CLASSIFICATION OF BRAIN TUMORS USING DEEP LEARNING

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Abstract— Brain tumors affect around 11,700 people every year, with a 5-year survival rate of approximately 34% for men and 36% for women. These tumors can be classified as benign, malignant, or pituitary, and proper treatment and diagnostics are crucial to improve patients' life expectancy. Magnetic Resonance Imaging (MRI) is the best technique for detecting brain tumors, but manual examination of the images can be error-prone due to the complexity of brain tumors. Therefore, the use of automated classification techniques, such as Machine Learning (ML) and Artificial Intelligence (AI), using Deep Learning Algorithms like Convolution Neural Network (CNN) and Transfer Learning (TL) has shown higher accuracy than manual classification. The MRI images can be classified using different CNN, TL models with various Network Parameters, and the models with high accuracy are selected and deployed. The project's goal is to achieve higher accuracy and reliability for real-world MRI data using AI and ML knowledge and to provide ease of access to the software through cloud and mobile applications, web platforms, and accurately locate the tumors position and provide treatment suggestions.

Keywords—Transfer Learning, CNN, MRI, Machine Learning, Artificial Intelligence.

I. INTRODUCTION

The brain is one of the most important organ in the human body that consists of billions of cells. A group of abnormal cells formed from uncontrolled cell division is called a tumor. Brain tumors are the primary malignancies in 80-85% of CNS tumors, and their symptoms can differ depending on which part of the brain is affected, including migraines, seizures, vision problems, vomiting, and cognitive abnormalities. Headaches are often more severe in the morning and may improve with vomiting.

Other symptoms may include difficulties with walking, talking, or feeling, and unconsciousness may develop as the condition progresses. The five-year survival rate refers to the percentage of people who survive for at least five years after they have been diagnosed with cancer. The 5-year survival rate for individuals with malignant brain or CNS tumors is approximately 35%, with a 12-year survival rate of about 30%. As age increases, survival rates decrease, with a 5-year survival rate of over 75% for those under 15 years old, about 70% for those between 15-39 years old, and about 20% for those over 40.

A low-grade brain tumor is benign and does not spread to other parts of the brain. On the other hand, a high-grade tumor is malignant and can spread rapidly to other parts of the body, leading to death. To detect and model the progression of brain tumors, brain MRI images are used, which provide more detailed information about the brain structure and any anomalies in brain tissue compared to CT or ultrasound images. Over time, scholars have developed different automated methods for detecting and categorizing brain tumors using MRI images, including Neural Networks and Support Vector Machine methods. However, recently, Deep Learning models have become popular in machine learning due to their ability to represent complex relationships efficiently without requiring many nodes. As a result, Deep Learning models have become state-of-the-art in various health informatics areas such as bioinformatics, medical image analysis and medical informatics.

Brain tumors can be categorized into three main types: glioma, pituitary, and meningioma. Meningiomas, which are usually low-grade malignancies, are more common in older people and women.

Detecting brain tumors early is crucial for successful treatment, and MRI is an important diagnostic tool for this purpose. MRI is an essential diagnostic tool for detecting, treating, and monitoring brain tumors. However, interpreting MRI images can be a complex and time-consuming task that requires specialized expertise. Moreover, manually detecting malignancies can be challenging and may vary among clinicians due to their experience.

Effective segmentation and classification of MRI images can also be difficult. Therefore, the objective is to develop an intelligent network that can accurately detect malignant cells in brain MRI images. Over time, various researchers from different fields have utilized image recognition systems to detect brain tumor cells, and different machine algorithms have been tested to verify malignant cells' efficiency. Presently, deep and machine learning algorithms are widely used to predict brain tumors.

