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Brain Tumor Detection using Image Processing

Mr. Adarsh Salukhe[1], Mr. Varun Shitole[2], Ms. Nikita Salunkhe[3], Mr. Abhishek Tondare[4], Prof. Ajay T. Sonawane[5]

[1, 2, 3, 4]UG Student, [5]Asst. Professor, dept. of Information Tech, SKN Sinhgad Institute of Technology & Science, Lonavala, Maharashtra

Abstract: Classification method is very crucial to identifying the brain diseases. It has deep observed that brain tumor is majorly treatable tumor. As we know that recognizing the brain tumor is hard and tedious work and if the tumor is not identified in its early stage, it may convert into the precarious situations. For the classification of the brain tumor. The high-end Machinery is use to scan the brain for the detection of tumor. MRI (magnetic resonance images) are use to tackled the diseases and detection of the tumor and to identify the tumor stage as this Machine provides high resolution images of brain and it is cost effective. In this paper we will classify the brain tumor types using Machine Learning. There are mainly 4 types of tumors namely pituitary, meningioma and glioma. Identifying the tumor manually is hard so the algorithms are deep developed.

Keywords: Image Processing, MRI Images, Tumor Detection

I. INTRODUCTION

A Brain tumor occurs when abnormal cells formed in the tissues of the brain. The tumor is mainly divided into 2 groups primary and Secondary tumor. The primary tumor is formed inside the brain and the secondary tumor is formed in other parts of the body except brain. The tumor can be cancerous normally referred as (malignant), and non-cancerous tumor referred as (benign)the tumor which located outside the brain is known as brain metastasis tumor. The common symptoms of the tumor are headache, vomiting, seizures and vision problem, other problems may be walking difficulty, sensation problem, speaking or even unconsciousness. The brain tumor is further classified into 3 types meningioma, glioma, and pituitary adenoma this are tumors caused inside brain. Glioma is most threating tumor and normally affects adults primarily. Gliomas is mostly affected in glial cells. Glioma cancer is of 3 types astrocytoma, oligodendroglioma. Som of the gliomas is very dangerous as they are fast growing tumor but they can be curd if they are detected in its early stage. Glioma can be graded as high grad and low grad. However, the most suitable treatment should be given to the patient to save the life. To give the treatment the first is to understand the position of the tumor, and further is to compare the tissues of the tumor with the normal tissues in brain which are not being affected by tumor. Sometimes this task may be very difficult it is totally based on the size and stage of the cancer tumor. The cause of the brain cancer is unknown. But most of the brain cancer can be caused due to CT scan radiations. The primary tumor in adults is meningiomas and in children the most common is malignant. The tumors are further divided into grads and severity. Secondary, brain tumor is about four times as common as primary brain tumor. brain tumor is about four times as common as primary brain tumor.

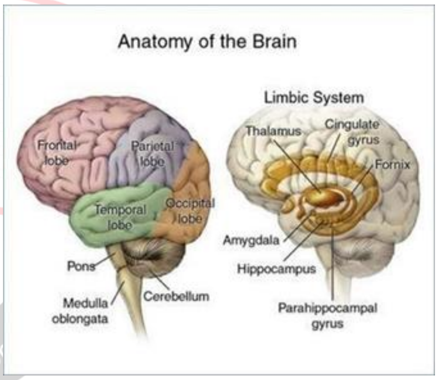
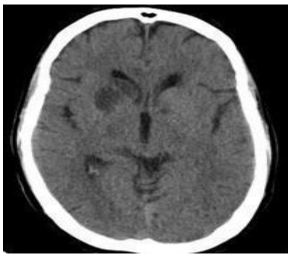


fig1. Anatomy of the Brain



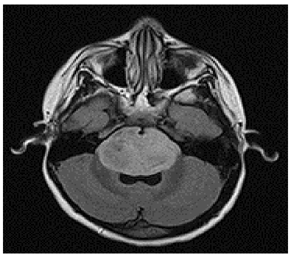


Fig2. Brain with Tumor Fig3. Brain with No Tumor

II. BACKGROUND STUDY

Brain Tumor discovery using image processing is a critical area of medical exploration and healthcare that leverages advanced digital imaging ways to identify and classify brain tumor. This approach plays a vital part in early opinion, treatment planning, and patient car. In this section, we will explore the crucial generalities and

