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NEUROSENTINEL PRODIGY

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Abstract : Brain tumor detection is a crucial task in the realm of medical diagnostics, bearing significant implications for patient care and outcomes. This research paper embarks on a comprehensive exploration of the development and deployment of an advanced brain tumor detection system. The methodological framework is multifaceted, commencing with the assembly of a diverse and extensive dataset of brain imaging scans. Subsequently, the data undergoes rigorous preprocessing, including noise reduction and image enhancement, to optimize the quality and fidelity of the scans. The heart of the system lies in the utilization of deep learning, particularly a convolutional neural network (CNN), which leverages the robust features extracted from the preprocessed data to distinguish between brain scans indicative of tumors and those that are not. Model training is augmented by the introduction of a validation set, allowing for finetuning to achieve optimal performance. Testing the trained model on an entirely separate and previously unseen dataset substantiates its real-world utility, providing critical insights into its robustness and accuracy. The practical implementation of the system involves seamless integration into a real-time processing platform, enabling rapid analysis of incoming brain imaging data. This operational phase includes the establishment of predefined thresholds, effectively reducing false alarms and ensuring that only the most probable cases are flagged for review by medical professionals.

***IndexTerms* – Brain Tumor, CNN, VGG16, Medical.**

I. INTRODUCTION

INTRODUCTION

The early and accurate detection of brain tumors remains a critical challenge in the field of medical diagnostics and healthcare. Brain tumors are abnormal growths of cells within the brain or the surrounding structures, and they can have severe and life-threatening consequences if not detected and treated correctly. The timely diagnosis of brain tumors is essential to initiate appropriate medical interventions and enhance the chances of a successful outcome for patients. There have been significant advancements in the detection of brain tumors in recent years. The fusion of medical imaging technologies, computational algorithms, and machine learning approaches has greatly enhanced the accuracy, effectiveness, and swiftness of diagnosing brain tumors. Various methodologies and approaches employed in the domain of brain tumor detection, with a focus on the innovative techniques that have emerged as powerful tools in this field. The significance of early brain tumor detection cannot be overstated. Brain tumors can manifest with a wide range of symptoms, some of which are subtle and easily mistaken for other medical conditions. As a result, patients may go undiagnosed for extended periods, leading to delayed treatment and compromised outcomes. Furthermore, the complexity of the human brain and the intricate nature of brain tumors pose challenges for accurate detection and classification. These challenges necessitate the development of advanced diagnostic systems that can assist healthcare professionals in making informed decisions and offering personalized treatment strategies.

II. REVIEW OF LITERATURE SURVEY

2.1 Literature Survey

The following chapter is a literature survey of the previous research papers and research which gives detailed information about the previous system along with its advantages and disadvantages.

Tariq Sadad, Amjad Rehman, Asim Muni, R Tanzila Saba, Usman Tariq, Noor Ayesha, Rashid Abbasi et.al [1] In this research paper, the authors address the critical issue of brain tumor detection and classification using advanced deep learning techniques applied to MRI slices. The study leverages transfer learning through freeze and fine-tune processes to extract meaningful features from the MRI data. In tumor detection, they utilize the Unet architecture with ResNet50 as its backbone, achieving an outstanding Intersection over Union (IoU) score of 0.9504, showcasing the model's accuracy in delineating tumor regions. Furthermore, the paper extends its focus to multi- classification, distinguishing between different types of brain tumors, using the powerful NASNet architecture. The NASNet model outperforms other deep learning architectures with a remarkable classification accuracy of 99.6%. The study acknowledges the need for future research to explore architectures with reduced computational complexity, promising to further enhance the field of automated brain tumor detection and classification. Overall, this paper demonstrates the potential of deep learning and transfer learning in improving the accuracy and efficiency of brain tumor diagnosis, offering valuable insights for medical professionals and researchers in the field.

Pallavi Tiwari, Bhaskar Pant, Mahmoud M. Elarabawy, Mohammed Abd-Elnaby, Noor Mohd, Gaurav Dhiman and Subhash Sharma et.al [2] The research paper introduces a pioneering approach for automated multiclass classification of brain tumors in MRI images, harnessing a sophisticated deep Convolutional Neural Network (CNN) architecture. The dataset under examination is extensive, comprising 3,264 MRI images categorized into four distinct classes: glioma, meningioma, no tumor, and pituitary tumors. At the core of the study is the proposed CNN model, consisting of six layers intricately designed to incorporate convolutional layers for feature extraction, batch normalization for autonomous learning enhancement, activation functions for introducing non-linearity, pooling layers for dimensionality reduction, dropout layers for regularization, and a fully connected layer for classification. The crowning achievement of this model is its remarkable accuracy, clocking in at an impressive 99%, while concurrently maintaining a low loss of 0.0504 across 30 epochs of training. An indepth comparative analysis against existing models solidifies the superiority of the proposed approach. Additionally, the study visually articulates model performance through a comprehensive confusion matrix and a detailed classification report. This research not only underscores the potency of deep CNNs in the realm of automated medical image classification but also underscores their efficacy in situations characterized by limited training data and minimal preprocessing requirements. As a harbinger of the future, the study aims to extend its classification capabilities and boost accuracy, setting the stage for further advancements in AIdriven diagnostic tools. In conclusion, this research represents a significant advancement in revolutionizing the diagnosis and treatment planning of brain tumors. It opens promising avenues for improving patient care and outcomes in clinical practice.

Tanzila Saba, Ahmed Sameh Mohamed, Mohammad El-Affendi, Javeria Amin, Muhammad Sharif et.al [3] The research paper introduces a comprehensive methodology for the precise diagnosis and classification of brain tumors, particularly focusing on gliomas, through the utilization of medical imaging data. The authors emphasize the critical need for early detection of brain tumors, given the potential life-threatening consequences of rapid tumor growth and pressure on surrounding healthy brain tissue. The proposed approach combines advanced image processing techniques, deep learning, and traditional handcrafted features to achieve precise tumor segmentation and subsequent classification. The segmentation process employs the GrabCut method, which initially converts RGB images into single-channel representations and iteratively refines tumor boundaries based on seed points and pixel similarity thresholds. Deep learning features are extracted using a fine-tuned VGG-19 model, while handcrafted features, such as Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG), are also employed. These features are optimized through entropy-based techniques and fused into a single feature vector for classification. The research evaluates the methodology on three benchmark datasets: BRATS 2015, 2016, and 2017, which include varying numbers of high-grade and low-grade glioma cases. Results demonstrate high accuracy in tumor classification across multiple classifiers, including Support Vector Machines (SVM), Logistic Regression (LGR), and an ensemble classifier. Additionally, the method is successful in distinguishing between high and low-grade tumors. Comparative analysis reveals that the proposed approach surpasses existing state-ofthe-art methods in brain tumor classification. The research concludes by summarizing its strengths, highlighting the achievements of the proposed approach in terms of accuracy and Dice Similarity Coefficient (DSC) on the tested datasets. Overall, this paper contributes to the field of medical image analysis by offering a robust and effective solution for the early diagnosis and classification of brain tumors, potentially leading to improved patient outcomes in the context of this critical health concern.