Leveraging these technologies, the proposed intelligent system aims to provide accurate and efficient detection of malignant cells in brain MRI images. The system utilizes a range of algorithms to effectively segment and classify the images, enabling more precise diagnosis and treatment of

brain tumors. Ultimately, the goal is to improve patient outcomes and reduce the need for invasive procedures Therefore, an intelligent system that can accurately detect malignant cells in brain MRI images is proposed.
This system uses a range of algorithms, including machine learning and deep learning, to segment and classify the images, allowing for more precise diagnosis and treatment of brain tumors.
The aim is to improve patient outcomes and reduce the need for invasive procedures. The proposed method involves using Transfer Learning model for classifying brain tumors from MRI images, into four categories i.e., glioma, meningioma, and pituitary tumor categories.

II. LITERATURE SURVEY

[1]. In [20], the authors suggest a CNN model that performs a crucial comparison both before and after data augmentation. They demonstrate that their model's accuracy improves significantly after data augmentation, as evidenced by their testing on three datasets, with the highest accuracy of 98.43% achieved for identifying pituitary tumors.

[2]. Jude Hemanth et al. [21] present a model for identifying brain abnormalities using MRI scans, addressing the convergence time period issues of traditional artificial neural networks (ANNs). They modify two existing models, CPN and KNN, to create MCPN and MKNN, respectively. Their main objective is to reduce the number of iterations required for ANN models to achieve convergence, which they successfully accomplish. As a result of these modifications, the accuracy rates for MKNN and MCPN are 95% and 98%, respectively.

[3]. In the approach suggested by the authors [22], there is no segmentation or pre-processing. Multiple logistic regression is used to classify the data. A pretrained CNN model and segmented pictures are used in the suggested technique. Three data sets are used to test the model. To increase accuracy, several data augmentation approaches are applied. On both the original and expanded data sets, this method was tested experimentally. In comparison to past studies, the results offered are quite persuasive.

[4]. Sachdeva et al. [23] proposed a technique for classifying tumor focusing to make the CAD system more interactive. They used different datasets to check the accuracy of their proposed model. The first dataset contains five classes and the second dataset contains three classes of tumors. The technology used is modifying the SVM and ANN model by using them with a Genetic algorithm (GA) leading to proposing two models, namely, GA-SVM and GA-ANN. The suggested model was able to effectively increase the accuracy of the model from 79.3% to 91% for SVM and from 75.6% to 94.9% for ANN.

[5]. Tahir et al. [24] looked at a variety of preparation approaches in order to improve classification results. There were three types of approaches: noise reduction, edge detection, and contrast enhancement. To test the various combinations, image sets are utilized. According to the authors, combining different forms of data might lead to better outcomes. It is more beneficial to use many pre-processing techniques than just one. The suggested model of the authors achieves an accuracy of 86 percent.

[6] Researchers S. Ahmad and P.K Choudhury utilized transfer learning techniques on deep learning models in 2022, and then employed comparative analysis of different machine learning models to achieve successful classification. Their findings showed that the top-performing model was an SVM-based one.

III. DATASET

Data collection is a systematic process of gathering and analyzing data from diverse sources to address research problems, test hypotheses, and evaluate outcomes.
The Brain Tumor Classification dataset used in this study was sourced from Kaggle and consists of MRI images of four types of tumors: glioma, meningioma, pituitary, and no tumor.
The images have been acquired from Kaggle and they are collected from MRI data. The images are split into Training and Testing datasets. The dataset has a total of 3264 images in each of the four classes. Each folder in the dataset has four subfolders. These folders have MRIs of the four different tumor classes that have been chosen suitable for the model. This dataset was selected because it shares similarities with features used in previous studies, and all features are numerical, making it suitable for the project requirements.

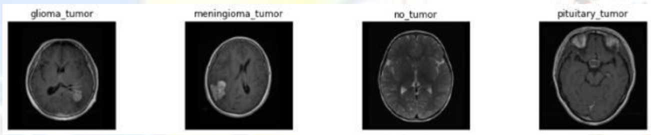

Fig 1: Four types of files in the dataset.

IV. METHEDOLOGY

A. DATA COLLECTION:

Gather a collection of images of brain tumors to create a dataset. You may obtain these images from different sources or by utilizing publicly available datasets like the Brain Tumor Segmentation (BraTS) dataset.