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methodologies associated with brain tumor discovery using image processing. Several imaging modalities are generally use in brain tumor discovery, including glamorous Resonance Imaging (MRI). Each modality provides distinct perceptivity into the tumor position, size, and characteristics, allowing for a comprehensive assessment. Prior to analysis, medical images must suffer preprocessing to enhance their quality and reduce noise. ways like noise reduction, discrepancy adaptation, and image enrolment are applied to prepare the data for farther processing. Once the tumor regions are segment, image processing ways employ bracket algorithms to identify the type of tumor. Machine literacy, particularly deep literacy model like Convolutional Neural Networks (CNNs), has shown remarkable success in classifying brain tumor into orders similar as glioma, meningioma, pituitary tumor, and nontumor case.

III. LITERATURE SURVEY

1 Brain Tumor Detection and Classification by Medical Image Processing:

In their pursuit of accurately brain tumor detection, Gobhinath, Anandkumar, Dhayalan, Ezhilbharathi, and Haridharan collected and curated a diver's datasets of MRI images containing two distinct types of brain tumors. They employed state-of-the-art techniques, including Convolutional Neural Networks (CNN) and Kernel Support Vector Machine (KSVM), to perform the classification task. The CNN was utilized for its ability to learn complex features from the images, while the KSVM offered robust classification capabilities.

Their efforts yielded a promising framework with distinct advantages. It proved to be highly user-friendly, enabling easier implementation and faster computation. This framework demonstrated robustness in handling a variety of image inputs. However, it's worth noting that the model they generated exhibited sensitivity to noise, an area they acknowledged as a potential avenue for further improvement.

2 A Review on Brain Tumor Segmentation and Classification for MRI Images:

Preeti Sharma and Anand Shukla undertook a comprehensive review of existing methods for brain tumor segmentation and classification, ultimately proposing an efficient procedure for the tasks. Their data collection involved a meticulously curated datasets designed to enhance the robustness of their model. The model was trained using a sophisticated approach that combined segmentation and classification techniques, leveraging their expertise in both domains.

Their method boasts several advantages. The carefully selected training data proved to be easily traceable for report generation and calibration, making it valuable for future research. Additionally, their approach simplified the process of data retrieval and analysis. However, the model's sensitivity to noise, while noted as a limitation, provides an avenue for potential enhancements in the future.

3 Brain Tumor Detection using Deep Learning:

Avigyan Sinha, Aneesh R P, Malavika Suresh, Nitha Mohan R, Abinaya D, and Ashwin G Singerji tackled the challenge of brain tumor detection through deep learning techniques. Their research was centered on the analysis of MRI images to identify abnormal conditions and accurately segment tumor regions. The use of Convolutional Neural Networks was a natural choice, given their ability to extract intricate features from medical images.

Their model exhibited commendable strengths. The efficient image processing capability, coupled with a high accuracy rate, marks a significant achievement. However, they encountered the computational challenge of high resource requirements, which points to the need for optimizing the model for more accessible implementation.

IV. METHODOLOGY

Supervised Learning:

The code follows a supervised learning approach, where the model is trained on a labeled dataset. This means that each image in the training sets is associated with a specific tumor type label (e.g., glioma, meningioma, no tumor, or pituitary). During training, the model learns to map input images to their corresponding class labels.

Data Splitting:

The code effectively splits the available data into separate sets for training, validation, and testing. This data splitting methodology is crucial for assessing the model's performance accurately. The 'Training' directory is partitioned into training and validation sets, allowing the model to learn from a subset of the data and evaluate its performance during training. Additionally, there's a separate 'Testing' directory use for final model valuation.

