Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 6, 2025

TOWARDS SMART NEURO DIAGNOSIS: CLOUD AND IOMT BASED BRAIN TUMOR DETECTION USING HIERARCHICAL DEEP LEARNING

Naveed Mukhtar[1], Gullelala Jadoon[2], Tahira Ali[3], Ishfaq Khan[4], Waqar Hussain[5], Ajab Khan[*6], Noshaba Qasim[7], Muhammad Zubair Khan[8],

[1]Faculty of Computer Science & Information Technology, Superior University, Lahore, Pakistan
[2]Department of Information Technology, University of Haripur, Pakistan
[3]Computer Science and Information Technology Department, NED University of Engineering and Technology, Pakistan
[4]Institute of Computing (IOC), Kohat University of Science & Technology (KUST), Kohat, Pakistan
[5]Department of Artificial Intelligence, University of Kotli Azad Kashmir, Pakistan
*[*6]Director ORIC, Abbottabad University of Science and Technology, Pakistan*
[7]National Centre for Bioinformatics, Quaid-i-Azam University, Islamabad, Pakistan
[8]Department of Computer Science, Green International University, Lahore, Pakistan

[*6]ajabk66@yahoo.com

DOI: https://doi.org/10.5281/zenodo.15880550

Keywords
Brain Tumor, Convolutional Neural Network, Glioma, Meningioma, Pituitary

Article History
Received: 08 April, 2025
Accepted: 25 June, 2025
Published: 30 June, 2025

Corresponding Author: * Ajab Khan

Abstract
Brain tumors may be the key source of psychiatric complications such as depression, panic attacks, etc. The most important point towards curing the tumor is that recognition of a tumor in the brain should be timely and fast. The use of Medical Image Processing is having a very significant role in assisting the man in diagnosing the various illnesses. An important element is the Brain Tumor classification which depends on the experience and the knowledge of the doctor. An intelligent brain tumor detection and classification system is necessary to aid the doctors and physicians. The uniqueness of the research is that Brain tumors were separated into Glioma, Meningioma, and Pituitary using a hierarchical deep learning technique. The classification of the tumor and its diagnosis is very crucial in the rapid and effective treatment and processing of medical images with the Convolutional Neural Network is bringing great results in this regard. Convolutional Neural Network (CNN) exploits the pieces of the image as a way of training the information and categorizing the images into the classes that are later to be types of tumors. CNN is proposed to detect and classify brain tumors and create Hierarchical Deep Learning-Based brain tumor classifier. The suggested system categorizes the data entry into four categories that are named as Glioma, Meningioma, Pituitary and No-Tumor. The proposed model attained 96.54% Accuracy and Miss Rate is 3.46% better as compared to the earlier projects of segmentation and diagnosis of brain tumor. The suggested system will provide the clinical support in the field of medicine.

INTRODUCTION
The human brain is a complex and a vital organ as it is the control unit of the central nervous system. It processes the input received via the senses, controls the functions of the body, and facilitates complex abilities such as emotion, decision-making, and memory using a dense network of neurons

(Srinivasan et al. 2024). Yet, its intricacy, at the same time, makes it susceptible to fatal health risks, especially the brain tumors. A brain tumor is caused by the growth of cells abnormally and uncontrollably within the brain and it is just possible to put pressure on other tissues and affect neurological functioning. These are some of the most dangerous kinds of cancer in view of the fact that they are aggressive, have high mortality rates and they are also quite difficult to diagnose because of this (Huda & Ku-Mahamud, 2025).

We normally group brain tumors into two; benign and malignant. Benign ones are non-malignant, and they usually develop leisurely, but due to their occurrence in delicate areas, the risks may severely affect health. Malignant tumors, in contrast, are cancerous and are very invasive and can even spread to immediate healthy brain (Khaliki & Başarslan, 2024). The Gliomas, Meningiomas, and Pituitary tumors rank among the common brain tumors in adults. Gliomas are malignancies that develop in the glial cells, which assist the development of neurons, and they have an aggressive nature and poor prognosis (Asiri et al. 2024). Meningiomas are usually benign, and they develop as growths of the meninges which protect the brain and the spinal cord, and they may remain unnoticed for more than several years. Pituitary tumors claim an influence on the gland that regulates hormones and may disturb the body endocrine activity. These tumors must be diagnosed accurately and at an early stage to enhance positive outcomes of treatment and minimize the risk of having long-term neurological deficits (Khan et al. 2025; Akter et al. 2024).

Early identification of brain tumors is a very complicated process. Radiologists have challenges in distinguishing between types of tumors because of the identical appearance, poor shapes and irregular sizes. Reaction to an incorrect diagnosis or delayed treatment may lead to even aggravated conditions: psychological disorders, depressions, or panic attacks (Gupta et al. 2024). Some of the effective diagnostic techniques that are needed are MRI (Magnetic Resonance Imaging) and CT scans which give more detailed displays of the structures of the brain. Nonetheless, it is tedious, time consuming, and clinician dependent to interpret such images manually (Nazir et al. 2024; Shoaib et al. 2025).