B. DATA PREPROCESSING:

To prepare the data for training a deep learning model, it is necessary to clean and preprocess the dataset. This may involve performing tasks such as data augmentation, normalization, and resizing.
Data augmentation is a technique that involves modifying the training dataset by performing various image transformations, such as flipping, rotating, zooming, or adjusting brightness and contrast. This can help increase the range of the dataset and enhance the model's ability to generalize to new images.

Normalization involves scaling the pixel values of the images to a range between 0 and 1. T
his can help the model converge faster during training and improve its accuracy.
Resizing is another important step in pre-processing the data.
This involves adjusting the size of the images to a fixed size that can be used as input to the deep learning model. It is important to ensure that all images have the same dimensions to prevent any issues during the process of training and testing.

C. MODEL SELECTION:

To perform image classification, it is recommended to select a deep learning model that is specifically designed for this task. The most used models for image classification are Convolutional Neural Networks (CNNs).
You can choose from a variety of pre-trained models such as ResNet, VGG, or Inception models, which have been trained on large datasets and achieved high accuracy in image classification. Alternatively, you can build your model from scratch, depending on your requirements and available resources.

D. MODEL TRAINING:

To train the deep learning model, the preprocessed data is used as input, and the model's weights are adjusted to minimize the loss function, which measures the discrepancy between the predicted output and the actual output. The optimization algorithm that is typically used to train deep learning models is Stochastic Gradient Descent (SGD) with backpropagation.
After training the deep learning model, it is important to evaluate its performance using a separate test dataset. This will give an estimate of how well the model can generalize to unseen data.
The evaluation can be done by calculating various performance metrics such as accuracy, precision, recall, and F1-score. These metrics give insight into how well the model is performing in terms of correctly classifying the images. In addition to numerical metrics, visualization techniques such as confusion matrices or ROC curves can be used to gain a better understanding of the model's performance. Confusion matrices show the number of true positives, true negatives, false positives, and false negatives, while ROC curves show the trade-off between true positive rate and false positive rate at different classification thresholds.

E. MODEL DEPLOYMENT:

Once the deep learning model is trained and evaluated, it can be deployed to classify new, previously unseen brain tumor images. The model can be used to classify images in real-time or in batches, depending on the needs of the application.

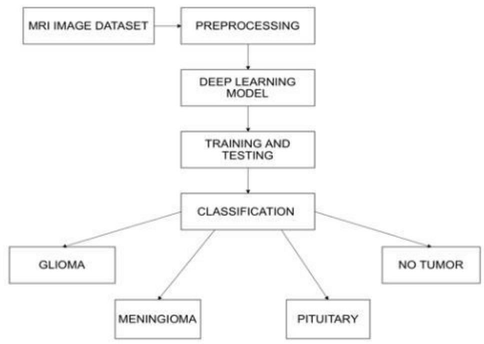

Fig 2: Architecture Diagram of classification of Brain Tumors

V. IMPLEMENTATION

The dataset that is chosen for the classification of Brain Tumors contains images of four types, namely glioma tumor, meningioma tumor, pituitary tumor and no tumor. The images have been acquired from Kaggle and they are collected from MRI data. The images are split into Training and Testing datasets. Each folder in the dataset has four subfolders.
These folders have MRIs of the four different tumor classes that have been chosen suitable for the model. This dataset was selected because it shares similarities with features used in previous studies, and all features are numerical, making it suitable for the project requirements.
Firstly, all the necessary libraries in Python are imported such as TensorFlow, NumPy, Pandas, Seaborn to name a few. Then the dataset containing all the images is imported.
Then the data is prepared by appending all the images from the directories into a Python list and then converting them into NumPy arrays after resizing it.
The dataset is then divided into Training and Testing sets and one Hot Encoding is performed on the labels after converting it into numerical values.

