoint invariance in the activities of neurons. We do this by the means of max pooling (e.g. 2 × 2 pixels) that consecutively looks at regions in the above described 2D matrix and selects the largest number in each region. As result, we get what we wanted — invariance of activities. Invariance means that by changing the input a little, the output still stays the same. And activity is just the output signal of a neuron. In other words, when in the input image we shift the object that we want to detect by a little bit, networks activities (outputs of neurons) will not change because of max pooling and the network will still detect the object.

•The above described mechanism is not very good, because max pooling loses valuable information and also does not encode relative spatial relationships between features. Because of this, CNN are not actually invariant to large transformations of the input data.

•Data Augmentation: CNNs are not still not quite robust to adversarial attacks, rotations, reflections etc.

•A lot of training data is needed for the CNN to be effective and that they fail to encode the position and orientation of objects. They fail to encode the position and orientation of objects. They have a hard time classifying images with different positions.

•Overfitting, exploding gradient, and class imbalance are the major challenges while training the model using CNN.

Convolutional Neural Networks (CNNs) are a type of deep learning model that are widely used for image processing and computer vision tasks.

**In General**

The advantages of CNNs include:

1. Effective feature extraction: One of the key advantages of CNNs is their ability to automatically extract useful features from raw input data, such as pixels in an image, without the need for manual feature engineering. This can be particularly helpful when working with high-dimensional input data (such as images) where manually identifying and extracting meaningful features can be time-consuming and challenging.

2. Robustness to image transformations: CNNs are designed to be invariant to small changes in the position, scale, and orientation of objects in an image, which is useful when working with image data that may vary in these ways (e.g., different lighting conditions, camera angles, etc.).

3. Efficiency: Due to their use of shared weights and sparse connections, CNNs can be more computationally efficient than fully connected networks with the same number of parameters. This makes it possible to train and deploy very large CNNs on large datasets.

4. Accurate: In many cases, CNNs are able to achieve state-of-the-art accuracy on a wide variety of image-related tasks.

The disadvantages of CNNs include:

1. High computational resource requirements: While CNNs can be more computationally efficient than fully connected networks, they can still require significant computational resources to train and deploy, particularly for large models and datasets.

2. Overfitting: Due to their high complexity and large number of parameters, CNNs can be prone to overfitting, particularly when working with small datasets or when the model is not properly regularized.

3. Black-box nature: The internal workings of a CNN can be difficult to interpret and understand, meaning that it can be challenging to understand why a CNN is making particular predictions or identify potential sources of error.

4. CNNs require a large amount of training data which can be time-consuming and prohibitively expensive to acquire (like annotating images).

5. Limited to the task that is was made for, A CNN that is great at image classification will not be good at detecting object in the video.

**3.3 IMPLEMENTATION METHODOLOGY**

**3.3.1 Software Requirements:**

**Window: Phyton, Numpy, Tensorflow,keras**

**Python**

Python is a high-level, general-purpose programming language. Its design philosophy emphasizes code readability with the use of significant indentation. Python is dynamically-typed and garbage-collected. It supports multiple programming paradigms, including structured, object-oriented and functional programming.

**Numpy**

NumPy offers comprehensive mathematical functions, random number generators, linear algebra routines, Fourier transforms, and more.NumPy is a Python library used for working with arrays.

**Tensorflow**

TensorFlow is a free and open-source software library for machine learning and artificial intelligence. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks.

**Keras**

Keras is a high-level, deep learning API developed by Google for implementing neural networks. It is written in Python and is used to make the implementation of neural networks easy. It also supports multiple backend neural network computation.

,And other python **libraires** like openCV and matplotlib

**openCV**

OpenCV-Python is a library of Python bindings designed to solve computer vision problems. cv2. imread() method loads an image from the specified file. If the image cannot be read (because of missing file, improper permissions, unsupported or invalid format) then this method returns an empty matrix.

**matplotlib**

Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. Matplotlib makes easy things easy and hard things possible. Create publication quality plots.

**3.3.2 Hardware Requirements:** Hardware Requirements: Processor: Intel® Core™ i3-2350M CPU @ 2.30GHz Installed memory (RAM):4.00GB System Type: 64-bit Operating System Image Acquisition: Kaggle dataset: Images can be in the form of .csv (comma separated values), .dat (data) files in grayscale, RGB, or HSV or simply in .zip file as was in the case of our online Kaggle dataset. It contained 98 healthy MRI images and 155 tumor-infected MRI images.

**3.4 Image Processing Steps**

Here is an outline of the image processing steps

1. Data Collection: Collect a dataset of brain MRI scans (or use an existing dataset such as LGG and HGG dataset)

2. Preprocessing: The raw MRI scans will likely need to be preprocessed before they can be used as input to the CNN. Common preprocessing steps include:

- Resizing or cropping the images to a uniform size

- Normalization

- Noise reduction

- Converting the images to grayscale

This may also include formatting the data into a form that can be ingested by your deep learning framework of choice(Pytorch, TensorFlow, Keras)

3. Data Split: Divide the data into a training set, validation set, and test set.

4. Data augmentation: You could apply data augmentation techniques that can be helpful in Increasing the dataset of images which would result in better training of the model. Data augmentation can include Image Rotation, Scaling, and others.

5. Convolutional Layers: Pass the input images through one or more convolutional layers, which will extract features from the images. These layers will include trainable filter that will extract features from the input image.

6. Activation Function: within the convolutional layers apply a non-linear function to the output, most commonly used function is ReLU.

7. Pooling layers: In between convolutional layers, place a pooling algorithm such as MaxPooling2D to reduce the complexity of the model, number of parameters, and reduce the overfitting.

8. Flatten: After the final convolutional layer, the output layer must be flattened to a 1D array to be forwarded to a fully connected layer.

9. Fully connected Layer: After the last convolutional layer, you would need to create a fully connected layer where the outputs from the previous layer are connected to each of the neurons of the usually single connected layer, where the output is decided.

10. Output Layer: on this layer you would have one neuron for each class to predict, in this case just one, since it is a binary classification problem, sigmoid activation function would be a good choice here.

11. Loss Function: Use a loss function like binary cross-entropy (also called log loss) that is well suited to binary classification problems.

12.Once the model is trained, you can input new images into the model to obtain predictions.

It is important to point out that in real-world applications, it may be necessary to perform preprocessing steps specific to the data being used. For instance, MRI data often contains artefacts from the scanning process that may need to be removed or non-uniformities in the images that need to be corrected. It is important to consult with experts in the domain to understand if the specific dataset will require additional pre-processing.

In addition, we would need to mention like every other deep learning model, it is also important to tune the hyperparameters of the model, including the number and size of the convolutional filters, the number of convolutional and fully connected layers, and the learning rate and batch size during training, which can all impact the performance of the model.

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