Data Augmentation:

To enhance model robustness and reduce overfitting, the code incorporates data augmentation techniques. Data augmentation is a methodology that introduces variations into the training data by applying transformations such as rotation, shifting, zooming, and flipping to the images. This approach helps the model generalize better to use data and improves its performance.

Convolutional Neural Networks (CNNs):

CNNs are a fundamental methodology in image classification tasks. The code implements a custom CNN model, which consists of convolutional layers followed by

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fully connected layers. CNNs are specifically designed for features extraction from images and are widely use in computer vision tasks.

Model Evaluation:

Model valuation is a crucial methodology for assessing the model's performance. The code utilizes the categorical cross-entropy loss function and accuracy as valuation metrics. This metrics are commonly use in classification tasks to measure the model's ability to correctly classify images.

Bias-Variance Analysis:

The code conducts a bias-variance analysis, which is a methodology to analyze the trade-off between model complexity and performance. It employs different model with varying levels of bias and variance to understand how model complexity impacts classification accuracy. This analysis helps in making informed decisions about model selection.

User Interaction and Input:

The code introduces use interaction as a methodology, allowing users to provide input in the form of a class name. Users can specify a tumor class, and the code retrieves and displays images from that particular class.

V. CLASSIFICATION

Brain tumor can be classified into 2 types benign and malignant. To classify the brain tumor, we need to train the Machine learning model using large number of MRI scan images and a raw data of the brain tumors need to be served to the model to achieve an exact outcome from the model. Machine learning model is use in this classification. Usually, semi-supervised learning method is use to train model but we have use supervised learning method and it has deep presented in this paper.

Classification is a process of finding or discovering the function which helps to separate the data in several classes. In supervised learning there is a supervisor as a teacher and the data is already deep labelled. In our Machine learning model, we have used most important libraries which are essential to train the model and classifying the model using the data. TensorFlow allows to rate dataflow graphs that describes how data moves through a graph. Matplotlib and Seaborn is use to visualize the data in graphs and plot a statistical graph. Keras is a Neural network and high-even API use to train the model and it runs on top of TensorFlow. Splitting data into phases is crucial as we divide the training part with 70-30 ratio of the data, 70% of data is processed while training the model and 30% data is utilized to test the model on bass of trained model.

Data Validation means checking the accuracy and quality of source data before training the model, it ensures that any of the infrequent data is not silently ignored by the model. Data Augmentation is use to improve the accuracy of the algorithm by 50% in Machine learning and enhance the efficiency and flexibility of the model to boost the variety and volatility of training datasets. Preprocessing is use to improve the performance of deep learning model also known as data normalization and data augmentation. Data Augmentation is specially use when the training datasets is small to train the model and we need large number and variety of data to train. Data augmentation can be use in types of data such as time series, photos, text, audio. In advanced techniques we had an approach of already defined functions of deep learning using Keras library. Sequential function is use to add Conv2D, Maxpooling2D, Flatten, Dens. 2 activation functions are utilized in this model 'relu', 'softmax'. Visualizing the accuracy and loss of the model while the model is in training phases to check whether the model is trained in a perfect manner or easier it is false trained.

A. TRAINING PHASE:

The training phase is an important stag in the process of developing a brain tumor detection model using image processing techniques. It involves training a Machine learning model, often based on convolutional Neural Networks (CNNs), to learn and recognize patterns and features in medical images that distinguish between different types of brain tumors and healthy brain tissue.

Import the Library Files and Modules:

The initial step in our research involves importing essential Python libraries and modules. We use libraries such as NumPy, TensorFlow, Keras to facilitate image processing.

Split the Data into Train, Test and Validation:

To easier the effectiveness of our model, we resolve our datasets into training, testing, and validation sets. This division allows us to train the model, finetune its parameters, and test its performance using use data.

Data Preprocessing:

Data addition ways are applied to increase the datasets size and diversity, perfecting the model's capability to generalize. Preprocessing way involve image normalization, resizing, and other necessary metamorphosis.

