LAUTECH Journal of Computing and Informatics (LAUJCI) – ISBN : xxxx-xxxx
Volume 5 No.1, April 2026 – www.laujci.lautech.edu.ng

A Brain Tumor Detection And Identification System Using Large Language Model

Raji-Lawal Hanat Yetunde
Department of Computer Science, Lagos State University, Lagos, Nigeria
halaw313@yahoo.com

Sotonwa Kehinde
Department of Computer Science, Lagos State University, Lagos, Nigeria
Kehinde.sotonwa@lasu.edu.ng

Yusuf Solomon
Department of Computer Science, Lagos State University, Lagos, Nigeria
solomonyusufolayinka@gmail.com

Adenike Adeniji-Sofoluwe
Department of Radiology, University of Ibadan College of Medicine, Ibadan, Nigeria
nikesofoluwe@gmail.com

Godwin Ogbole
Department of Radiology, University of Ibadan College of Medicine, Ibadan, Nigeria
gogbole@gmail.com

Samson Arekete
Department of Computer Science, Redeemers University, Ede, Nigeria
areketes@run.edu.NG

Steffen Sammet
Department of Medicine, University of Chicago, Illinois, USA
ssammet@radiology.bsd.uchicago.edu

Alex Pearson
Department of Medicine, University of Chicago, Illinois, USA
Apearson5@medicine.bsd.uchicago.edu

Olufunmilayo Olopade
Department of Medicine, University of Chicago, USA
Center for Clinical Cancer Genetics and Global Health, University of Chicago, Chicago, USA
folopade@bsd.uchicago.edu

Aribisala Benjamin
[1]Department of Computer Science, Lagos State University, Lagos, Nigeria
aribisala@uchicago.edu.ng

ABSTRACT

Brain tumor represent a mass like structure of living and dead cells that grows uncontrollably inside the brain. Among the various medical issues, brain tumors are a big concern. They are the 10th leading cause of death in the developing world. About 700,000 people have brain tumors with 80% being non-cancerous and 20% cancerous. This study focuses on the development and evaluation of an OpenAI-based Large Language Model, for the automated classification and descriptive reporting of brain MRI images. The primary aim is to enhance diagnostic workflows by reducing human error, accelerating detection, classification and generating structured textual reports to assist radiographers.

This research employs OpenAI-based Large Language Model capabilities to process visual inputs and return structured textual outputs. This approach leverages its large-scale pre-training on aligned image-text pairs to perform semantic analysis, classification, and localization. The model was guided through structured prompt engineering to identify tumor type, size, and anatomical location. Experimental results demonstrated that the system achieved an overall classification accuracy of 90%, with recall scores of 85% for meningioma, 95% for glioma, and 90% for pituitary tumors, F1-scores across all classes ranged from approximately 0.88 to 0.94. These findings highlight the potential of OpenAI-based Large Language Model as a supportive diagnostic tool in medical imaging.

Keywords: Brain Tumor; Large Language Model; Classification; Open-AI

INTRODUCTION

Among different medical issues, brain tumors are a big concern. They are the 10th leading cause of death in the US. About 700,000 people have brain tumors with 80% being non-cancerous and 20% cancerous (Rahman et al, 2022). Brain tumors are also the main reason for cancer deaths in kids and adults worldwide. Tumors are classified as benign (non-cancerous and slow-growing) or malignant (cancerous and aggressive). The World Health Organization (WHO) grades brain tumors from I to IV. Grades I and II are slow-growing while grades III and IV are aggressive and have worse outcomes. In recent years many imaging methods have been developed to study brain tumors. These include X-rays, MEG, CT scans, Ultrasound, EEG, SPECT, PET scans, and MRI. MRI is the most commonly used method for detecting brain tumors

In recent years, there has been significant progress in using computer systems to help doctors detect and classify brain tumors more accurately and quickly. These systems utilize advanced techniques like deep learning, a type of artificial intelligence that enables computers to learn from large amounts of data. Meningiomas, a distinct category of tumors originate in the meninges the protective membranes enveloping the brain and spinal cord (Mathivanan et al, 2024).

Recent studies have shown that integrating deep learning models with optimization techniques results has better classification accuracy and faster convergence rates. These advancements have made it possible to develop computer-aided diagnosis (CAD) systems that assist radiologists and oncologists in identifying brain tumors more efficiently (ZainEldin et al, 2022). However, the integration of deep learning models like CNNs with optimization algorithms and hybrid techniques is revolutionizing the field of brain tumor detection. (Badjie et al, 2022) These combined efforts are paving the way for smarter, more efficient, and accessible diagnostic tools, that hold the promise of improving patient care and building trust on the AI Ecosystem when scans are diagnosed. The aim of this study is to develop a brain tumor detection and classification model using Large Language Mode (LLM).