Artificial intelligence (AI) has been majorly promising in recent years with its ability to revolutionize medical diagnostics by putting into use machine learning (ML) and deep learning (DL) models. Such technologies help automate the analysis of medical images and increase the accuracy and efficiency of diagnosing. In these, the most effective deep learning models on image-based applications have turned out to be the Convolutional Neural Networks (Ye et al. 2024). Based on the idea of the human visual system, CNNs can be used to detect complex patterns and characteristics in the MRI scans that are instrumental in tumor classification. They are very effective in the detection and segmenting of brain tumors into various types like Glioma, Meningioma, and Pituitary because they can learn spatial hierarchies of features (Liu et al. 2024).

CNNs have a systematic pipeline comprising of preprocessing, feature extraction, training, validation and classification. During preprocessing, MRI data are also cleaned and cleared up to eliminate the noise. The feature extraction process implies the usage of convolutional layers which identifies meaningful patterns in the image, and pooling layers help to lower computational complexity (Ramakrishnan et al. 2024). The latter are given to flatten layers which interpret the data and identify the categories of tumors in the image to predetermined classes. Such a strategy is also highly accurate in the identification of tumors and been found to be highly effective compared to the conventional ways of diagnostics (Sudhakar et al. 2024).

Nevertheless, even though these innovations have been made, there are restraints. Reasonably, annotated datasets of brain tumors in real-time are limited and many authors prefer using publicly available datasets such as those found in Kaggle or BRATS CNNs are also computationally expensive, and hyperparameter might need painstaking tuning to accommodate a wide range of imaging parameters (Rasool et al. 2025).

The necessity to have a strong automated and clinically relevant system of brain tumor classification involves this study. This paper will use a hierarchical CNN-based deep learning model that seeks to categorize the brain MRI into four various classes

ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 6, 2025

consisting of No Tumor, Glioma, Meningioma, and Pituitary. The strategy also allows early detection as well as help radiologists to identify the place of origin of the tumor and the right mode of treatment. The solution proposed fills the gap between scientific innovation and clinical practice which provides a practical tool that allows increasing the speed of disease diagnosis and its reliability.

1 Related Work

Dutta et al. (2024) realized Extreme Learning Machine (RELM) was introduced together with GIST descriptors in brain tumor classification. The strategy employed a preprocessing of the images based on its use on min-max normalization to increase image contrast and feature extraction based on the spatial structure of input images. One of the neural networks was a form of feedforward neural network, RELM, trained with these features on the tumor classification of the three types of tumor data set namely Meningioma, Glioma and Pituitary. On 233 MRI images, the model was tested and performed well by segmentation and classes.

The method proposed by Saeed et al. (2024) harmonized Multilayer Perceptron (MLP) with an Improved Whale Optimization Algorithm (IWOA). A Median Filter was used to eliminate noise and Otsu thresholding was carried out to segment. Using the optimized WOA method the features were selected and then classified with MLP-based classifier. Such a composite system performed better than the traditional classifiers on both accuracy and robustness.

Sajol and Hasan (2024) presented an integrated system that entails Deep Autoencoder (DAE) and Bayesian Fuzzy Clustering (BFC) in the classification of brain tumor. BFC carried out the segmentation whereas Non-Local Mean Filtering was used to eliminate noise. The entropy-based feature extraction used sophisticated algorithms such as Wavelet Packet Tsallis Entropy, and the advanced DAE using Jaya Optimization and SoftMax regression were used in making the classification. The approach offered better results in the classification of healthy and unhealthy brain MRI pictures.

The architecture that trained and tested their DAE-based classification model was also exemplified by Zahoor et al. (2024). The pre-processing, the segmentation and the feature extracting were included in the training stage and the classification of MRI brain images into the simplified and the complex tumor groups was performed in the test stage using the trained classifier. They had modular designs to enhance the system classification and their computation.

Muis et al. (2024) suggested a heterogeneous model that used Particle Swarm Optimization Support (PSO), Local Binary Pattern (LBP), and Capsule Networks. To remove skull, Brain Surface Extraction was conducted, and feature extraction was carried out by LBP and feature selection by Genetic Algorithm. Capsule Network was also used to achieve efficient and accurate detection of brain tumors using fine-tuned Capsule Network to classify it.

The study of Iftikhar et al. (2025) was developed to solve the problem of detecting IDH1 alterations in the Glioma using a data augmentation model that uses Pairwise Generative Adversarial Network (GAN). The expansion of the training data with the help of GAN enhanced tumor classification. This model applied post-processing at the patient. Moreover, it performed better at the detection of IDH1 mutation than traditional methods, particularly when only a small amount of training data was available.