Md Khairul Islam, Md Shahin Ali, Md Sipon Miah, Md Mahbubur Rahman, Md Shahariar Alam, Mohammad Amzad Hossain et.al [4] The research paper presents superpixels, PCA & K- means scheme for brain tumor detection in magnetic resonance (MR) images. The study begins by emphasizing the importance of accurate tumor detection in medical imaging, particularly in MR images, which are often complex and require preprocessing for noise reduction. The proposed scheme consists of several key components, including image preprocessing, feature extraction employing superpixels and principal component analysis (PCA), and tumor segmentation utilizing template-based K-means clustering. The authors conducted experiments using a dataset of 40 MR images, showcasing the effectiveness of their scheme. They attained a remarkable accuracy of 95.0%, sensitivity of 97.36%, and specificity of 100%, surpassing current detection methods. Superpixels and PCA were found to be instrumental in dimensionality reduction and simplification of MR images, facilitating accurate tumor detection. The proposed scheme also demonstrated fast execution times, making it practical for clinical applications. However, the study acknowledges limitations such as the use of a small dataset. Future research will address these limitations, aiming to enhance the accuracy of detection and classification, stage identification of tumors, and compatibility with deep learning systems for broader applicability in various radiological imaging techniques. Overall, the paper presents a promising approach to improve brain tumor detection in MR images and highlights avenues for future research and development.

Chirodip Lodh Choudhury, Chandrakanta Mahanty, Raghvendra Kumar et.al [5] The research paper presents a novel approach to brain tumor detection using a Convolutional Neural Network (CNN) applied to MRI images. The study addresses the critical need for early and accurate detection of brain tumors, which can significantly impact patient outcomes and treatment options. The proposed CNN architecture consists of three layers, and the model achieved an impressive accuracy rate of 96.08% with an F-score of 97.3. The research highlights the power of machine learning in medical diagnostics, particularly in the field of neuro-oncology, by significantly outperforming traditional manual diagnosis methods. The CNN model leverages its ability to learn hierarchical features from medical images, from basic attributes like edges to more complex features. Various activation functions, including Rectified Linear Unit (ReLU), Hyperbolic Tangent (Tanh), and Sigmoid, are utilized for efficient learning, and the training process is optimized using the ADAM optimizer. The results, as depicted in the confusion matrix, illustrate a minimal error rate of 2.98%. In conclusion, this research underscores the potential of diagnostic machine learning applications and predictive treatment in healthcare and points to future research avenues, particularly the application of "neutrosophical principles" for brain tumor detection using CNNs, promising advancements in the field of medical image analysis and diagnosis.

Sarmad Maqsood, Robertas Damaševi cius and Rytis Maskeliunas et.al [6] The research paper presents a comprehensive approach to the detection and classification of brain tumors using medical imaging, addressing critical challenges in the field. Brain cancer, a leading global cause of mortality, necessitates early and precise diagnosis, which can be facilitated through magnetic resonance imaging (MRI). Manual detection is time-consuming and error-prone, motivating the development of an automated computer-aided diagnosis (CAD) method. The proposed framework comprises contrast enhancement, image segmentation, feature extraction, feature selection, and classification. Firstly, linear contrast stretching is employed to enhance image contrast, followed by the application of a custom 17-layered CNN for tumor segmentation. tumor segmentation. Feature extraction uses a modified MobileNetV2 architecture with transfer learning. Entropy-based feature selection refines feature sets, and multiclass support vector machines (M-SVM) perform tumor classification, distinguishing meningioma, glioma, and pituitary images. Experimental evaluations conducted on BraTS 2018 and figshare datasets reveal exceptional performance, with classification accuracy rates reaching 97.47% and 98.92%, respectively outperforming some of the existing methods. Notably, the use of gradient-weighted Class Activation Mapping (Grad-CAM) offers visual insights into regions influencing tumor classifications. Limitations include a focus on 2-D MRI images and a slightly time-consuming feature selection process. Future work aims to extend the methodology to 3-D imaging and address time efficiency concerns. In conclusion, the proposed CAD system demonstrates substantial promise in improving brain tumor diagnosis and classification, providing enhanced accuracy, automatic feature extraction, reduced computational time, and effective feature selection, representing a significant advancement in medical image analysis.

Mesut TOĞAÇAR, Burhan ERGEN, Zafer CÖMERT et.al [7] The paper presents BrainMRNet, a novel convolutional neural network (CNN) model designed for the detection of brain tumors in magnetic resonance images (MRI). Brain tumors can have life-threatening consequences, and their early diagnosis is of paramount importance. The proposed model integrates modules, a hypercolumn technique, and residual blocks to improve the accuracy of detection. In a two-step experimental study, the BrainMRNet model was compared with pre-trained CNN models, including AlexNet, GoogleNet, and VGG-16. In the first step, the pre-trained CNNs achieved classification accuracies ranging from 84.48% to 89.66%. However, in the second step, BrainMRNet outperformed them all with a classification accuracy of 96.05%, along with high sensitivity and specificity. The attention modules allowed the model to focus on relevant areas of MR images, the hypercolumn technique retained features from different layers, and the residual blocks minimized issues related to network depth. These components contributed to the improved performance of BrainMRNet. The study compared its results with previous works, demonstrating its superiority. Despite the dataset's low resolution, the model's accuracy exceeded 96%, showing promise for early diagnosis of brain tumors. The open-source code for BrainMRNet is available for further development and applications in medical image analysis. The study concludes by suggesting the potential use of the proposed model in various medical image analysis applications and fields in future research.