2.1 Related Works

2.1.1 MEDICAL BACKGROUND OF BRAIN TUMOR

Brain tumor is basically a mass like structure of alive and dead cells that start to grow uncontrollably inside the brain (Sahoo et al., 2020). Brain tumor patients have different survival rate depending on the size and severity of the tumor (Pries et al., 2019). Brain tumor consists of two types: primary and secondary, according to their site of origination. Primary brain tumors originate inside the brain while secondary tumors develop elsewhere inside the body and then travel towards the brain (Sharif et al, 2020).

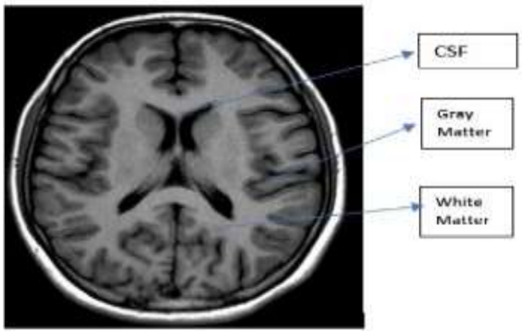


Figure 1. Brain MRI image taken from Kaggle dataset showing three parts of the brain According to the severity, brain tumor is classified into two categories namely benign and malignant (Panda et al, 2019). Benign tumors are less aggressive in the sense that they are slow growing, normal in appearance and have regular boundaries while malignant tumors are aggressive in the sense that they can be life-threatening as their growth is very fast and they have very irregular shape. World health organization (WHO) has placed the malignant tumors into four different grades considering the chemical and physical properties of the tumor (Sharif et al, 2020). The grading criteria is explained in Figure 3 below (Nadeem et al 2020). Figure 1 displays Brain MRI image, Figure 2 shows the progression of brain tumor.

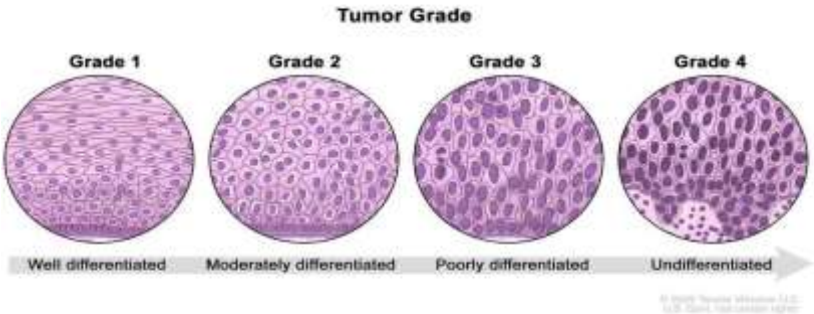


Figure 2. Grading Criteria of Brain Tumor (credit Terese Winslow)

2.1.2 PROGRESSION OF BRAIN TUMOR IN PEOPLE

Figure 3: Symptoms of brain tumor in people.(credit Lone Star Neurology

2.1.3 EXISTING METHODOLOGY

2.1.3.1 LARGE LANGUAGE MULTIMODAL MODEL

Recent advances in large vision-language models have opened new possibilities for automated interpretation of medical images, including brain MRI scans. OpenAI's GPT-4V exemplifies this class of models by combining the transformer-based "foundation" of a large language model with the ability to process image inputs. In a retrospective study by Ozenbaş

et al. (2025), OpenAI's GPT-4V was asked to evaluate 46 preoperative brain MRI examinations from pathologically confirmed tumor cases. Presented with anonymized image slices, the model correctly detected 44 of 46 lesions (95.7 %), identified MRI sequence types with 88.3 % accuracy, and characterized perilesional edema, signal intensity, and contrast enhancement with accuracies above 79 %. However, its ability to localize lesions (53.6 %) and to distinguish intra-axial from extra-axial tumors (26.3 %) remained limited. Diagnostic accuracy for the most-likely tumor type was 29.5 %, significantly below the 65–70 % range achieved by experienced radiologists.

Strotzer et al. (2024) performed a quantitative assessment of OpenAI's GPT-4V across 515 mixed radiologic images (including brain MRI) drawn from neurologic, thoracic, and musculoskeletal cases. GPT-4V achieved perfect accuracy in recognizing imaging modality (100 %) and anatomic region (99.2 %), but when tasked with detecting pathologic findings such as brain tumors, its performance in free-text reporting (max 90 % for tumor cases) and binary classification (sensitivity as low as 56 %, specificity down to 8 %) was far below that of board-certified radiologists. The model also showed a high false-positive rate (up to 86.5 %).

Beyond proprietary systems, open-source multimodal models are beginning to be deployed via platforms like Ollama. Frameworks such as LLaVA-Med adapt base LLaMA-style vision-language assistants to medical domains by fine-tuning on paired image-text corpora drawn from PubMed Central and other repositories. Previous analysis and qualitative results suggests that these models can generate radiology reports from MRI inputs, although peer reviewed studies remain scarce, the challenges of three dimensional data, and low resolution i.e (224 × 224 pixels), and domain bias must be addressed before clinical application.