In Fuzzy Brain-Storm Optimization (FBSO) algorithm introduced by Rahman et al. (2024), a hybrid of fuzzy logic and swarm intelligence, brain tumor classification is presented. BSO created several solutions, and the best solution was found by iteration. FBSO strategy yielded better results than the classical algorithms of optimization and provided high-precision and accurate classification of the tumors.

Nancy and Maheswari (2025), Naive Bayes Classifier was used in early brain tumor detection and it used image reduction and segmentation. The steps deployed in preprocessing included Wiener filtering and morphological processing, hence expelling noise. The Legendary Level Sets Algorithm was used to extract features. The last category was extremely categorical; it was used to define tumor and non-tumor images according to their image density characteristics.

Kale and Gadicha (2025) have supplied a model to detect signs of endometrial cancer at an early stage via using Gaussian Mixture Models and CNNs. CT scan images in TCIA dataset were preprocessed and thresholding was applied in detecting cancer regions. This model was called FISHMAN and assisted in evaluating tumor growth and shrinkage so that early management and planning of interventions could be carried out. The results demonstrated the efficiency of the proposed system in the diagnostic procedure against cancer.

A CNN-based model, namely Covid-Segnet proposed by Khan & Auvee (2024), contains Feature Variation as well as PASPP blocks to localize regions of lungs infected with COVID-19. The encoder -decoder model divided 3D lung images with high accuracy by locating diseased tissue. The application of FV and PASPP patches improved the capability of the network in capturing fine-grained features. The model was effective when used to visualize the areas of infection on CT scans.

Disci et al. (2025) achieved an automated deep learning framework to segment Glioma by a triple pathway CNN framework. The remarkably autonomous building anticipated entire tumor (WT), tumor main (TC) and increasing tumor (ET) areas. The model was also tested on BraTS2018 dataset, and the model showed high dice scores on all of the tumor types. This modular design enhanced the accuracy of segmentation by quite a large margin.

Ganapathy et al. (2024) introduced a dual path-based convolution-deconvolution network, which has micro and large kernels in order to learn various features of brain MRIs. Segmentation was done through down sampling and up sampling, and a pixel-wise classification was done. It was trained on BRATS datasets getting accurate tumor region detection using the model. Effective pixel labeling was facilitated using the SoftMax classification.

2 Proposed Methodology

The research suggests a diagnostic system developed using smart healthcare Brain Tumor Classifier to effectively classify brain tumors with the help of MRI images. The model employs the potential of Convolutional Neural Networks and the Internet of medical Things (IoMT) in order to enable remote, in-time healthcare diagnosis. The architecture is categorized into two main phases; these are the Training Phase and the Validation Phase. The general workflow guarantees lifelong learning, distributed diagnostics, and effective tumor classification. The following Figure 1 shows the entire structure of the proposed Brain Tumor Classifier Model.