Model generation using Advanced Techniques:

The core of our exploration is the application of advanced ways for model generation. We employ convolutional Neural Networks (CNNs) with multiple layers, icing the model's capacity to prize features from brain images effectively.

Training the Model:

Training the model involves optimizing the network's weights and impulses using ways like stochastic grad descent and backpropagation. This phase is essential for

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tutoring the model to distinguish between different brain tumor classes and healthy brain reviews.

Visualization report of Accuracy and Loss:

After training, we fantasize the model's performance using graphs that depict delicacy and loss. This visualization aids in understanding the model's literacy process and relating implicit overfitting or underfitting issues. The trained model achieved an accuracy of 99.19% and loss of 0.03%.

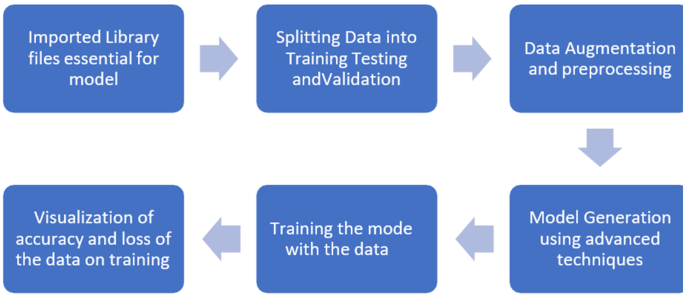

Fig4. Overview of Training Phase

fig5. Accuracy and Loss Report of the Trained Model

B. TESTING PHASE:

The testing phase in brain tumor discovery using image processing is a critical step that follows the training phase, and it plays a vital part in assessing the performance and trust ability of the developed model. This phase involves assessing the model's capability to directly classify brain tumor images and make prognostications grounded on use data. In testing phase, the crucial part is to calculate the confusion matrix and calculate the bias and variance of the model which is based on the trained model. A confusion matrix is a matrix that summarizes the performance of a Machine learning model and sets of test data. In our model we have to classify 4 classes so we will use 4X4 matrix table to demonstrate the value of data. The matrix illustrates the true positive (TP), true negative (TN), false positive (FP), false negative (FN). Understanding the confusion matrix is itself easy but some of the terminologies are pretty confusing. Confusion matrix is use to demonstrate the performance of the model when we are testing the model using the hidden data. Sometime there might be the error in model the confusion matrix is known as error matrix. Using this model we can calculate the Accuracy, Recall, F1-score, Precision, measure, Error rate and ROC curve.

Calculate Confusion Matrix (TP, FP, TN, FN):

In the testing phase, we calculate a confusion matrix to assess the model's bracket performance. The matrix provides perceptivity into true cons, false cons, true negatives, and false negatives, which are essential for understanding the model's delicacy.

Calculate Bias and Variance (Low and High):

We dissect the bias and friction of the model's prognostications. Low bias and friction indicate that the model generalizes well, whereas high bias and friction suggest underfitting or overfitting issues.

Bias: Bias is simply defined as the inability of the model because of that there is some difference or error occurring between the model's predicted value and actual values.

High bias and Low bias

Variance: Variance is the measure of spread in data from its man position. The model changes the performance of the predictive model when the subset of data is being changed.

High variance and Low variance

Image generation for the Trained Model:

We induce images to fantasize the model's response to input data. This helps in relating areas where the model might struggle or exceed in classifying brain tumor images.

Image Classification of 4 classes

(no tumor, glioma, meningioma, pituitary):

The model classifies images into four distinct classes' No Tumor, '' Glioma, '' Meningioma, 'and' Pituitary. ' Each class corresponds to a specific type of brain tumor or the absence of a tumor. We bandy both the training and testing phases, pressing the significance of accurately bracket for different brain tumor types and the absence of tumor.