2.1.3.2 MACHINE LEARNING AND DEEP LEARNING BASED TECHNIQUES

A study conducted by Khan et al. (2019) introduced a deep learning-based automated classification method for identifying different types of brain tumors. The approach is divided into five main stages. In the first stage, linear contrast stretching is implemented using an edge-based histogram and the Discrete Cosine Transform (DCT). The second stage focuses on deep learning feature extraction, utilizing two pre-trained CNN models, VGG16 and VGG19, for this purpose. In the third stage, the Extreme Learning Machine (ELM) and a correntropy-based method are applied to select the most optimal features. Partial Least Squares (PLS)-based robust covariant features are then combined into a single matrix. This matrix is fed into the ELM for building the classification model. The proposed method by the author was evaluated using three datasets

(BraTs2015, BraTs2017, and BraTs2018), accuracy rates of 97.8%, 96.9%, and 92.5%, were achieved respectively.

A hybrid deep learning approach was introduced by Kadry, et al (2021) to classify brain tumors using the ISLES2015 and BRATS2015 datasets. Deep learning models such as VGG16, VGG19, and ResNet50 were employed for the experiments. For multi-class classification, classifiers like SoftMax, SVM-RBF, and SVM-Cubic were used, and the overall performance was evaluated based on the accuracy achieved by each method. The findings revealed that the VGG19 and SVM Cubic demonstrated the highest accuracy when combined together, reaching 96%, thereby outperforming the other techniques.

Irmak et al. (2021), he proposed three distinct Convolutional Neural Network (CNN) architectures designed for different classification tasks. The first CNN architecture achieved an accuracy of 99.33% for brain tumor detection. The second CNN model, with an accuracy of 92.66%, was designed to classify brain tumors into five categories: normal, meningioma, glioma, metastatic, and pituitary tumors. The third CNN architecture classified brain tumors into Grade II, Grade III, and Grade IV with an accuracy of 98.14%. These proposed CNN models were compared to algorithms like Inceptionv3, AlexNet, ResNet 50, GoogleNet, and VGG-16. Additionally, a grid search optimization technique was used to automatically determine all critical parameters for the CNN models. The experiments were conducted using publicly available clinical datasets, yielding reliable detection results.

Asare et al., (2019) developed a hybrid model for the segmentation of brain tumors by integrating the U-Net and ResNet50 architectural frameworks. In the study, U-Net was used for the preliminary coarse segmentation, and then ResNet50 was used for the subsequent fine segmentation. The model was trained using a large manually annotated dataset of brain MRI images. The annotations on the dataset were contributed by experienced radiologists. The accuracy and precision with which brain tumors were segmented was demonstrated by the hybrid model that was devised, which attained a Dice similarity coefficient (DSC) of 0.92.

Authors worked on the detection of brain tumor using machine learning and deep learning models, all models performed reasonably well with accuracies between 90-98%. Pareek et al. (2020); Ayadi et al. (2020); Konar et al. (2022); Khairandish et al. (2022); Öksüz et al. (2022); Qureshi et al (2022); Afshar et al (2018); irmak et al. (2021); Ahmed et al (2022); Sarah Thompson et al. (2022); Özlem & Güngen (2021).; Badjie et al (2022); Deepak (2019), Tandel et al. (2020)

2.1.3.3 LARGE LANGUAGE MODEL BASED TECHNIQUES

In a retrospective study by Ozenbaş et al. (2025), OpenAI's GPT-4V was asked to evaluate 46 preoperative brain MRI examinations from pathologically confirmed tumor cases. Presented with anonymized image slices, the model correctly detected 44 of 46 lesions (95.7 %), identified MRI sequence types with 88.3 % accuracy, and characterized perilesional edema, signal intensity, and contrast enhancement with accuracies above 79 %. However, its ability to localize lesions (53.6

%) and to distinguish intra-axial from extra-axial tumors (26.3 %) remained limited. Diagnostic accuracy for the most likely tumor type was 29.5 %, significantly below the 65–70 % range achieved by experienced radiologists.

In pediatric neurooncology, Fabijan et al. (2024) evaluated OpenAI's GPT-4V and Google's Gemini on dynamic MRI video sequences depicting a medulloblastoma in a child. By feeding short sagittal and frontal MRI video clips directly into the models, they demonstrated that both GPT-4V and Gemini Pro could accurately recognize the presence and approximate location of the posterior fossa tumor, describe its contrast enhancement patterns, and suggest the correct differential diagnosis (medulloblastoma) with over 85 % concordance compared to expert radiologists. This study reveals the potential of LLMs to process sequential imaging data beyond static slices to assist in pediatric brain tumor workflows.