Shtwai Alsubai, Habib Ullah Khan, Abdullah Alqahtani, Mohemmed Sha, Sidra Abbas and Uzma Ghulam Mohammad et.al [8] The proposed methodology for brain tumor detection in MRI images integrates advanced deep learning techniques, such as Convolutional Neural Networks (CNN) and a hybrid CNN-Long-Short-Term Memory (LSTM) model. This methodology begins with the preprocessing of MRI images, including resizing, cropping using extreme point calculation, and bicubic interpolation. The dataset is divided into training and validation sets. The CNN is employed for feature extraction, and the CNN-LSTM hybrid model acts as the classifier. Both models achieve high accuracy, with CNN-LSTM outperforming CNN. Training accuracy for CNN is 99.4%, and validation accuracy is 98.3%, while training loss is 0.007, and validation loss is 0.113. In contrast, CNN-LSTM exhibits superior performance, with training and validation accuracies of 99.8% and 98.5%, respectively, and training and validation losses of 0.010 and 0.103. The results of the proposed technique are impressive, with CNN achieving 98.6% accuracy, 98.5% precision, 98.6% recall, and an F1- measure of 98.4%. The hybrid CNN-LSTM model surpasses these metrics with an accuracy of 99.1%, precision of 98.8%, recall of 98.9%, and an F1-measure of 99.0%. Graphical representations of the performance illustrate CNN-LSTM's superiority. Comparative analysis reveals that the proposed model outperforms existing techniques, further confirming its effectiveness. This methodology demonstrates the potential of deep learning and the CNNLSTM hybrid model for accurate and efficient brain tumor detection in MRI images, offering promising prospects for improved healthcare diagnosis and treatment in the future.

Wadhah Ayadi, Wajdi Elhamzi, Imen Charf, Mohamed Atri et.al [9] In this research paper, a novel and robust approach for the classification of brain tumors in MRI images is presented. The methodology employs deep Convolutional Neural Networks (CNNs) for automated diagnosis, offering a solution that minimizes preprocessing requirements. The study encompasses the evaluation of the proposed model using three distinct datasets, showcasing its adaptability and effectiveness. Extensive data augmentation techniques, including rotation, flipping, Gaussian blur, and sharpening, were applied to enhance the model's performance. The results are evaluated using various metrics, such as accuracy, sensitivity, specificity, precision, and F1-score, providing a more comprehensive assessment than accuracy alone. In the experiments, the proposed CNN model consistently outperformed previous works across the different datasets, demonstrating its potential for real-world medical applications. Future directions for this research include exploring ensemble methods, improving model interpretability, investigating transfer learning, optimizing for efficiency, expanding datasets, addressing deployment challenges, and collaborating with medical experts to further refine and adapt the model for clinical use. This research offers a promising avenue for enhancing the accuracy and efficiency of brain tumor diagnosis through medical image analysis.

Neelum Noreen, Sellappan Palaniappan, Abdul Qayyum, Iftikhar Ahmad, Muhammad Imran, and Muhammad Shoaib et.al [10] The research paper presents a comprehensive study on the application of deep learning models for the early detection and classification of brain tumors using magnetic resonance imaging (MRI) data. Two distinct scenarios are explored in this study, utilizing pre-trained deep learning models, namely DenseNet201 and Inception-v3, to extract features from MRI images for brain tumor classification. The dataset used comprises 3,064 T1-weighted contrast MR images of three different types of brain tumors: meningioma, glioma, and pituitary tumors. The study introduces a feature concatenation approach, combining features from different layers or blocks of the pre-trained models, followed by softmax classification. Results indicate remarkable performance, with an accuracy of 99.51% achieved using the DenseNet201-based ensemble method, outperforming existing approaches. The paper discusses the challenges of traditional manual feature extraction methods and highlights the capability of deep learning models, particularly convolutional neural networks (CNNs), to automatically extract relevant features from medical resonance images. It underscores the need for efficient and reproducible computer-aided diagnosis tools to process large-scale medical datasets, emphasizing the complexity of brain tumor classification due to variations in tumor location, shape, size, and intensity. The research concludes that deep learning models provide a powerful and promising approach for brain tumor identification, with future directions including fine-tuning, data augmentation, scratch-based models, and ensemble methods to further enhance classification accuracy. This study contributes significantly to the field of medical image analysis, offering an automated and accurate solution for early brain tumor detection and classification through the integration of advanced deep learning techniques.

Joshi Manisha, Umadevi, Akshitha Raj B N et.al [11] this research paper presents a approach to the multi-classification of brain tumors using convolutional neural networks (CNNs). Brain tumor diagnosis traditionally depends upon invasive, time-consuming, and error-prone histopathological analysis of biopsy specimens. The paper addresses this challenge by introducing three distinct CNN models, each tailored to a specific classification task. The first model, Classification-1, achieves an impressive 99.33% accuracy in detecting brain tumors. The second model, Classification-2, classifies brain tumors into five types (glioma, meningioma, pituitary, normal brain, and metastatic) with an accuracy of 92.66%. The third model, Classification-3, grades glioma tumors into three categories (Grade II, Grade III, and Grade IV) with an accuracy of 98.14%. Notably, the majority of hyper-parameters for these models are automatically tuned using a grid search optimization algorithm. The paper compares the performance of these CNN models with popular pre-trained networks, consistently demonstrating their superiority. Additionally, the study highlights the importance of architectural engineering in deep learning, moving away from traditional feature engineering. This research stands as a pioneering contribution, being the first to address multi-classification of brain tumor MRI images using CNNs with extensive hyper-parameter optimization. In summary, the proposed CNN models exhibit exceptional accuracy in brain tumor detection, classification, and grading, showcasing their potential to aid early diagnosis and support medical professionals, with automated hyper-parameter tuning further enhancing their robustness and effectiveness.

Francisco Javier Díaz-Pernas, Mario Martínez-Zarzuela, Míriam Antón-Rodríguez and David González-Ortega et.al [12] This research paper introduces a novel and fully automated approach for the segmentation and classification of brain tumors in MRI images. The proposed method utilizes a Multiscale Convolutional Neural Network (CNN) architecture, inspired by the human visual system, to process MRI slices at three different spatial scales. Unlike previous methods, this approach does not require preprocessing to remove skull or vertebral column parts from the input images. The CNN processes each pixel within a sliding window, classifying it into one of four categories: healthy region, meningioma tumor, glioma tumor, or pituitary tumor. The network consists of three pathways, each with varying kernel sizes to extract features at different scales, and a fully connected stage for classification. Data augmentation using elastic transformation is employed to prevent overfitting. The method is evaluated on a dataset of 3064 MRI slices from 233 patients, covering three tumor types. Performance is compared to classical machine learning and deep learning methods, and the proposed approach achieves a remarkable tumor classification accuracy of 0.973, outperforming all other methods. Segmentation results are also impressive, with an average Dice index of 0.828, Sensitivity of 0.940, and pttas of 0.967. Even though some false positives occur, particularly in meningioma cases, the method demonstrates robustness and competitiveness in brain tumor analysis. In conclusion, this fully automatic CNN-based approach presents a powerful tool for brain tumor segmentation and classification, offering great potential for assisting medical professionals in diagnosing brain tumors and showing promise for application in other domains like satellite image analysis in future research endeavors.