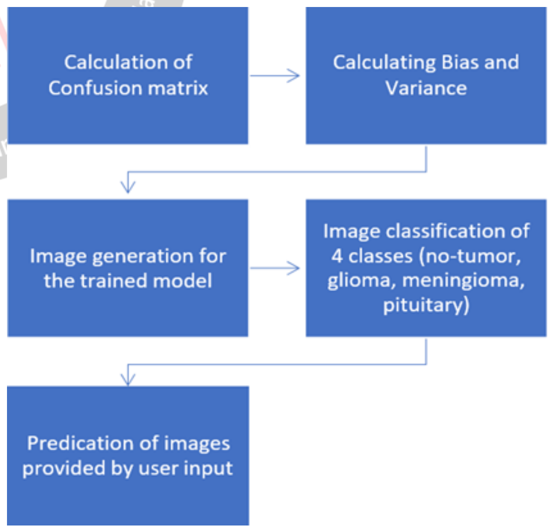

Fig6. Overview of Testing Phase

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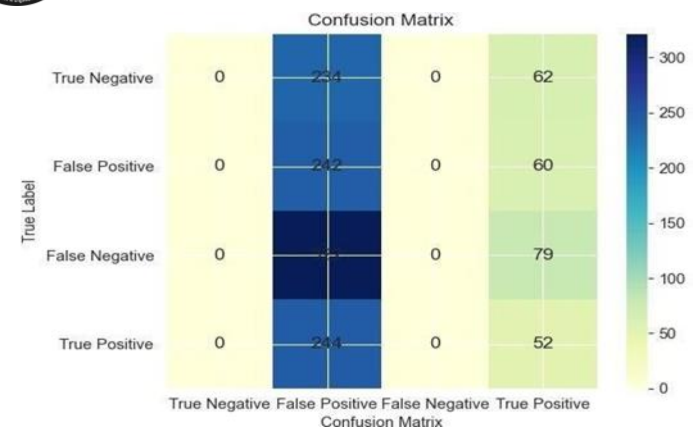

Fig7. Confusion Matrix

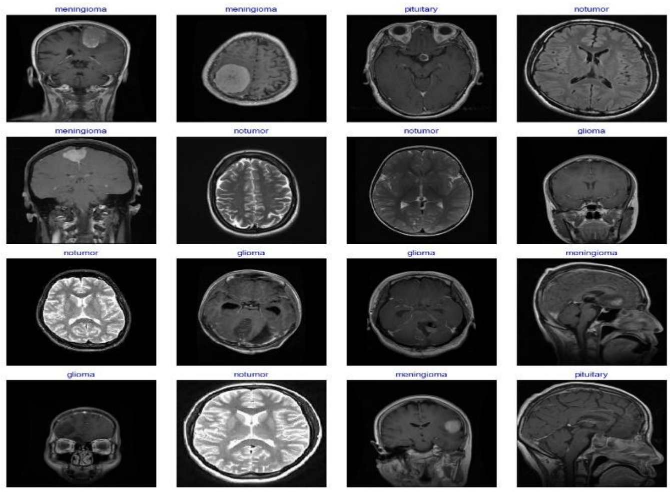

Fig8. Image classification by model

As per the Training and Testing phase, it was crucial to implement all the image generation and classification techniques, it gave accurate results by predicting several images that belongs to the same class.

Nonetheless the model is perfectly trained and the output is well executed as per the needs.