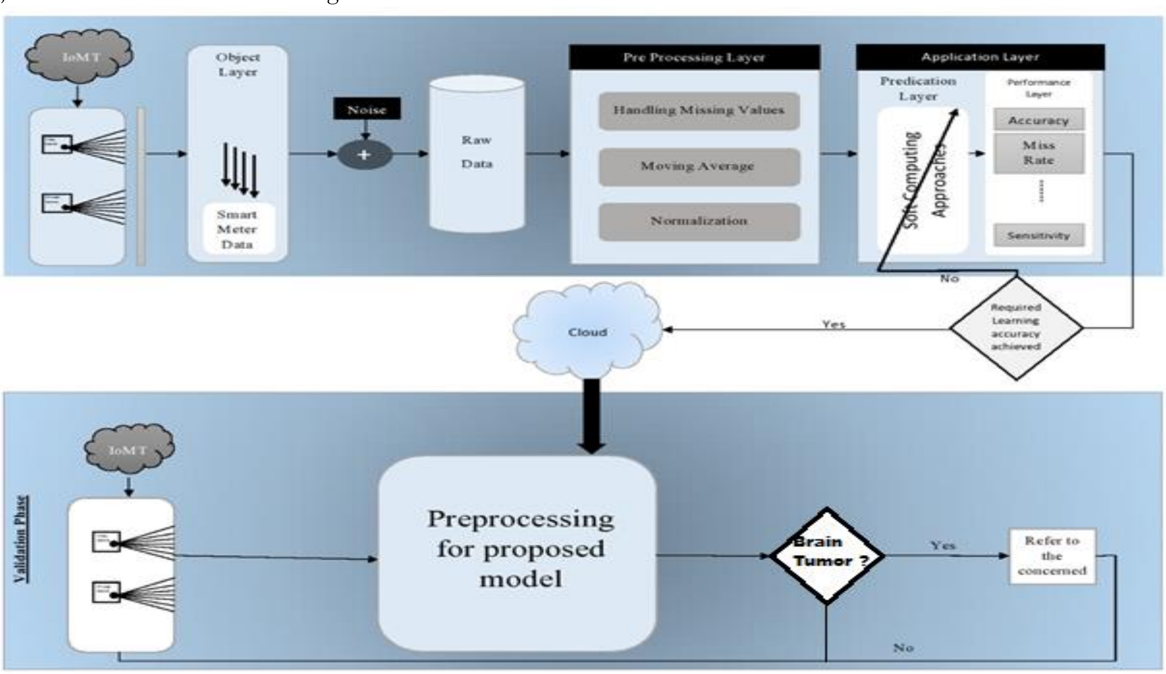

Figure 1: Architecture of the Proposed Brain Tumor Classifier Using Convolutional Neural Network

3.1 Data Acquisition via IoMT
The data must be obtained with the help of IoMT enabled devices. MRI brain images are gathered on a real time basis and projected to the system. Such images are provided as raw data to be further processed. Data Acquisition Layer will support data of quality and compatibility with connected healthcare devices [27].

3.2 Preprocessing
Preprocessing is applied to incoming MRI images and comprises standardization and size normalization. The action makes data more ready to be used in CNN since image intensity is more consistent, and the researcher can also specify consistent dimensions. Learning becomes efficient.

3.3 CNN-Based Feature Extraction
Convolutional Neural Network is applied to deep features learned by the processing of preprocessed images. CNN is made up of several layers:
- Convolutional Layers: They use learnable spatial features using filters.
- ReLU Activation: This introduces non-linearity to look at complicated patterns.
- Pooling Layers: A down sampling is applied (mainly max pooling) to keep the dimensionality low and to prevent over modeling.

These layers allow automatic hierarchical learning of image features like edges, textures and the rocks of the tumor.

3.4 Classification using Fully Connected Layers
Features maps obtained through pooling are flattened into a single vector and connected to fully connected (FC) layers. An Artificial Neural Network (ANN) module is finally connected to the output stage and is used to classify the input as one of the four that are: There is no Tumor, Glioma, Meningioma and Pituitary Tumor
The classification layer provides the probability distribution of classes of possible classes and the output with the highest confidence as the answer of classifying the type of tumor.

3.5 Evaluation and Retraining
An Evaluation Layer judges the performance of a model based upon measures such as accuracy and miss rate. When the performance is unsatisfactory across a certain specified level, the model is automatically retrained against the backpropagation and optimization parameters in a bid to enhance the learning and generalization.

3.6 Cloud Storage and Validation
After training, the model can be saved in a cloud server and used later during the inference process. The validation phase involves acquiring and preprocessing the new MRI images in the same acquisition and preprocessing pipeline. The set of new inputs is then classified with the help of the saved CNN model that is retrieved through the cloud.

3 Results and Simulation
The hierarchical deep learning model dealing with the diagnosis of brain tumors based on the Convolutional Neural Network (CNN) algorithm was implemented and tested to evaluate its possibilities in the field of brain tumors intelligent detection and classification. The proposed Smart Healthcare system, based on CNN, will recognize and classify types of brain tumors with a very high degree of precision, thus helping to make tests and plans in the process of early diagnosis. This work was based on a dataset that has been taken as a part of [16] taking into account four different classes, one of them labelling the No-tumor cases and other three labelling the type of tumor, namely, Glioma, Meningioma and Pituitary tumors.
The model incorporated three thousand and twenty-six images of MRI, and these were allocated as such: 926 images of Glioma, 937 images of Meningioma, 901 images of the Pituitary tumour, and five hundred images of the No-tumor category. The hierarchy Deep learning proposed structure works in two main levels that is the training stage and the validation stage. In the part of the training work, 87 percent of images in each class were chosen randomly to train the CNN, whereas 13 percent of the images were saved to be used in validating the model and measuring the model generalization abilities.
To check the model performance, there are parameters like Accuracy (ACC), Miss Rate (MR), etc. which were computed. These figures give us an

idea of how effective the model in the proper classification of brain tumors is and reducing false negatives, which is vital in clinical practice. Hierarchy of the model, in addition to boosting the accuracy in classification, makes it more robust in terms of feature extraction and decision-making processes both successively.

$$\mathrm{M}_R = \frac{\left({}^{\epsilon_{\eta c}}/_{c} + {}^{\epsilon_{c}}/_{\eta c}\right)}{c+\eta c} \times 100$$

$$\mathrm{A}_{cc} = \frac{\left({}^{\epsilon_{c}}/_{c} + {}^{\epsilon_{\eta c}}/_{\eta c}\right)}{c+\eta c} \times 100$$

The smart brain tumor identification model that has been proposed groups the incoming information into four unique classes including No-tumor, Glioma, Meningioma, and Pituitary tumor. The input matrix of the brain tumor classifier is shown in Table 1 specifying the number of images by each category. There were a total of 3,264 MRI images that were used in training and validation so that sufficient training in evaluating the model performance was achieved.