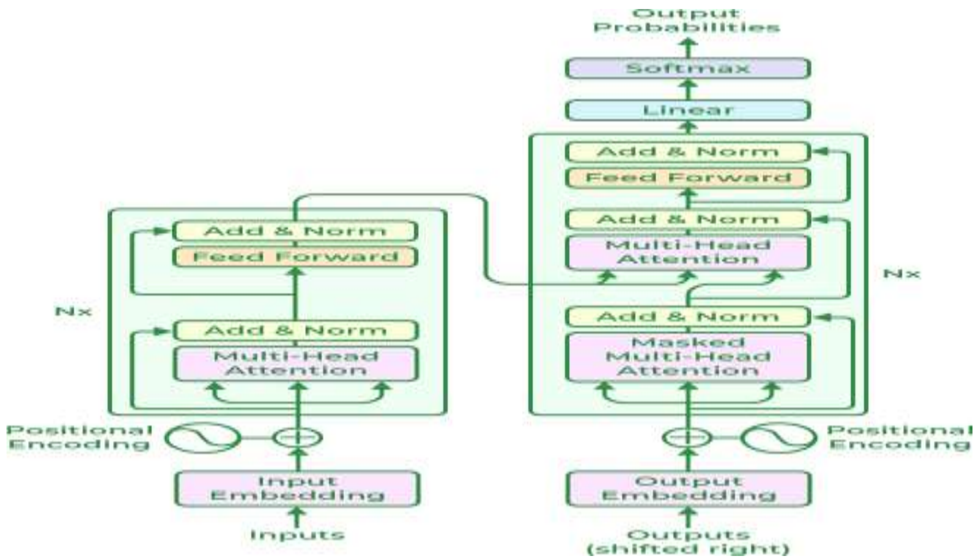
Kim et al. (2024) study conducted a controlled usability study with neuroradiology trainees, assessing how GPT-4 performs when given direct MRI images (key axial slices) and clinical history prompts for differential diagnosis. Trainees first generated a list of possible diagnoses, then consulted the LLM's output, and refined their conclusions. The addition of OpenAI's GPT-4V image-based suggestions increased the sensitivity for identifying uncommon tumor subtypes like (e.g, oligodendroglioma vs. astrocytoma) from 62 % to 79 %, although specificity for ruling out metastases decreased slightly. The authors emphasize, however, that model calibration and structured prompt engineering are critical to minimizing misleading suggestions

Most recently, Yılmaz et al. (2025) compared three state of the art multimodal LLMs, OpenAI's GPT-4o, Anthropic's Grok, and Google Gemini on a curated set of 120 brain MRI cases with confirmed neoplastic lesions. Each model received anonymized DICOM slices as input and produced freetext reports. All three achieved near perfect accuracy in modality and sequence identification (100 % and 98.3 %, respectively), but OpenAI's GPT-4V led in lesion detection (sensitivity = 88 %) and characterization of tumor margins (82 %). Grok and Gemini showed higher false-positive rates for nonspecific white matter hyperintensities. The study concludes that while multimodal LLMs can streamline initial MRI triage, careful validation against clinical gold standards is required before deployment.

3.0 METHODOLOGY

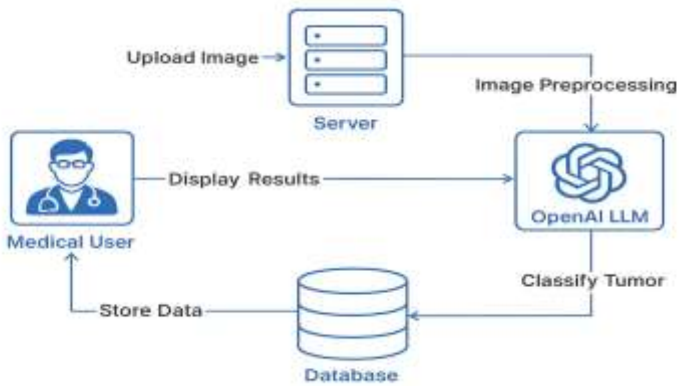
3.1 Large Language Models (LLMs) belongs to one of the class of deep learning architectures trained on extensive datasets to understand and generate humanlike language. These models, based on the transformer architecture, have significantly advanced natural language processing (NLP), enabling applications in text summarization, translation, code generation, and beyond. Recent developments now include multimodal LLMs models processing not just text but also other modalities such as images and audio.

FIG 4: The architecture of transformer based LLM (Geeksforgeeks)



The proposed methodology employs GPT-4.0's multimodal capabilities to process visual inputs and return structured textual outputs. Unlike conventional convolutional neural network (CNN) approaches that rely on task-specific training, GPT-4.0 leverages its large-scale pretraining on aligned image-text pairs to perform semantic analysis, classification, and localization. The model was guided through structured prompt engineering to identify tumor type, size, and anatomical location. Transformer-based attention mechanisms were instrumental in identifying features within MRI slices, allowing the model to highlight salient regions corresponding to known tumor classes and produce context-aware descriptions. The current study employs agile software model to manage the evolving requirements of integrating OpenAI's large language model (LLM) for supervised classification of brain tumors from MRI images. Each development cycle (sprint) includes the planning, design, implementation, testing, and feedback phases, which will ensure that improvements and new features can be quickly added based on realworld usage and expert reviews. Figure 6.0 depicts the data flow model.