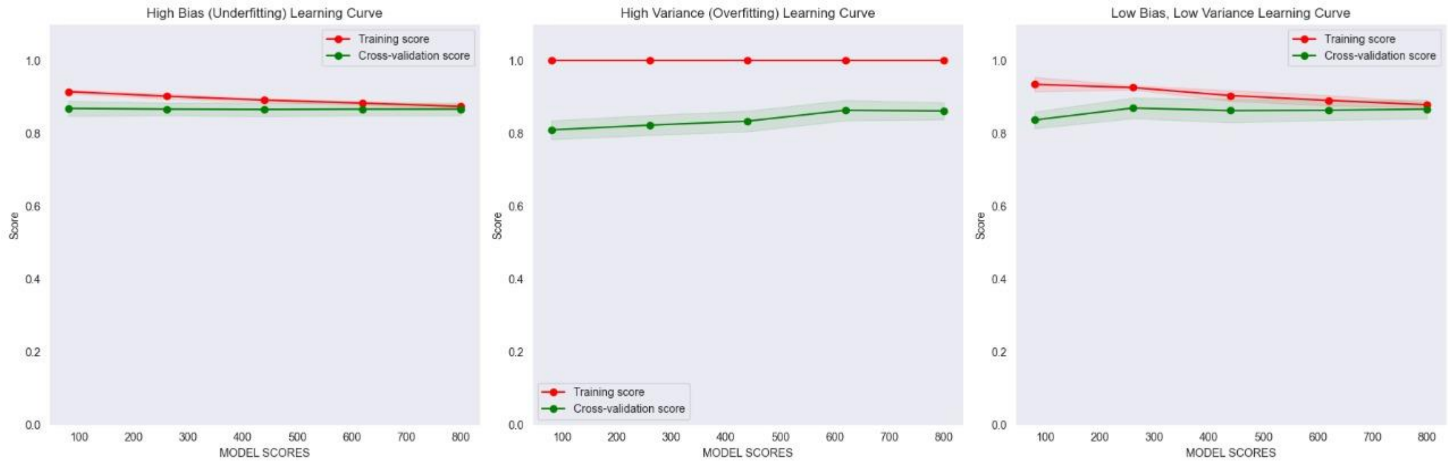

Fig9. Bias and Variance Analysis

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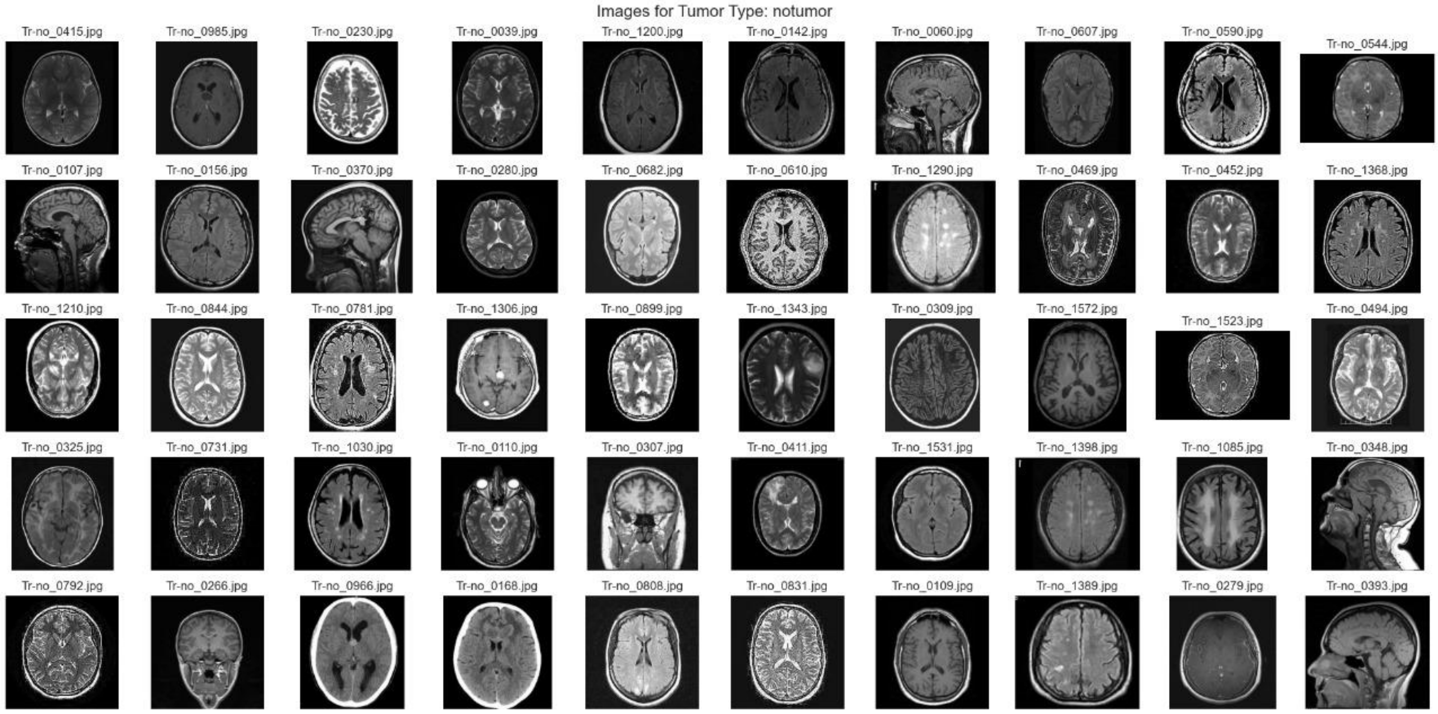