All the data, 2,870 images or 87 percent of the total input were assigned to the training process so that they can teach it to identify patterns within each type of tumor and healthy brain images. The rest of the data (1303-394=909 = 13%) was selected to be used during the validation stage, whose role would be to evaluate the generalization capabilities of the model used, and how well unseen data could be classified by the model.

The data will also be stratified to arrive at the following class-wise distribution namely 926 images of Glioma tumors, 937 of Meningioma, 500 images of the No-tumor category and 901 images of Pituitary tumors. This is representative and varied data so that the model can imbibe discriminating features of every class which improves the accuracy and reliability of the model in clinical practice.

Table 1: Input Data Distribution for the Proposed Brain Tumor Classifier

Number of Input Images	Glioma	Meningioma	No Tumor	Pituitary
Training Phase	826	822	395	827
Validation Phase	100	115	105	74
Total Inputs	926	937	500	901

826 MRI images were also used to train the classifier in predicting the Glioma tumors accurately. Such pictures will be taken at different angles to improve the ability of the model to learn as well as guarantee successful feature extraction under different visual aspects. This difference in input data enhances the generalization and accuracy of detecting the model to a great extent.

The classifier accurately classified 780 Glioma of the 826 included in the experiment, which shows good results compared to identifying this type of tumor. Nevertheless, 44 Glioma images were labelled as Meningioma, 2 were assigned into No-tumor and, therefore, there is a slight cross-over between the patterns of features within these classes.

Figure 2 shows examples of some representative pictures of the dataset introduced into the training process of the MRI. The examples demonstrate the variability concerning the orientation and structural characteristics, which exist in the Glioma class, which extends the classification effectiveness of the created model.

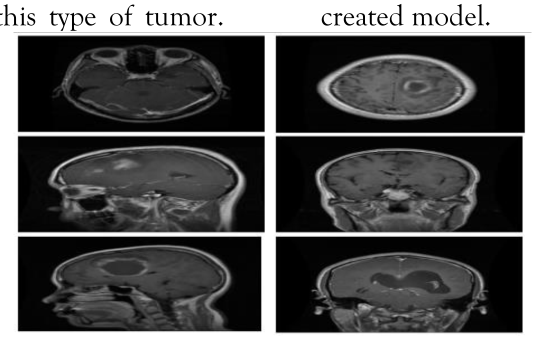

Figure 2: Sample MRI Images Used as Input for Screening

Table 2 indicates the training phase output of predicting the model of Brain Tumor Classifier, which has been trained with 2, 870 MRI images distributed by four classes, i.e. 826 images of Glioma, 822 images of Meningioma, 395 images of No-tumor and 827 images of Pituitary tumor. In Glioma class, exact 780 out of 826 samples were correctly classified and 44 samples were predicted as Meningioma whereas 2 were predicted as No-tumor. As it regards Meningioma, of the 822 images, 779 were classified correctly, but 39 were misclassified as Glioma, and 4 as No-tumor. In the No-tumor class, 375 out of the 395 pictures were precisely identified whereas 18 were incorrectly recognized as Meningioma and 2 as Pituitary. Finally, the model well classified 788 and 39 misclassified in the 827 samples of Pituitary tumor. These values indicate good performance of the classifier in the training regime when a high level of performance and a relatively small percentage of misclassification in all the four classes were observed.

Table 2: Confusion Matrix of the Proposed Brain Tumor Classifier

Decision matrix for suggested Brain Tumor Classifier					
Input Samples = 2870 (87% Training Images)		Output ($\theta_{gl}, \theta_m, \theta_{n.t}, \theta_p$)			
		θ_{gl}	θ_m	$\theta_{n.t}$	θ_p
Input Images	$\gamma_{gl} = 826$	780	44	2	0
	$\gamma_m = 822$	39	779	4	0
	$\gamma_{n.t} = 395$	0	18	375	2
	$\gamma_p = 827$	0	0	39	788

The performance of the proposed Brain Tumor Classifier at the training stage is shown in figure 3 where it shows the accuracy and the miss rate of the four tumors categories. The classification rates were very high when configured as 94 percent in Glioma and 95 percent each in Meningioma, No-tumor and Pituitary class. Accordingly, the Glioma achieved 6 percent misclassification, whereas Meningioma, No-tumor and Pituitary recorded five percent misclassification, which is evidence of minimal misclassification instances during training. These findings indicate that the model has a high potential to generalize over unique features of the training data, hence good value and accuracy in classifying tumors. The high level of accuracy in each of the classes shows the capabilities of a very prominent CNN architecture to deal with the various types of tumors and normal brain images.