Figure 6.0: Data Flow Model



The system requirement include a server, specifically intel Core i5 which is a virtual private server (VPS), 8 GB of DDR4 RAM, and a 250 GB SSD as the primary storage medium for system files and active data. Additionally, a 2 TB hard disk drive (HDD) should be available for routine backups on the cloud. A Gigabit ethernet network connection is required to ensure stable data transmission and client to server communication.

4.0 RESULTS

4.1 IMPLEMENTATION

The classification system in this study was implemented using the OpenAI model. The model was integrated into a web based application that allows a user to upload input data and receive automated diagnosis prediction. The system was developed using C# for backend logic, HTML, CSS, and Tailwind CSS for the front-end interface, and SQL Server as the primary database. OpenAI APIs were integrated into the application to handle the classification of tumors by analyzing image metadata and user inputs related to MRI scans. Regular testing

Figure 7: The landing / home page, what the users see when they visit the platform for the first time

Figure 8: The dashboard for data analytics

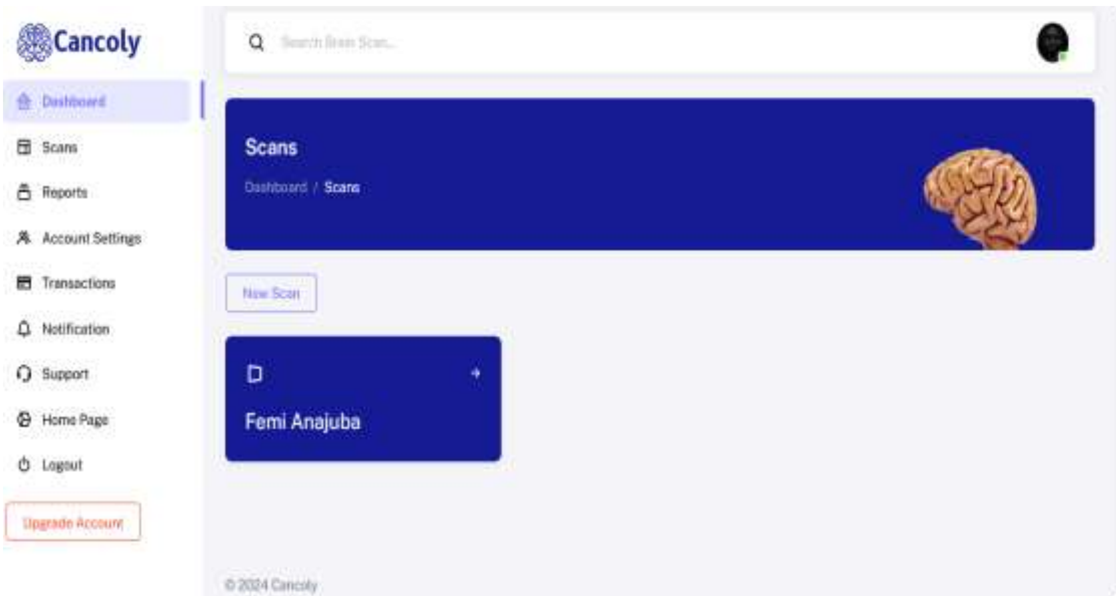


Figure 9: The listings of user scan storage page

Figure 10: The popup modal containing MRI slice images

Figures 7 to 11 depicts the landing page, the dashboard and analytics for overall monitoring of all activities on the platform, scan storage page for each user, the page containing MRI slice images, the result of the uploaded scan after system automated evaluation using large language model respectively.