Transfer learning is a machine learning method that enables a model trained on a particular task to be utilized or adjusted for a related but different task. Instead of starting from scratch to develop a new model for a new task, transfer learning employs the knowledge and skills learned from a prior task to improve performance on the new task. This approach is particularly valuable when the new task's dataset is small or when training a model from scratch requires excessive computational resources. Transfer learning can result in better performance on the new task and faster training convergence by reusing the pre-trained model's knowledge. Fine-tuning and feature extraction are two transfer learning methods: in fine-tuning, the pre-trained model's parameters are adjusted using the new dataset, while in feature extraction, a new classifier is trained based on the extracted features.
Transfer learning has been utilized effectively in various fields such as computer vision, natural language processing, and speech recognition and has significantly advanced the state-of-the-art in these domains.

Transfer learning allows the use of a pre-trained CNN model, which was developed for another related application. Deep convolutional neural network models may take days or even weeks to train on very large datasets.
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.
Top performing models can be downloaded and used directly or integrated into a new model for your own computer vision problems.
The EfficientNetB0 model is used in this project which is an application from Keras present in TensorFlow which returns a Keras image classification model, optionally loaded with weights pre-trained on Image Net.

We may omit the top layer/output layer of the pre-built model from the network by setting the include top option to False. This allows us to tailor the output layer to our individual requirements.

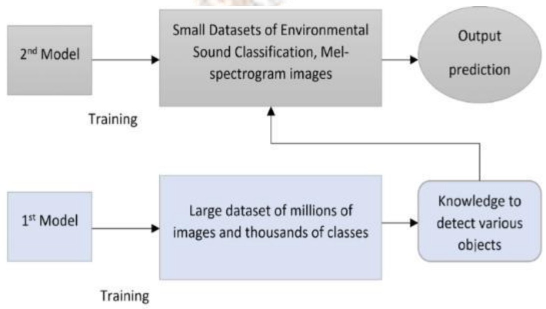

Fig 3: General Block diagram for Transfer Learning

The CNN has layers which helps in making it more efficient by decreasing the load on the machine and avoiding overfitting.
GlobalAveragePooling2D is a layer that performs similarly to Max Pooling layer in Convolutional Neural Networks (CNNs). However, instead of taking the maximum value while pooling, it uses the average value. This significantly reduces the computational burden on the system. The Dropout layer eliminates some of the neurons at each step from the layer, which makes them more independent of neighboring neurons. This helps prevent overfitting. The selection of neurons to be excluded is random and determined by the rate parameter, which indicates the likelihood of a neuron activation being set to 0 and thereby dropped out.
Dense is the output layer that assigns the input image to one of the four possible classes. It uses the SoftMax function, which is a generalized version of the sigmoid function.
The model is compiled after implementing all the layers from TensorFlow using Keras library.
Callback functions are implemented after the model has been compiled since they can help you address errors faster and develop better models.
They can assist you in visualizing the progress of your model's training and can even help prevent overfitting by implementing early stopping or customizing the learning rate on each iteration.
The callback functions that have been implemented in the Transfer Learning model are Tensor Board, Model Checkpoint and ReduceLROnPlateau callback functions.
The next step in the implementation is to train the model. This project requires a lot of computational power, so a good Graphics Performance Unit (GPU) is advised to be used.

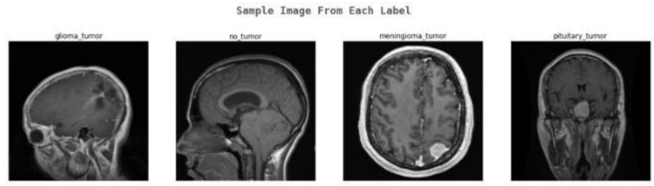

Fig 4: Sample Image from each of the four labels.

In deep learning, the process of training a neural network involves the model reading the input dataset and performing various calculations to learn the patterns within the data. However, the model doesn't do this just once - it continues to learn from the input data and previous trial results in multiple iterations. Each of these iterations is called an epoch, and it involves the model processing the entire training dataset once.
On training the model, it is required that the validation accuracy improves to get the best possible value. In the model there are 12 iterations/epochs after which the validation accuracy reaches a saturation level.
The argmax function is then used to do the prediction, as each row of the prediction array has four values for the appropriate labels.
The largest value in each row is the projected output of the four probable possibilities. The index associated with the projected outcome may be determined using argmax.
Widgets have also been implemented in which images can be uploaded by the user and predict whether the MRI scan has a Brain Tumor or not and to classify which Tumor it is.