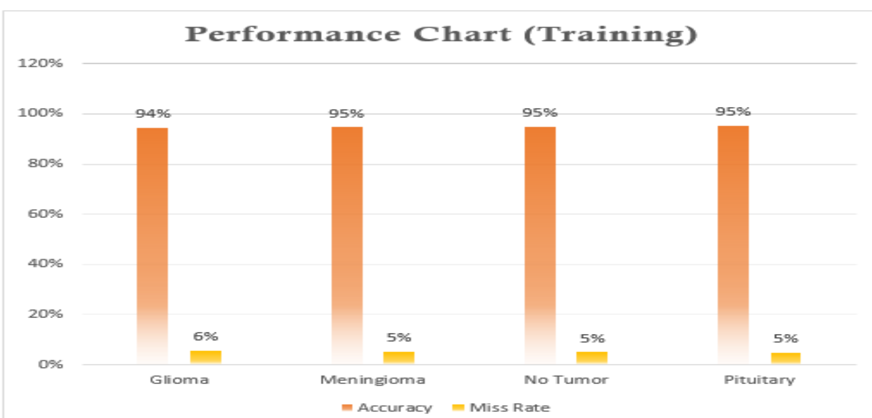

Figure 3: Performance Metrics of the Proposed Brain Tumor Classifier during Training Phase

The results of the validation of the proposed Brain Tumor Classifier were represented in table 3. The total number of images that have been validated using MRI was 394, divided into four groups namely;

100 images of Glioma, 115 images of Meningioma, 105 images of No-tumor and 74 images of Pituitary tumors. In the case of Glioma class, the model represented a score of 92 out of 100 and 8 of the test samples were misclassified as Meningioma. The accuracy in the prediction of the 115 samples in Meningioma was 106, 7 of the samples were predicted as Glioma and the rest 2 as No-tumor. In the case of the No-tumor class, there were 94 out of 105 images correctly classified, among which 9 and 2 were incorrectly classified as Meningioma and Pituitary respectively. Finally, in case of the Pituitary classification, 71 out of 74 images were correctly classified, 3 were wrongly classified as No-tumor. The validation outcomes signify that the classifier has a high predictive precision when applied to unseen data, and this way, it can be considered an appropriate and effective tool in terms of generalization potential to distinguish among various types of brain tumors and healthy ones.

Table 3: Confusion Matrix of the Brain Tumor Classifier during Validation Phase

Decision matrix for suggested Brain Tumor Classifier					
Input Samples = 394 (13% Validation Images)		Output ($\theta_{gl}, \theta_m, \theta_{n.t}, \theta_p$)			
		θ_{gl}	θ_m	$\theta_{n.t}$	θ_p
Input Images	$\gamma_{gl} = 100$	92	08	0	0
	$\gamma_m = 115$	07	106	2	0
	$\gamma_{n.t} = 105$	0	9	94	2
	$\gamma_p = 74$	0	0	3	71

Results on figure 4 show the performance achieved by the presented Brain Tumor Classifier according to the validation stage, accuracy and miss rate of each of the tumor categories. Accuracy scores of the model in Glioma and Meningioma were 92%, 90% of No-tumor and 96% of Pituitary tumors. Accordingly, Glioma and Meningioma that made up 8%, No-tumor that was 10%, and Pituitary that was 4% were also the misses. Such findings attribute to the high precision, and reliability of this classifier when separating the types of tumors and non-tumorous cases, which represents good generalization to relatively unseen validation data.

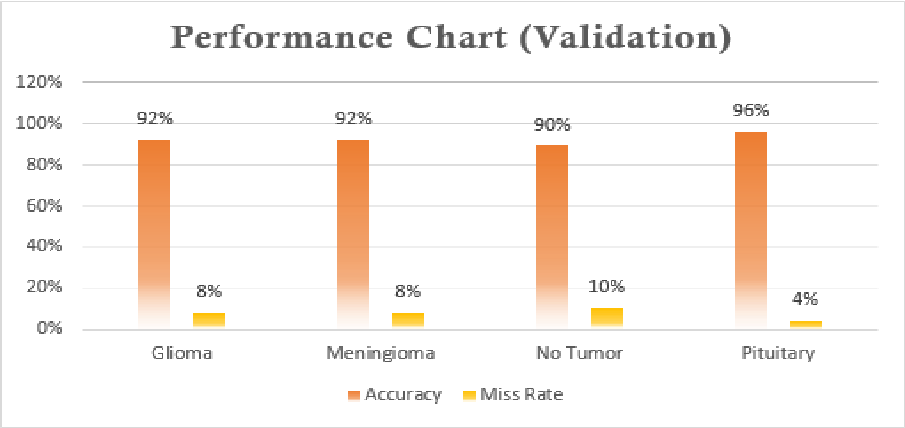

Figure 4: Performance Metrics of the Proposed Brain Tumor Classifier during Validation Phase

The total efficiency of the proposed Brain Tumor Classifier as a summary of its performance during the process of training and during the process of validation. At training stage, the model attained 98.84% accuracy and 1.16% corresponding miss rate implying that the model learns powerfully in regard to the given data. During the validation stage, the classifier had a high accuracy of 96.54% and a miss rate is 3.46%, which indicates good generalization to unseen values. These findings further affirm the validity and soundness of the suggested model towards proper detection and classification of brain tumors.