Fig10. Image prediction by user input

VI. DISCUSSION

The code demonstrates a thorough performance of a brain tumor detection system utilizing image processing and deep knowledge ways. It commences by importing a range of essential libraries, involving TensorFlow, Keras, and Seaborn, to grease tasks like data manipulation, engine knowledge, and visualization. To begin, the code specifies the cortege lines for the training and testing datasets, a foundational step for data loading and preprocessing. subsequently, it employs the Image- Data-creator class to portion the data into training and evidence sets. This data splitting path is vital for an accurately valuation of the model's interpretation. Data extension and preprocessing ways are applied to the training data. This missions, analogous to rotation, relocating, and whirring, enhance the model robustness and its capability to generalize beyond the training data. They play a vital portion in perfecting the model's interpretation. The code processing to establish two distinct model architectures. The first model is a preparatory Convolutional Neural Networks (CNN), while the second is a more improved model predicated on the Inception V3 architecture. The InceptionV3 model, pertained on the ImageNet datasets, represents a transfer knowledge path that leverages previously learned features for brain tumor detection. latterly, it initiates the model training process on the training data, with the option to adjust the number of training periods to fin- tuna model interpretation. Also, the code enables the saving and loading of the trained model, allowing for model durability and subsequently operation. This functionality is vital for planting the model for conclusion or fresh training. For model valuation, the code calculates a distraction matrix, offering perceptivity into the model's interpretation, involving the number of true cons, false cons, true negatives, and false negatives. The distraction matrix is visually described as a pie chart, simplifying the understanding of type effects. To decode deep into model valuation, the code includes a bias-disunion dissection utilizing knowledge. This angles support determines whether the model is overfitting, underfitting, or generalizing effectively by conniving training and cross-validation grudges. The code also facilitates image generation and exposition from the training datasets, furnishing a visual representation of the nonidentical classes and image quality within the datasets. also, it allows for use commences, allowing stoners to define a tumor class. The code also erratically selects and displays images from the taken class, promoting a farther grasp- on exploration of the data. Initially, the code extends its avail by taking input images for tumor type prophecy. It utilizes the trained model to make predictions on the handed images, showcasing the model's real- world operation in diagnosing brain tumor. In substance, this code encapsulates a complete and interactive workflow for the evolution, training, and valuation of a brain tumor detection model.

VII. CONCLUSION

In this paper, we had reviewed different techniques for brain tumor classification using Magnetic Resonance Images (MRI). The significance of this work extends beyond the realm of classification. These techniques have the potential to be further harnessed for the classification

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of various brain abnormalities, expanding their utility in the field of neuroimaging. The motivation behind this research is to provide a comprehensive overview of the methodologies employed in the classification of brain tumors based on scanned MRI images. Accurate identification and classification of brain anomalies are fundamental in the diagnosis and treatment of neurological disorders, and the methods explored in this paper serve as a foundation for more extends applications in the medical field. The paper not only reviews existing techniques but also paves the way for future research and innovation in the critical area of brain imaging and diagnosis. These techniques play a vital role in assisting medical professionals in making accurately and timely diagnosis. The scanned images are categorized into four primary types, including no-tumor, glioma tumor, meningioma tumor, and pituitary tumor, each necessitating a distinct approach to classification.

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