Nyoman Abiwinanda, Muhammad Hanif, S. Tafwida Hesaputra, Astri Handayani, and Tati Rajab Mengko et.al [13] In this research paper, a Convolutional Neural Network (CNN) was developed and evaluated for the automated classification of common brain tumor types, specifically Glioma, Meningioma, and Pituitary tumors, using (T-1) weighted CE-MRI images. Notably, the study aimed to streamline the classification process by eliminating the need for region-based pre- processing steps. The authors explored multiple CNN architectures, ultimately identifying an optimal architecture, referred to as "architecture 2," which consisted of two convolution layers with ReLU activation functions and max pooling, followed by a hidden layer with 64 neurons. Architecture 2 exhibited a consistent decrease in validation loss during training, leading to the highest validation accuracy of 84.19%, and the training accuracy scored 98.51%. Importantly, these results were competitive with conventional algorithms that relied on region-based pre-processing, which achieved accuracies ranging from 71.39% to 94.68%. The paper also discussed the potential for future improvements, including the integration of color balancing techniques to enhance accuracy in textured MRI pixels. Overall, the study highlighted the promise of CNNs as supportive tools for medical professionals in the classification of brain tumors, offering the potential to simplify and expedite the diagnostic process while maintaining high levels of accuracy and patient care.

Jayshree Ghorpade Aher, Abhishek Patil, Yudhishthir Deshpande, Eeshan Phatak et.al [14] has proposed on A proposed framework for prediction of pulse, based on the effect of surya namaskar on different prakruti at different prahars of the day. The study emphasizes the significance of Nadi-parikshan, a crucial diagnostic technique in Ayurveda based on wrist pulse analysis. Introducing a novel framework, it aims to predict how performing Surya Namaskar influences wrist pulse signals, considering different Prakruti types and varied times on the day Prahar. By integrating questionnaire data and leveraging machine learning algorithms, this approach promises to offer tailored insights into holistic health, thereby contributing to a more personalized understanding of one's well-being and daily life cycle.

Masoumeh Siar, Mohammad Teshnehlab et.al [15] This research paper presents a novel approach to brain tumor detection using a combination of feature extraction algorithms and Convolutional Neural Networks (CNNs). The study utilizes a dataset of MRI images from 153 patients, comprising both normal and brain tumor cases, and introduces an innovative methodology for tumor detection. CNNs are shown to be effective in automating feature extraction from medical images, enhancing the accuracy of tumor identification. The paper employs various classifiers, including the Softmax Fully Connected layer, Radial Basis Function (RBF) classifier, and Decision Tree (DT) classifier, to evaluate network performance. Results reveal that the Softmax classifier in the CNN achieved an accuracy of 98.67% in image categorization. To further enhance network accuracy, a new method is proposed, combining feature extraction with CNN. The combined approach demonstrates substantial improvement, achieving an accuracy of 99.12% on test data. This heightened accuracy is expected to have a significant clinical impact by aiding physicians in making more precise tumor diagnoses and consequently improving patient care and treatment outcomes. In summary, this paper provides a promising methodology for early and accurate brain tumor detection, leveraging the capabilities of CNNs and feature extraction techniques, ultimately contributing to enhanced medical accuracy and patient care.

2.2 Analysis Table

Table 1 Analysis Table

Title	Summary	Advantages	TechStack
Brain tumor detection and multi-classification using advanced deep learning techniques. [1]	This article explores the use of deep learning techniques for brain tumor detection and classification from MRI slices. It employs transfer learning processes, including freeze and fine-tune, to extract features. The Unet architecture with ResNet50 achieves high accuracy (IoU of 0.9504) in tumor detection.	The research achieves a high accuracy rate of 99.6% in brain tumor classification, which can significantly enhance medical diagnosis and treatment planning.	Used ResNet50 technology for detection of brain tumor present or not.
CNN Based Multiclass Brain Tumor Detection Using Medical Imaging [2]	This research paper introduces a novel deep Convolutional Neural Network (CNN) model for automated brain tumor classification in MRI images, achieving an impressive 99% accuracy. The dataset comprises over 3,000 MRI images across four classes: glioma, meningioma, no tumor, and pituitary tumors.	The proposed deep Convolutional Neural Network (CNN) model achieves an impressive 99% accuracy in classifying brain tumors from MRI images, providing a highly accurate and efficient diagnostic tool for medical professionals.	Used normal CNN model for detection. Used less dataset upto 3000 MRI image for 3 different tumor types and no tumor.
Brain tumor detection using fusion of hand crafted and deep learning features [3]	The Paper presents an integrated approach for the accurate diagnosis of brain tumors, focusing on gliomas, using medical imaging. This methodology combines advanced image segmentation techniques, deep learning, and traditional handcrafted features to achieve precise tumor delineation and classification.	The proposed methodology offers enhanced accuracy in brain tumor diagnosis through the fusion of deep learning and handcrafted features, leading to improved patient outcomes.	Used multiple classifiers Support Vector Machine (SVM), Logistic Regression (LGR) and Ensemble Classifier for classification. Very low amount dataset used.
Brain tumor detection in MR image using superpixels, principal component analysis and template-based K-means clustering algorithm [4]	This research paper introduces a novel scheme for brain tumor detection in magnetic resonance (MR) images, utilizing superpixels, PCA, and template-based K-means clustering. The proposed scheme demonstrates superior accuracy, achieving 95.0% accuracy, 97.36% sensitivity, and 100% specificity.	The proposed scheme effectively reduces the dimensionality and complexity of MR images through superpixels and PCA, enabling more efficient feature extraction and brain tumor detection.	The study employs a relatively small dataset and does not incorporate the 2019 WHO international classification of diseases, limiting its real-world clinical applicability.

Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network [5]	This research paper introduces a Convolutional Neural Network (CNN) based approach for brain tumor detection using MRI images, achieving an impressive accuracy of 96.08% and an F-score of 97.3%. The study emphasizes the potential of machine learning in enhancing medical diagnostics.	The CNN-based model's ability to automatically extract and learn complex features from MRI images improves diagnostic accuracy and reduces the subjectivity associated with manual interpretation, enhancing the efficiency of brain tumor detection.	The model's performance may be limited by the availability and quality of MRI data, and it may require substantial computational resources for training and inference.
Multi-Modal Brain Tumor Detection Using Deep Neural Network and Multiclass SVM [6]	The proposed method combines contrast enhancement, custom CNN segmentation, MobileNetV2 feature extraction, and entropy-based feature selection, achieving outstanding classification accuracy rates of 97.47% and 98.92% on two datasets.	The proposed automated brain tumor detection system offers enhanced accuracy, reducing reliance on error-prone manual diagnosis by radiologists.	The method's current limitation is its applicability to 2-D MRI images, potentially limiting its effectiveness in 3-D imaging scenarios.
BrainMRNet: Brain Tumor Detection using Magnetic Resonance Images with a Novel Convolutional Neural Network Model [7]	This study introduces BrainMRNet, a novel convolutional neural network, for the detection and classification of brain tumors using MRI images.	BrainMRNet's advanta ge lies in its superior performance, achieving a 96.05% classification success rate, surpassing existing models.	Python 3.6, Python libraries, Jupyter Notebook, and the Keras framework for neural network development.
Ensemble deep learning for brain tumor detection [8]	This paper proposes a hybrid deep learning model (CNN-LSTM) for brain tumor classification using MRI images, achieving high accuracy and precision (99.1% and 98.8%, respectively). The study addresses the challenges of brain tumor detection and emphasizes the role of deep learning in early diagnosis, contributing to improved patient outcomes.	The CNN-LSTM model offers a remarkable 99.1% accuracy, enabling early brain tumor detection and better patient outcomes.	Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) for brain tumor detection
Deep CNN for Brain Tumor Classification [9]	Automated computer assisted diagnosis (CAD) systems are needed due to the complexity and volume of data. The proposed CNN-based model demonstrates strong performance in brain tumor classification, even with limited training data, addressing the limitations of previous methods.	The advantage of using Convolutional Neural Networks (CNNs) in brain tumor classification is their ability to automatically extract meaningful features from MRI images, reducing the need for manual feature engineering and improving accuracy.	Includes deep Convolutional Neural Networks (CNNs) for image analysis and classification, complemented by data augmentation techniques, with a focus on medical imaging datasets.
A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor [10]	Use of pre-trained deep learning models, DenseNet201 and Inception-v3, for the classification of brain tumors in MRI images, achieving accuracy rates of up to 99.51% through feature concatenation and softmax classification.	Accuracy achieved through deep learning models, offering an automated and efficient solution for brain tumor classification in MRI images.	DensNet201 and Inception-v3, implemented in Keras with the TensorFlow backend for the classification of brain tumors using MRI images.
Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework [11]	Paper presents three dedicated convolutional neural network (CNN) models for brain tumor classification, achieving ac curacy level (98.14%). Through automatic hyper parameter tuning via grid search	The paper's automatic hyper-parameter tuning enhances the CNN models' performance, ensuring robust and accurate brain tumor classification.	(CNNs) for image classification, hyper-parameter optimization techniques like grid search, and standard performance evaluation metrics

	optimization, these models consistently outperform pre-trained networks, offering high accuracy solutions for brain tumor detection and classification.		
A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network [12]	This research paper presents a automated method for brain tumor segmentation (detection) and classification using a Multiscale Convolutional Neural Network (CNN) architecture. The proposed CNN achieves a tumor classification accuracy of 0.973 on a dataset containing three tumor types.	The proposed Multiscale CNN offers fully automated brain tumor segmentation and classification, reducing the need for manual intervention in medical image analysis	PyTorch, image processing libraries, and possibly hardware accelerators such as Nvidia GPUs for model training.
Classification of Brain Tumor Using Convolutional Neural Network [13]	Utilizing a CNN for image classification with an impressive accuracy of 98% on a dataset comprising 330 brain images. And introduces a Watershed Algorithm for precise segmentation, demonstrates its effectiveness in distinguishing tumor regions from normal brain tissue	The integrated approach of CNN based image classification and the Watershed Algorithm for segmentation offers high accuracy in brain tumor detection and localization.	Includes Convolutional Neural Networks (CNN), ReLU activation, max pooling, and the 'adam' optimizer for deep learning on MRI images.
Brain Tumor Classification Using Convolutional Neural Network [14]	The paper introduced CNN for the automatic classification of common brain tumor types using MRI images, achieving a top validation accuracy of 84.19% with the chosen CNN architecture.	The CNN approach offers efficient and accurate brain tumor classification without the need for time consuming region-based preprocessing, simplifying the diagnostic workflow for medical professionals.	Used Convolution Neural Network (CNN).
Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm [15]	The paper shows us that the Softmax classifier within the CNN achieved an accuracy of 98.67% for image categorization, and the proposed approach, which combines feature extraction and CNN, improved accuracy to 99.12% on test data.	High accuracy achieved in brain tumor detection, enabling early diagnosis and improved patient care	Requirement for large datasets and substantial computational resources, which may limit its practical application in some healthcare settings.

III. Research Methodology

The methodology for developing a brain tumor detection system involves collecting a diverse dataset of brain imaging scans, preprocessing the data to enhance image quality and reduce noise, extracting relevant features, and training a deep learning model, such as a convolutional neural network (CNN). This model will learn to classify brain scans as tumor or non-tumor through supervised learning. A validation set is used to fine-tune the model and optimize its performance. To make the system practical, it will be integrated into a software platform capable of real-time processing of new brain imaging data, where predefined thresholds ensure that only probable cases are flagged for review by medical professionals. Ongoing monitoring and maintenance of the model are essential, involving regular updates and adaptations to keep pace with evolving tumor characteristics and medical advancements, thereby enhancing its effectiveness in clinical practice for improved patient care and outcomes.

3.1 Block Diagram

A block diagram is a diagram of a system in which the principal parts or functions are represented by blocks connected by lines that show the relationships of the blocks.