The proposed Brain Tumor Classifier with higher accuracy is shown comparatively in table 4 with other state-of-the-art algorithms. The model created as part of this research was 96.54 percent accurate, exceeding accuracy of models developed by Khan and Auvee (2024), and Zahoor et al. (2024), which stood at 93.8 percent and 95.5 percent, respectively.

Table 4: Performance Comparison of the Proposed Brain Tumor Classifier with Existing Literature

Study / Method	Year	Technique Used	Classification Classes	Accuracy (%)	Remarks
Khan and Auvee	2024	Deep Learning (CNN)	Glioma, Meningioma, Pituitary	93.8	Focused on basic CNN architecture
Zahoor et al.	2024	Hybrid CNN + SVM	Glioma, Meningioma, Pituitary	95.5	Combined CNN features with SVM classifier
Proposed Brain Tumor Classifier	2025	Hierarchical CNN (Deep Learning)	Glioma, Meningioma, Pituitary, No-Tumor	96.54	Introduces hierarchical structure and No-tumor class for enhanced classification accuracy

Such an increase in accuracy proves that the proposed hierarchical deep learning can be utilized to make more accurate brain tumor detection and classification thus justifying its application as a competitive and reliable solution in the facial image analysis domain of the medical field.

5. Conclusion

Brain tumors are one of the deadliest cancerous illnesses that attack the adults and children. The common types of primary brain tumors that happen in the case of adults are Glioma, Meningioma and Pituitary tumors. Many approaches and procedures have been proposed and have been performed in the literature over the years in the aspect of diagnosis and classification of brain tumors to enhance treatment chances and survival measures of the patients. In this paper, it is proposed to develop a Hierarchical Deep Learning based Brain Tumor Classifier with a Convolutional Neural Network. In addition to determining whether a tumor is present, the system can also determine the type of tumor that a patient is facing and give a more accurate and diagnostic observation. Two directions are postulated as future work. The first one is the enhancement in classification performance which might be observed using an implementation of real time clinical data along with the application of the profound learning techniques. Second, the formulation of the mixture of the proposed strategy and the incremental model of learning which will be applicable in better condition with regards to adapting the changing types of the tumor in real-life situations. Furthermore, it may also happen that the structure of the proposed Brain Tumor Classifier might be applicable to diagnosing other types of diseases and classifying them as well, and, therefore, might be extensively applied in the broad sense of medical image analysis.

References

Srinivasan, S., Francis, D., Mathivanan, S. K., Rajadurai, H., Shivahare, B. D., & Shah, M. A. (2024). A hybrid deep CNN model for brain tumor image multi-classification. BMC Medical Imaging, 24(1), 21.

Huda, N., & Ku-Mahamud, K. R. (2025). CNN-Based Image Segmentation Approach in Brain Tumor Classification: A Review. Engineering Proceedings, 84(1), 66.

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(1), 2664.

Asiri, A. A., Shaf, A., Ali, T., Aamir, M., Irfan, M., & Alqahtani, S. (2024). Enhancing brain tumor diagnosis: an optimized CNN hyperparameter model for improved accuracy and reliability. PeerJ Computer Science, 10, e1878.

Khan, S. U. R., Asif, S., Bilal, O., & Rehman, H. U. (2025). Lead-cnn: lightweight enhanced dimension reduction convolutional neural network for brain tumor classification. International Journal of Machine Learning and Cybernetics, 1-20.

Gupta, B. B., Gaurav, A., & Arya, V. (2024). Deep CNN based brain tumor detection in intelligent systems. International Journal of Intelligent Networks, 5, 30-37.

Nazir, M. I., Akter, A., Wadud, M. A. H., & Uddin, M. A. (2024). Utilizing customized CNN for brain tumor prediction with explainable AI. Heliyon, 10(20).

Shoaib, M. R., Zhao, J., Emara, H. M., Mubarak, A. S., Omer, O. A., Abd El-Samie, F. E., & Esmaiel, H. (2025). Improving brain tumor classification: An approach integrating pre-trained CNN models and machine learning algorithms. Heliyon, 11(10).

Akter, A., Nosheen, N., Ahmed, S., Hossain, M., Yousuf, M. A., Almoyad, M. A. A., ... & Moni, M. A. (2024). Robust clinical applicable CNN and U-Net based algorithm for MRI classification and segmentation for brain tumor. Expert Systems with Applications, 238, 122347.