VI. RESULT

The aim of the study was to create a system that could accurately and efficiently identify and classify brain tumors. To do this, a dataset of brain tumor images and masks for segmentation was used. The model is a Transfer Learning model based upon a convolutional neural network (CNN) architecture that has been successful in medical image segmentation tasks.
The dataset used for the classification task contained four types of brain tumors. The Transfer Learning model was trained on the dataset to classify brain tumors into these four categories.

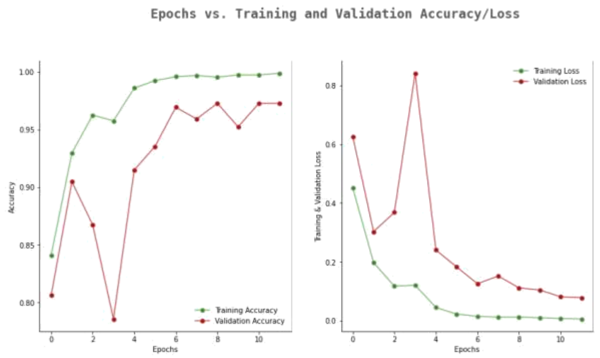

Fig 5: Graph showing the increasing validation accuracy with every iteration.

CNN is a neural network that is particularly well-suited for image classification tasks.

It consists of many CNN layers like GlobalAveragePooling2D, Dropout, Dense layer that can extract features from input images, followed by fully connected layers that perform the classification.

The use of CT scan images as input to the Transfer Learning model allowed for efficient and accurate classification of brain tumors, with the added benefit of being non-invasive. The proposed system was able to classify brain tumors into different areas based on the type of tumor, providing more detailed information to medical professionals.

This would enable them to make more informed decisions about the treatment and management of brain tumors.

In conclusion, the study shows that a multi-layer CNN model can be effective in both brain tumor segmentation and classification tasks. The system achieved high accuracy, potentially aiding medical professionals in the accurate diagnosis and treatment of brain tumors, which could ultimately lead to better patient outcomes.

A widget having and “Upload” and “Predict” button was also implemented using which the user could upload Brain Tumor MRI images and get predictions whether the image was a no tumor, meningioma tumor, glioma tumor or pituitary tumor.

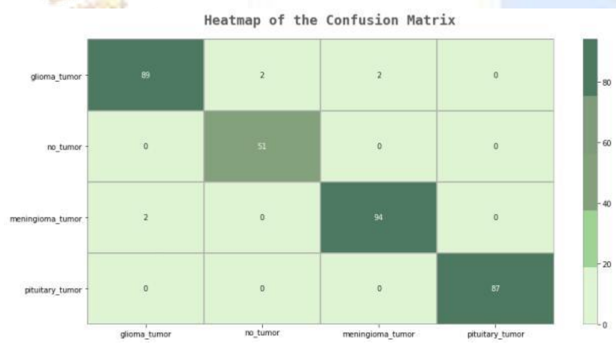

Fig 6: General Block diagram for Transfer Learning

While training the model, the validation accuracy increased from about 80% in the first iteration to almost 98% in the 10th iteration after which it seemed to reach a saturation level and remained the same in the subsequent iterations.

The accuracy of the classification model was finally reported to be around 98%, which means that the model performed very well in distinguishing between the different types of brain tumors.

VII. CONCLUSION

Our study aimed to explore the feasibility of using a Transfer Learning model, that allows us to use pretrained Convolutional Neural Network model which was developed for related applications. A wide range of machine learning technologies like TensorFlow, Keras, SKLearn, MatPlotLib and Seaborn are used in the making of the model.

The model that we have built shows a high accuracy of 98% which means that it is able to classify Brain Tumor MRI Images correctly into 4 classes : No Tumor, Benign Tumor, Malignant Tumor and Pituitary Tumor. Widgets are also implemented which allows users to upload images from their local machines to classify their images through our model.

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