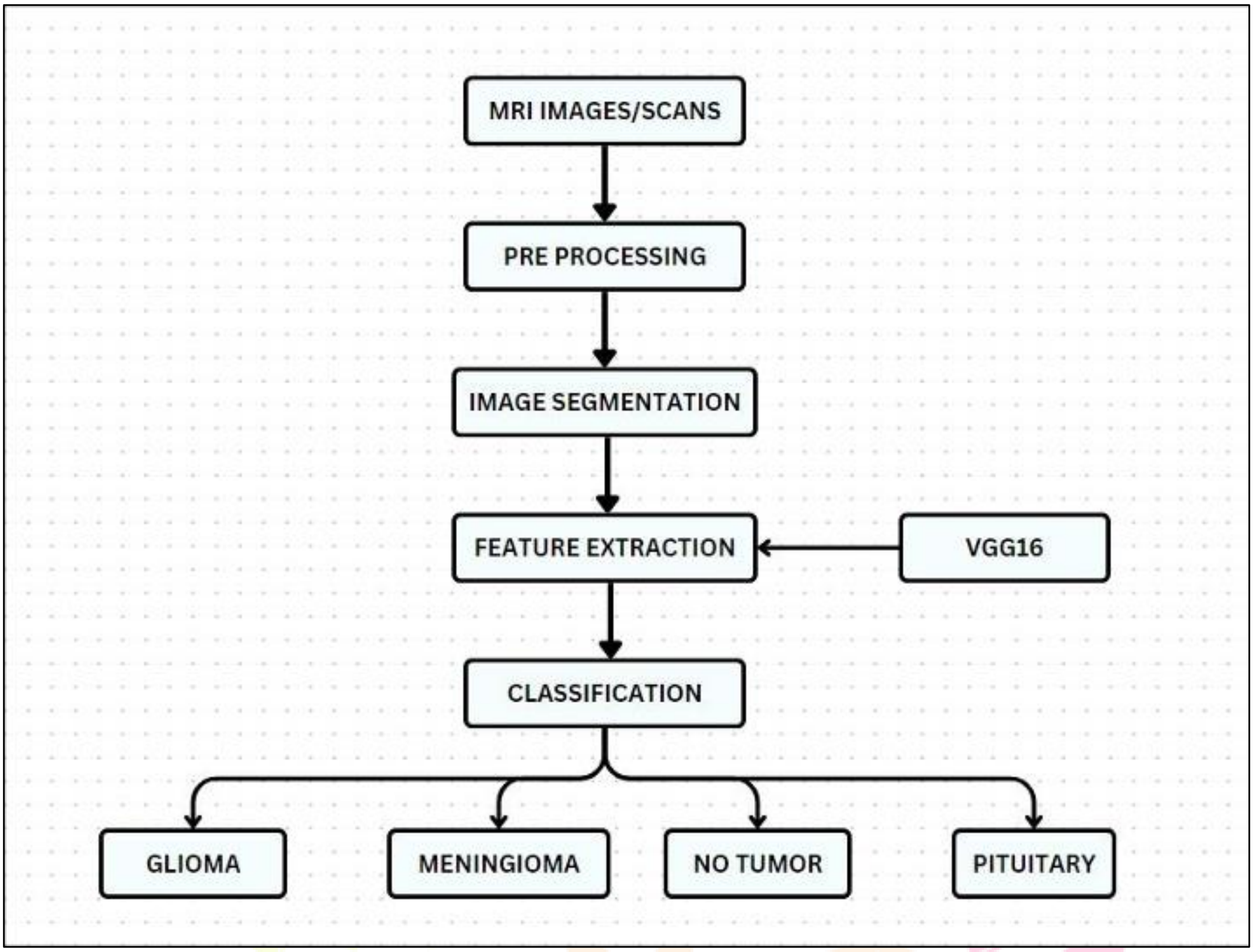

Fig 3.1 NeuroSentinel Prodigy Block Diagram

Figure 3.1 depicts the block diagram for the project. At starting it takes MRI images as input then it gets preprocessed based on the sizes. Then the image segmentation is carried out by CNN and Feature Extraction using 16-layer CNN (VGG16). Resultant classification is into Glioma, Meningioma, No Tumor and Pituitary.

IV. Results And Discussion

4.1 Results of NeuroSentinel Prodigy

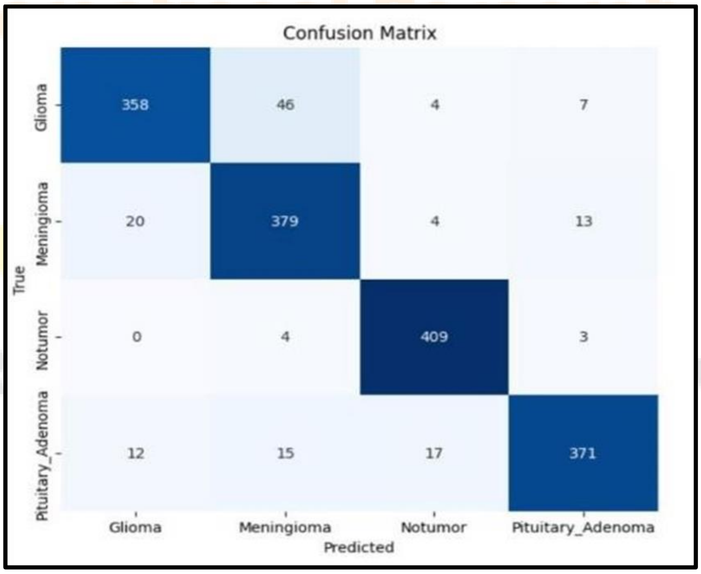

Fig. 4.1: Confusion Matrix

The confusion matrix above Fig 4.1 presents a comprehensive view of the classification performance of a machine learning model for brain tumor diagnosis, distinguishing between four primary types: glioma, meningioma, notumor, and pituitary.

Examining the matrix reveals both the model's successes and areas for improvement in accurately identifying each tumor type. Notably, the model demonstrates proficiency in correctly identifying glioma (358 true positives) and meningioma (379 true positives) tumors. However, it also misclassifies a notable number of instances, with glioma being frequently confused with meningioma (46 cases), notumor (4 cases), and pituitary (7 cases). Similarly, meningioma is occasionally misclassified as glioma (20 cases), notumor (4 cases), and pituitary (13 cases). While the model accurately identifies notumor in the majority of cases (409 true positives), it mistakenly labels some instances as glioma (4 cases) and pituitary (3 cases). Pituitary tumors also exhibit misclassification, with some instances being mistakenly identified as glioma (12 cases), meningioma (15 cases), and notumor (17 cases). This analysis underscores the necessity of refining the model to mitigate misclassifications and enhance its diagnostic accuracy for brain tumor classification.