Ye, J., Zhao, Z., Ghafourian, E., Tajally, A., Alkhazaleh, H. A., & Lee, S. (2024). Optimizing the topology of convolutional neural network (CNN) and artificial neural network (ANN) for brain tumor diagnosis (BTD) through MRIs. Heliyon, 10(16).

Liu, Y., Ma, Y., Zhu, Z., Cheng, J., & Chen, X. (2024). TransSea: hybrid CNN-transformer with semantic awareness for 3D brain tumor segmentation. IEEE Transactions on Instrumentation and Measurement.

Ramakrishnan, A. B., Sridevi, M., Vasudevan, S. K., Manikandan, R., & Gandomi, A. H. (2024). Optimizing brain tumor classification with hybrid CNN architecture: Balancing accuracy and efficiency through oneAPI optimization. Informatics in Medicine Unlocked, 44, 101436.

Sudhakar, B., Sikrant, P. A., Prasad, M. L., Latha, S. B., Kumar, G. R., Sarika, S., & Shaker Reddy, P. C. (2024). Brain Tumor Image Prediction from MR Images Using CNN Based Deep Learning Networks. Journal of Information Technology Management, 16(1), 44-60.

Rasool, N., Wani, N. A., Bhat, J. I., Saharan, S., Sharma, V. K., Alsulami, B. S., ... & Lytras, M. D. (2025). CNN-TumorNet: leveraging explainability in deep learning for precise brain tumor diagnosis on MRI images. Frontiers in Oncology, 15, 1554559.

Dutta, T. K., Nayak, D. R., & Zhang, Y. D. (2024). Arm-net: Attention-guided residual multiscale cnn for multiclass brain tumor classification using mr images. Biomedical Signal Processing and Control, 87, 105421.

Saeed, T., Khan, M. A., Hamza, A., Shabaz, M., Khan, W. Z., Alhayan, F., ... & Baili, J. (2024). Neuro-XAI: Explainable deep learning framework based on deeplabV3+ and bayesian optimization for segmentation and classification of brain tumor in MRI scans. Journal of Neuroscience Methods, 410, 110247.

Sajol, M. S. I., & Hasan, A. J. (2024, August). Benchmarking cnn and cutting-edge transformer models for brain tumor classification through transfer learning. In 2024 IEEE 12th International Conference on Intelligent Systems (IS) (pp. 1-6). IEEE.

Zahoor, M. M., Khan, S. H., Alahmadi, T. J., Alsahfi, T., Mazroa, A. S. A., Sakr, H. A., ... & Alshemaimri, B. K. (2024). Brain tumor MRI classification using a novel deep residual and regional CNN. Biomedicines, 12(7), 1395.

Muis, A., Sunardi, S., & Yudhana, A. (2024). Cnn-based approach for enhancing brain tumor image classification accuracy. Int. J. Eng, 37(5), 984-996.

Iftikhar, S., Anjum, N., Siddiqui, A. B., Ur Rehman, M., & Ramzan, N. (2025). Explainable CNN for brain tumor detection and classification through XAI based key features identification. Brain Informatics, 12(1), 10.

Rahman, M. A., Masum, M. I., Hasib, K. M., Mridha, M. F., Alfarhood, S., Safran, M., & Che, D. (2024). GliomaCNN: An Effective Lightweight CNN Model in Assessment of Classifying Brain Tumor from Magnetic Resonance Images Using Explainable AI. CMES-Computer Modeling in Engineering & Sciences, 140(3).

Nancy, A. M., & Maheswari, R. (2025). Brain tumor segmentation and classification using transfer learning based CNN model with model agnostic concept interpretation. Multimedia Tools and Applications, 84(5), 2509-2538.

Kale, P. V., & Gadicha, A. B. (2024, February). Deep CNN-based MRI imaging for brain tumor detection and classification. In 2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS) (pp. 1-6). IEEE.

Khan, M. A., & Auvee, R. B. Z. (2024, December). Comparative Analysis of Resource-Efficient CNN Architectures for Brain Tumor Classification. In 2024 27th International Conference on Computer and Information Technology (ICCIT) (pp. 639-644). IEEE.

Disci, R., Gurcan, F., & Soylu, A. (2025). Advanced Brain Tumor Classification in MR Images Using Transfer Learning and Pre-Trained Deep CNN Models. Cancers, 17(1), 121.

Ganapathy, S., Thoidingjam, V., & Sen, A. (2024). A brain tumor prediction system for detecting the tumor disease using mini batch K-Means clustering and CNN. Multimedia Tools and Applications, 83(35), 83053-83091.

https://www.kaggle.com/sartajbhuvaji/brain-tumor-classification-mri.