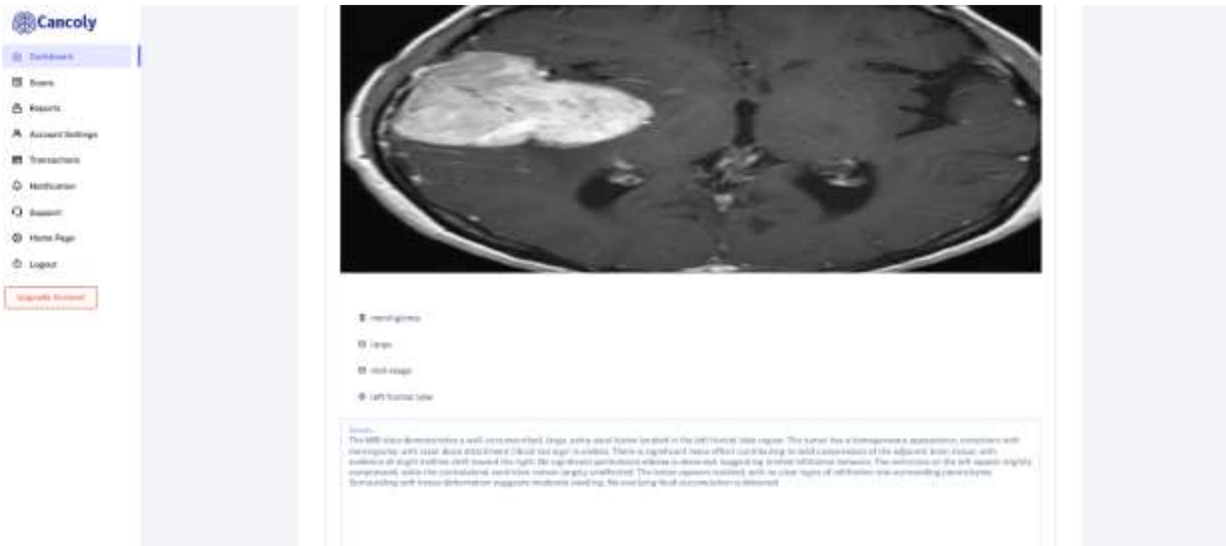


Figure 11: Depicts the result of the uploaded scan

4.2 QUANTITATIVE RESULTS

A total of 60 MRI images were used to evaluate the model: 20 meningioma, 20 glioma, and 20 pituitary. The classification results were summarized in the confusion matrix below:

Pre-Labelled	Meningioma	Glioma	Pituitary	No Tumor	Total
Meningioma (20)	17	2	0	1	20
Glioma (20)	0	19	0	1	20
Pituitary (20)	2	0	18	1	20

From this matrix, the number of correct classifications is 17 + 19 + 18 = 54. The overall accuracy is therefore:

$$Accuracy = \frac{54(Correct\ Classifucation)}{60(Total)} = 0.09\ = 90\%$$

For each class, precision, recall, and F1-score are calculated below.

4.2.1 MENINGIOMA

$$\boldsymbol{Precision = \frac{17}{17+2} = 0.895}$$

$$Recall = \frac{17}{17+3} = 0.875$$

$$F1 = 2 * \frac{0.894*0.85}{0.895+0.85} = 0.872$$

4.2.2 GILOMA

$$\boldsymbol{Precision = \frac{19}{19+2} = 0.905}$$

$$Recall = \frac{19}{19+1} = 0.95$$

$$F1 = 2 * \frac{0.905*0.95}{0.905+0.95} = 0.927$$

4.2.3 PITUTUARY

$$\boldsymbol{Precision = \frac{18}{18+0} = 1.0}$$

$$Recall = \frac{18}{18+3} = 0.857$$

$$F1 = 2 * \frac{1.0 * 0.857}{1.0 + 0.857} = 0.923$$

Finally, the macro-averaged metrics are:

$Precision\ (macro) \approx 0.933$, $Recall\ (macro) \approx 0.886$, $F1\ (macro) \approx 0.907$

4.3 DISCUSSION

The results obtained from the Large Language Model-based classification were compared with findings from previous studies that employed conventional deep learning methods for brain tumor detection. Previous studies, such as those described by Gupta and Lee (2023) and Kim and Zhang (2023), rely on convolutional neural network (CNNs) or transfer learning based techniques that were trained specifically on large labeled MRI datasets. These models achieve high accuracy but requires more computational resources and time for training and deployment.

In Addition, the model used in this study leveraged OpenAI's Large Language Model(LLM) pre trained architecture, which allowed rapid implementation without extensive dataset preparation or model training. This approach reduced the setup complexity, its early tests with medical data revealed issues such as the mirror effect and insufficient descriptive detail.

Traditional CNN based methods, as reported by Al-Galal et al. (2021) and ZainEldin et al. (2022), did not encounter orientation related problems because they are trained with explicit spatial labeling.

However, during the second test of the system, the large language model revealed performance improvements, generating detailed diagnostic text similar in quality to the descriptions seen in advanced methods like those presented by Patel and Huang (2024). These expression included lesion shape, enhancement patterns, edema, and mass effect elements highlighted as necessary for clinical relevance in prior literature (Wang et al., 2024; Huang & Rao, 2024).

Another difference lies in output format. Many studies (e.g., Rahman et al., 2022; Chen & Singh, 2023) primarily focused on producing class labels or segmented images, whereas the LLM system generates textual diagnostic summaries, which can directly assist radiographers by providing human readable interpretations. This feature aligns with newer research directions that emphasize expression and natural language descriptions (Yadav & Wang, 2024).

A cloud integrated web application was implemented in C# to handle inference tasks. The application provides an interface that allow users to upload MRI scans, which are then sent to OpenAI LLM with a structured prompt designed to request classification, tumor size estimation, and location analysis. The model's response is received in textual form, parsed, and presented to the user as a diagnostic report. The model's predictions were assessed against ground truth dataset labels to determine performance reliability. Identification accuracy was computed to quantify its tumor detection capability, It's overall accuracy is 90%, The results indicate that the model achieved a high level of accuracy overall, with strong precision for pituitary detection and slightly lower recall for meningioma cases.