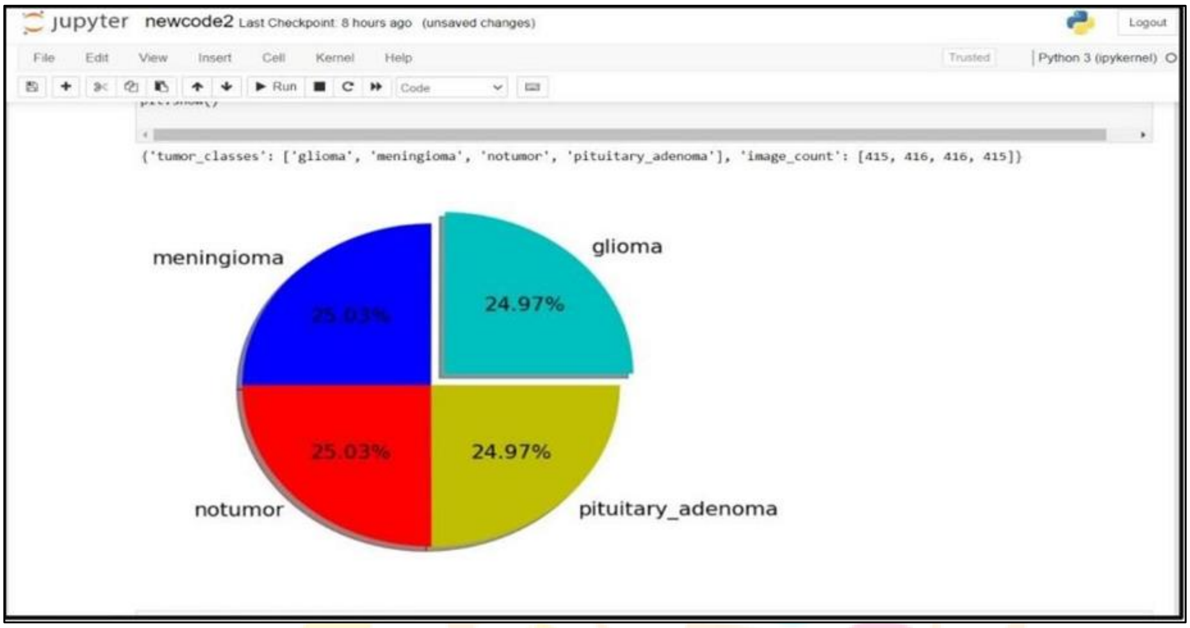

Fig. 4.2: Pie Chart Classes

The pie chart presented here Fig. 4.2 provides a overview of the distribution of brain tumor classes within a dataset earmarked for classification purposes. Each segment of the chart corresponds to one of four primary tumor types: glioma, meningioma, notumor, and pituitary. Interestingly, the dataset appears to exhibit a remarkably balanced distribution among these classes. Glioma and pituitary tumors each account for approximately a quarter of the dataset, mirroring one another's prevalence. Similarly, meningioma and the category of notumor occupy slightly larger portions, both comprising just over a quarter of the dataset. This equitable distribution underscores the diversity and richness of the dataset, which encompasses a comprehensive range of brain tumor types and includes instances without tumors. Such balanced representation is invaluable in training machine learning models effectively, as it ensures that the model learns from a diverse array of examples. Consequently, this dataset holds promise for the development of robust classification models capable of accurately discerning between different brain tumor types, ultimately aiding in clinical diagnosis and treatment planning.

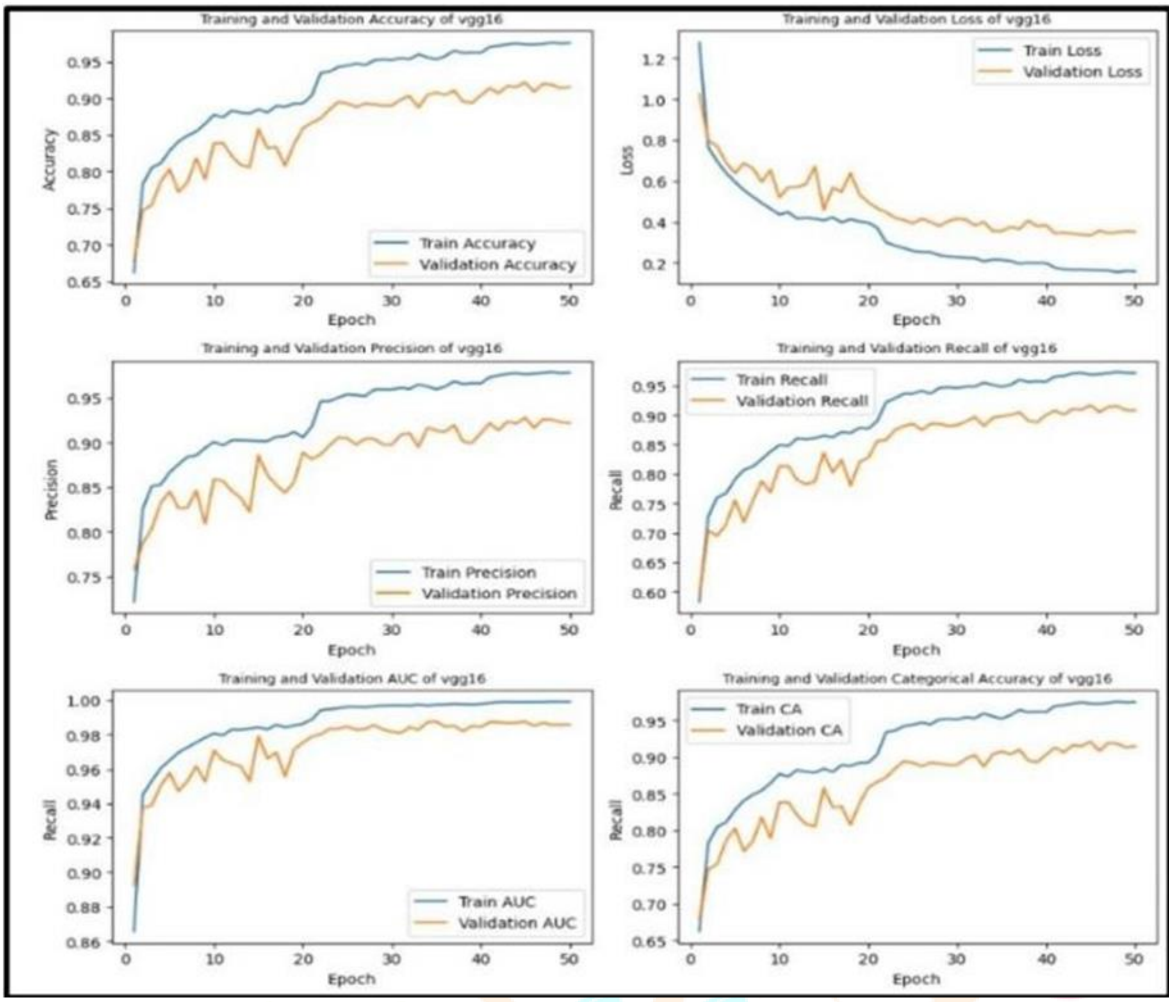

Fig. 4.3: Model's Accuracy

The image Fig 4.3 provides a comprehensive snapshot of the performance metrics for a brain tumor classification model, crucial for assessing its effectiveness in accurately identifying tumor types. Accuracy (97%), representing the overall correctness of predictions, is fundamental in evaluating the model's reliability. Loss serves as a barometer of the model's training progress, aiming to minimize errors between predicted and actual values. Precision highlights the model's ability to minimize false positives, crucial in medical diagnoses. Validation metrics offer insight into the model's generalization capabilities, ensuring robust performance beyond the training data. The Area Under the Curve (AUC)

metric offers a comprehensive assessment of the model's discriminatory power, while recall underscores its ability to capture all positive instances, minimizing false negatives. This visualization equips stakeholders with a nuanced understanding of the model's strengths and areas for improvement, facilitating informed decision-making in clinical applications of brain tumor classification.