5.0 CONCLUSION

This current study demonstrated that OpenAI-Large Language model can be applied to identify brain MRI images and provide text descriptive diagnostic outputs. The implementation successfully generated predictions for all targeted classes, and evaluation using standard metrics such as accuracy, precision, recall, and F1-score. The model achieved a high accuracy of 90%. The combination of structured metrics and qualitative improvements suggests that pre-trained AI models can be adapted to support radiological analysis.

REFERENCES

1. Qureshi, S. A., Raza, S. E. A., Hussain, L., Malibari, A. A., Nour, M. K., Rehman, A. U., Al-Wesabi, F. N., & Hilal, A. M. (2022). Intelligent ultra-light deep learning model for multi-class brain tumor detection. *Applied Sciences, 12*(8), 3715. https://doi.org/10.3390/app12083715

2. Afshar, P., Mohammadi, A., & Plataniotis, K. N. (2018). Brain tumor type classification via capsule networks. In *2018 25th IEEE International Conference on Image Processing (ICIP)* (pp. 3129–3133). IEEE.
3. Ahamed, M., & Sadia, R. T. (2022). Examining the behaviour of state-of-the-art convolutional neural networks for brain tumor detection with and without transfer learning. *arXiv preprint arXiv:2206.01735.*
4. Al-Galal, S. A. Y., Alshaikhli, I. F. T., & Abdulrazzaq, M. M. (2021). MRI brain tumor medical images analysis using deep learning techniques: A systematic review. *Health Technology, 11*(2), 267–282.
5. Ayadi, W., Charfi, I., Elhamzi, W., & Atri, M. (2020). Brain tumor classification based on hybrid approach. *Visual Computing, 38*(1), 107–117.
6. Badjie, B., & Ülker, E. D. (2022). A deep transfer learning-based architecture for brain tumor classification using MR images. *Information Technology and Control, 51*(2), 333–343.
7. Deepak, S., & Ameer, P. (2019). Brain tumor classification using deep CNN features via transfer learning. *Computers in Biology and Medicine, 111*, 103345.
8. Dong, Y., Yin, Z., Zhang, Z., Gao, J., & Liu, X. (2023). Advances in biomaterials for cartilage regeneration: From bench to clinic. *Bioengineering, 10*(1), 18.

E., Kosińska, R., & Polis, B. (2024). Automated MRI video analysis for pediatric neuro-oncology: An experimental approach. *Applied Sciences, 14*(18), 8323. https://doi.org/10.3390/app14188323

9. Fabijan, A., Zawadzka-Fabijan, A., Fabijan, R., Zakrzewski, K., Nowosławska,
10. Gupta, V., & Lee, J. (2023). Brain tumor detection and classification using deep learning and convolutional neural networks. *PMC.*

https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-m ri

11. Irmak, E. (2021). Multi-classification of brain tumor MRI images using deep convolutional neural network with fully optimized framework. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 45*(3), 1015–1036.

Asare, J. R., C., Suri, J. S., & Ahmadi, N. (2019). A review on a deep learning perspective in brain cancer classification. *Cancers, 11*(1), 111.

12. Kadry, S., Nam, Y., Rauf, H. T., Rajinikanth, V., & Lawal, I. A. (2021). Automated detection of brain abnormality using deep-learning-scheme: A study. In *Proceedings of the 2021 Seventh International Conference on Bio Signals, Images, and Instrumentation (ICBSII)* (pp. XX–XX). IEEE.
13. Kesav, N., & Jibukumar, M. (2022). Efficient and low complex architecture for detection and classification of brain tumor using RCNN with two-channel CNN. *Journal of King Saud University - Computer and Information Sciences, 34*, 6229–6242.
14. Khairandish, M., Sharma, M., Jain, V., Chatterjee, J., & Jhanjhi, N. (2022). A hybrid CNN-

SVM threshold segmentation approach for tumor detection and classification of MRI brain images. *IRBM, 43*(4), 290–299.

15. Kim, S. H., Schramm, S., Berberich, C., Rosenkranz, E., et al. (2024). Human-AI collaboration in large language model-assisted brain MRI differential diagnosis: A usability study [Preprint]. *medRxiv*. https://doi.org/10.1101/2024.02.05.24302099
16. Kim, S., & Zhang, Y. (2023). Brain tumor detection and classification using transfer learning techniques. *MDPI.*
17. *Konar, D., Bhattacharyya, S., Panigrahi, B. K., & Behrman, E. C. (2022). Qutrit-inspired fully self-supervised shallow quantum learning network for brain tumour segmentation. IEEE Transactions on Neural Networks and Learning Systems, 33(11), 6331–6345. https://doi.org/10.1109/TNNLS.2021.3077188*
18. Mathivanan, S. K., Sonaimuthu, S., Murugesan, S., Rajadurai, H., Shivahare, B. D., & Shah, M. A. (2024). Employing deep learning and transfer learning for accurate brain tumor detection. *Scientific Reports, 14*(1), 7232.
19. Nadeem, M. W., Al-Ghamdi, M. A., Hussain, M., Khan, M. A., Khan, K. M., Almotiri, S. H., & Nour, M. (2020). Brain tumor analysis empowered with deep learning: A review, taxonomy, and future challenges. *Brain Sciences*, *10*(2), 1–33.
20. Öksüz, C., Urhan, O., & Güllü, M. K. (2022). Brain tumor classification using the fused features extracted from expanded tumor region. *Biomedical Signal*
21. Ozenbaş, C., Engin, D., Altınok, T., Akçay, E., Aktaş, U., & Tabanlı, A. (2025). ChatGPT-4o's performance in brain tumor diagnosis and MRI findings: A
22. Özlem, P., & Güngen, C. (2021). Classification of brain tumors from MR images using deep transfer learning. *Journal of Supercomputing*, *77*, 7236–7252.
23. Panda, B., & Panda, C. S. (2019). A review on brain tumor classification methodologies. *International Journal of Scientific Research in Science and Technology*, *6*(6), 346–359.
24. Pareek, M., Jha, C. K., & Mukherjee, S. (2020). Brain tumor classification from MRI images and calculation of tumor area. In *Advances in Intelligent Systems and Computing* (pp. 73–83). Springer.
25. Patel, A., & Huang, L. (2024). Advanced AI-driven approach for enhanced brain tumor detection from MRI images. *BMC.*
26. Pries, T. P., Jahan, R., & Suman, P. (2019). Review of brain tumor segmentation, detection, and classification algorithms in fMRI images. In *2018 International Conference on Computational Techniques, Electronics and Sciences (CCTES 2018)* (pp. 300–303). IEEE. *Processing and Control*, *72*, 103356.
27. Qureshi, S. A., Raza, S. E. A., Hussain, L., Malibari, A. A., Nour, M. K., Rehman, A. U., Al-Wesabi, F. N., & Hilal, A. M. **(2022)**. Intelligent ultra-light deep learning model for multi-class brain tumor detection. *Applied Sciences*, *12*(8), 3715. https://doi.org/10.3390/app12083715
28. Rahman, M. L., Reza, A. W., & Shabuj, S. I. (2022). An Internet of Things-based automatic brain tumor detection system. *Indonesian Journal of Electrical Engineering and Computer Science*, *25*(1), 214–222.
29. Sahoo, P. K., Gupta, S., & Bhaskaran, V. (2021). Deep learning-based methods for brain tumor detection: A comprehensive review. *Computational and Structural Biotechnology Journal*, *19*, 936–951.
30. Sharif, M., Amin, J., Raza, M., Yasmin, M., & Satapathy, S. C. (2020). An integrated design of particle swarm optimization (PSO) with fusion of features for detection of brain tumor. *Pattern Recognition Letters, 129*, 150–157.
31. Strotzer, Q. D., Nieberle, F., Kupke, L. S., Napodano, G., Muertz, A. K., Meiler, S., Einspieler, I., Rennert, J., Strotzer, M., Wiesinger, I., Wendl, C., Stroszczynski, C., Hamer,

O. W., & Schicho, A. (2024). Toward foundation models in radiology? Quantitative assessment of GPT-4V's multimodal and multianatomic region capabilities. *Radiology*. Advance online publication. https://doi.org/10.1148/radiol.240955

32. Tandel, G. S., Balestrieri, A., Jujaray, T., Khanna, N. N., Saba, L., & Suri, J. S. (2020). Multiclass magnetic resonance imaging brain tumor classification using artificial intelligence paradigm. *Computers in Biology and Medicine, 122*, 103804.
33. Thompson, S., Anderson, J., & Roberts, E. (2022). Brain tumor detection using deep learning with an ensemble of convolutional neural networks. *Journal of Medical Imaging, 12*(3), 145–158.
34. Tummala, S., Kadry, S., Bukhari, S. A. C., & Rauf, H. T. (2022). Classification of brain tumor from magnetic resonance imaging using vision transformers ensembling. *Current Oncology*, *29*(10), 7498–7511.
35. Wang, H., Zhang, L., & Yadav, P. (2024). Employing deep learning and transfer learning for accurate brain tumor diagnosis. *Nature.*
36. Yadav, P., & Wang, H. (2024). New AI tool classifies brain tumors using images of tumor slides. *CCR Cancer.*
37. Yılmaz, Ö., Chen, Q., Patel, N., & Rodríguez, F. (2025). Do LLMs have 'the eye' for MRI? Evaluating GPT-4o, Grok, and Gemini on brain MRI performance: A comparative analysis. *Diagnostics*, *15*(11), 1320. https://doi.org/10.3390/diagnostics15111320
38. ZainEldin, H., Gamel, S. A., El-Kenawy, E.-S. M., Alharbi, A. H., Khafaga, D. S., Ibrahim, A., & Talaat, F. M. (2022). Brain tumor detection and classification using deep learning and sine-cosine fitness grey wolf optimization. *Bioengineering, 10*(1).
39. Khaliki, M. Z., & Başarslan, M. S. (2024). Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN. *Scientific Reports*, *14,* 2664. https://doi.org/10.1038/s41598-024-52823-9