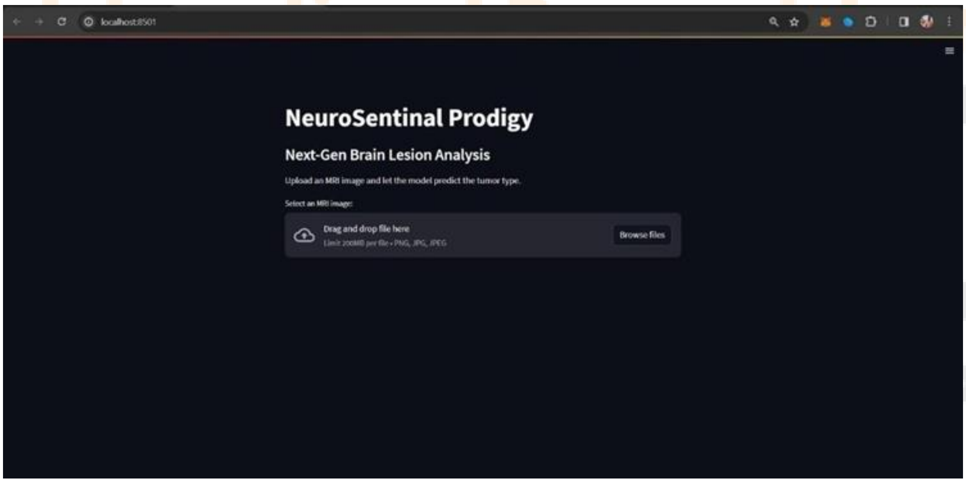

Fig. 4.4: User Interface of NeuroSentinal Prodigy

Fig. 4.4 presents the user interface (UI) of our project, showcasing a key feature designed to streamline the process of brain tumor diagnosis: the "Browse Images" functionality. This feature allows users to effortlessly select MRI images from their local storage for analysis regarding the presence or absence of brain tumors. By providing a simple and intuitive interface, our project aims to enhance accessibility and user experience, empowering both medical professionals and individuals to efficiently upload and examine MRI images. Through this user-centric design approach, we strive to democratize access to brain tumor diagnosis, ultimately improving healthcare outcomes and facilitating early detection and treatment.

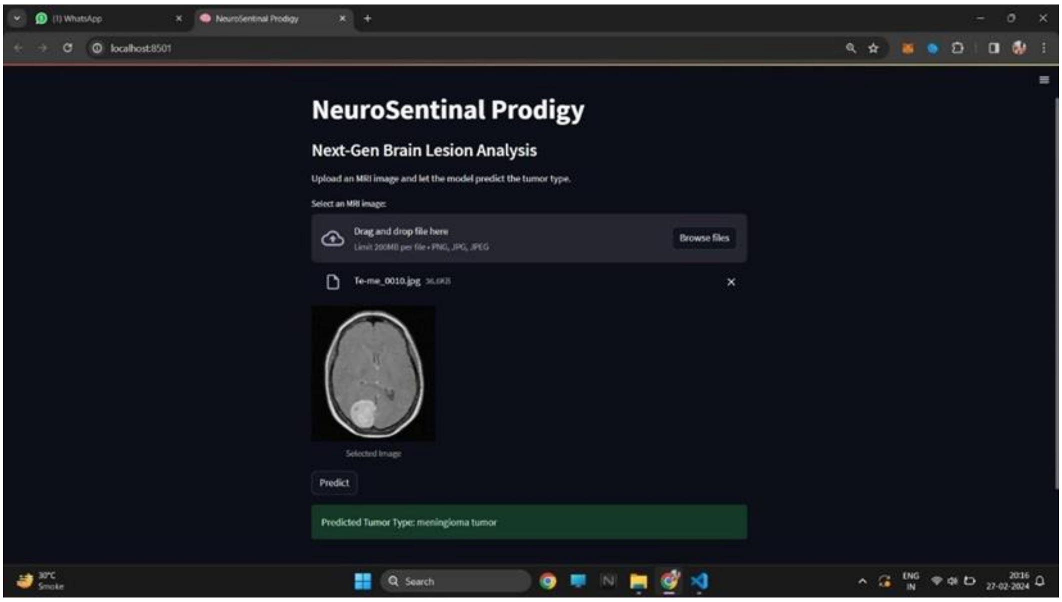

Fig 4.5: Classification of MRI images

In Figure 4.5, glimpse of project's user interface, where the predict of MRI images is classified enabling users to classify the selected MRI image to discern the presence or absence of a brain tumor. Moreover, it furnishes precise categorization into four distinct tumor types: glioma, meningioma, notumor, and pituitary. Through this intuitive and concise interface, our project streamlines the diagnostic workflow, delivering rapid and accurate assessments to both medical professionals and lay users.

V. CONCLUSION

In conclusion, NesuroSentinel Prodigy innovative Brain Tumor Detection is designed to empower healthcare professionals with a cutting-edge, automated solution for the early detection and precise classification of brain tumors. By harnessing the capabilities of advanced artificial intelligence and machine learning, NesuroSentinel Prodigy significantly streamlines the diagnostic process, accelerating the crucial intervention and treatment planning phase. The project's adaptability and user-friendly interface make it a valuable asset for medical practitioners and institutions, delivering faster and more accurate diagnoses. Beyond its efficiency gains, the system enhances the quality of patient care, equipping healthcare providers with the tools to make informed decisions and ultimately improve patient's tumor outcomes. NesuroSentinel Prodigy represents a significant stride forward in the field of medical image analysis, offering a promising path for future research and progress in the vital domain of brain tumor detection.

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