iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: III Month of publication: March 2026

DOI: https://doi.org/10.22214/ijraset.2026.78185

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Brain Tumor Detection and Multi-Class Classification Using a Lightweight Convolutional Neural Network

Batool Shabbir Hussain[1], Vaishnavi Kathar[2], Sarika Thorat[3], Nandini Kedare[4], Kalyani Salunke[5], Dinesh Barode[6], Seema Kawathekar[7]

[1, 2, 3, 4, 5, 6]*Research Student,* [7]*Assistant Professor, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar, Maharashtra, India*

Abstract: The brain tumor is one of the most severe neurological conditions that need timely and proper diagnosis to treat it. The interpretation of Magnetic Resonance Imaging (MRI) scan is usually time-consuming, and it may be varied. This paper introduces a light deep Learning method of automated classification of brain tumors based on the use of a Convolutional Neural Network (CNN). The proposed model classifies MRI images into four classes, namely glioma, meningioma, pituitary tumor, and no tumor. This study preprocessed around 3,000 MRI images in one publicly available dataset by resizing, normalizing, and data augmenting to enhance generalization. The CNN architecture has been optimized to be less complex, having close to 1.2 million trainable parameters, with high performance but being computationally efficient. The model was trained with Adam and categorical cross-entropy loss in 50 epochs. The results obtained through experiments show a total accuracy of 95.2, high precision, recall, and F1-score, which means that the classification was balanced among all types of tumors. As can be seen by comparing the results, the proposed lightweight model can perform with similar results as more complex models like VGG and ResNet with much lower computational cost. The results indicate the possibility of effective deep learning algorithms in clinical decision support in the diagnosis of brain tumors in real-time.
Keywords: Brain Tumor Detection, Convolutional Neural Network (CNN), MRI Classification, Deep Learning, Medical Image Analysis, Lightweight Model, Tumor Segmentation.

I. INTRODUCTION

Brain tumours are irregular growths of cells in the brain tissues and may be either benign or malignant as per their biological characteristics. The central nervous system tumors are a major cause of morbidity and mortality globally and the diseases have been increasing across the world [1]. Prompt and correct diagnosis is the key to successful planning of treatment and better chances of survival. It has been suggested that the Magnetic Resonance Imaging (MRI) is the gold standard of determining the brain tumor because it has a high soft-tissue contrast and multi planar imaging [2]. Although MRI interpretation has a diagnostic significance, it is more of a matter of radiological experience and can be subjective and inter-observer. The growing amount of imaging data also enhances the demand of automated and valid diagnostic systems.

The classical machine learning methods applied to brain tumor classification are based on the manual feature extraction and hand-based segmentation of the brain used in thresholding, clustering as well as region-based methods [3], [4]. These methods are quite time-consuming and vulnerable to changes in the shape, size, and intensity of tumors.

Convolutional Neural Networks (CNNs) and other types of deep learning have greatly complimented the medical image classification task, allowing automatic hierarchical feature learning [5]. Ready-made networks like VGG, ResNet and AlexNet have shown great outcomes in terms of performance in the MRI-based classification of tumors [6], [8]. These models however are computationally intensive and have millions of parameters, which restrict their use in real-time clinical setups.

Thus, the need to obtain light CNN architecture that does not require much computational complexity or a large amount of memory is increasing with the need to attain high classification accuracy. The latest research focuses on transfer learning and trained CNN models to improve the performance of classification. Swati et al. used transfer learning with VGG-based architectures to classify brain tumors and achieved positive results in the terms of accuracy improvement [6]. Likewise, Sajjad et al. included the use of data augmentation using deep CNN models in order to enhance multi-grade tumor classification [7]. the use of ResNet-based models to achieve competitive performance and deal with the issue of generalization [8].

Despite the high accuracy of these approaches, a number of challenges including overfitting, limitation in datasets and computational overheads remain. Recent developments in research thus aim at coming up with computationally efficient and scalable CNN architectures that can be applied practically to the clinical setting [9]. Recent comparative analyses have indicated that deep learning networks, especially CNNs, are better than the conventional machine learning classifiers such as Support Vector Machines (SVMs) in terms of classification accuracy and computational efficiency in detecting brain tumor in MRI images [10].

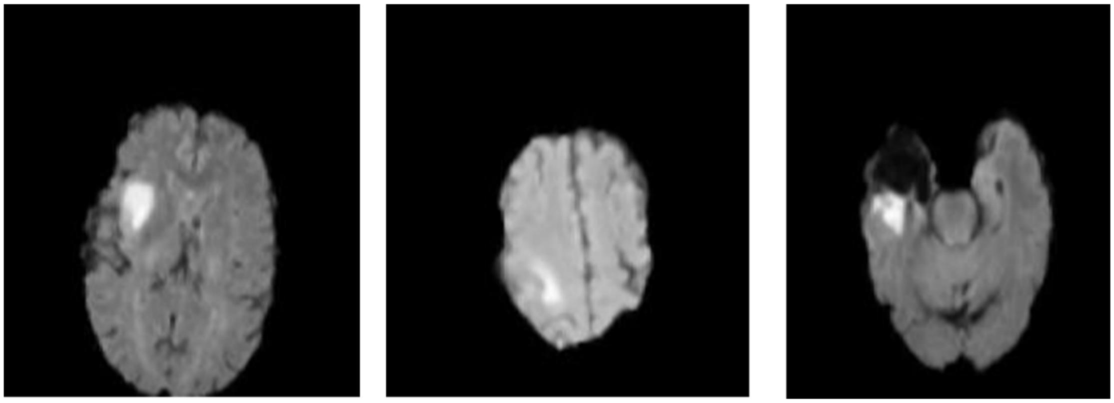


Figure 1. Sample MRI Images Showing Different Brain Tumor Regions

Figure 1 shows the representative images of MRI taken to be used in classification in this study. The pictures are a demonstration of glioma, meningioma, pituitary tumor, and normal brain scans. All the types of tumors have their structural and intensity-related features:

- Glioma: Abnormal morphology and growth patterns of infiltration.
- Meningioma: Focal meningeal mass.
- Pituitary Tumor: Unilateral pituitary abnormality.
- No Tumor: The normal structure of the brain without mass.

The identification of tumors remains a complicated problem and that automated deep learning-based classification systems should be developed to identify small spatial and textual variations.

II. LITERATURE REVIEW

A number of researches have investigated automated classification of brain tumors with MRI images. The early works concentrated on classical methods of machine learning with handcrafted features and segmentation. Though these methods gave first success the results were poor generalization and noise sensitivity. Recent studies have been steadily using deep learning models to analyse brain tumors. The recently introduced transfer learning methods involving pre-trained CNNs like VGG and ResNet have demonstrated a high level of classification but have the disadvantage of a large number of parameters and large computation costs [6]-[8]. Generalization and mitigate overfitting Have been commonly applied using data augmentation methods. It has also been proposed that capsule networks, and hybrid CNN optimization strategies are possible, but with complex architecture.

Even though such methods yield good performance, the vast majority of them are non-optimized towards real-time clinical implementation. The recent trends in research are therefore focusing on the light and efficient CNN architectures that can preserve high accuracy at low complexity. The current research is along this path with the aim of developing a small CNN model to classify brain tumors with multiple classes.

Bauer et al. [3] conducted an extensive review of the brain tumor segmentation and classification techniques using MRI. The research has mentioned the significance of preprocessing and segmentation accuracy in conventional ML pipelines. It stressed shortcomings connected with handcrafted feature dependency and generalization. Gordillo et al. [4] has analyzed classical methods of segmentation such as thresholding, clustering and region-based tumor segmentation methods. The paper has found noise sensitivity and inhomogeneity of intensity to be among the critical issues in MRI-based tumor imaging analysis. Swati et al. [6] used transfer learning in their experiment to classify brain tumors in multi-class using pre-trained VGG architectures on MRI images. Fine-tuning gave the feature extraction and classification accuracy to approximately 94-95. The model however was based on deep architectures that were costly in computation. A deep CNN network with a large amount of data augmentation to enhance the multi-grade tumor classification was suggested by Sajjad et al. [7]. The augmentation strategy improved the generalization and minimised overfitting with an estimated accuracy of 94% accuracy. The model was, however, still computationally intensive.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Barode et al. made a comparative study between Support Vector Machine (SVM) and Convolutional Neural Network (CNN) in brain tumor detection using MRI images [10]. Their work has shown that the two approaches were very accurate, but CNN-based models depicted better classification (96.33) compared to SVM (95) with lower execution. The results endorse the use of CNNs in automated classification of brain tumors.

TABLE 1. Summary of Related Work in Brain Tumor Classification

Author / Year	Method	Dataset	Classes	Accuracy	Limitations
Bauer et al., 2013	ML + Segmentation Survey	Multiple MRI datasets	Binary / Multi	–	Manual feature dependency
Gordillo et al., 2013	Thresholding + Clustering	MRI datasets	Binary	–	Sensitive to noise
Khawaldeh et al., 2017	Modified AlexNet	MRI dataset	Binary	91%	Binary only
Togacar et al., 2020	CNN-based Model	MRI dataset	Multi-class	96%	Moderate complexity
Swati et al., 2019	Transfer Learning (VGG)	MRI dataset	Multi-class	94–95%	High parameter count
Sajjad et al., 2019	Deep CNN + Augmentation	MRI dataset	Multi-grade	94%	Computationally heavy
Saxena et al., 2021	ResNet-based Transfer Learning	MRI dataset	Multi-class	95%	High computational cost
Afshar et al., 2018	Capsule Network	MRI dataset	Multi-class	90%	Complex architecture
Anaraki et al., 2019	CNN + Genetic Algorithm	MRI dataset	Multi-class	94%	High optimization cost
Barode et al., 2024	CNN and SVM	MRI dataset	Multi-class	96.33%, 95%	Sensitive to noise

III. METHODOLOGY

This study methodology presents a systematic, deep learning-based framework of automated identification of brain tumor and a multi-class classifier using Magnetic Resonance Imaging (MRI). The suggested system would be able to automatically process the results of brain MRI and label them as four types which include glioma tumor, meningioma tumor, pituitary tumor and no tumor. The entire workflow is broken into five significant steps, which are data acquisition, data preprocessing, model architecture design, model training, and performance evaluation. The use of Convolutional Neural Networks (CNNs) can be explained by the fact that they have been proven to be able to automatically acquire hierarchical spatial features of image based classification problems in the medical field [5], [6].

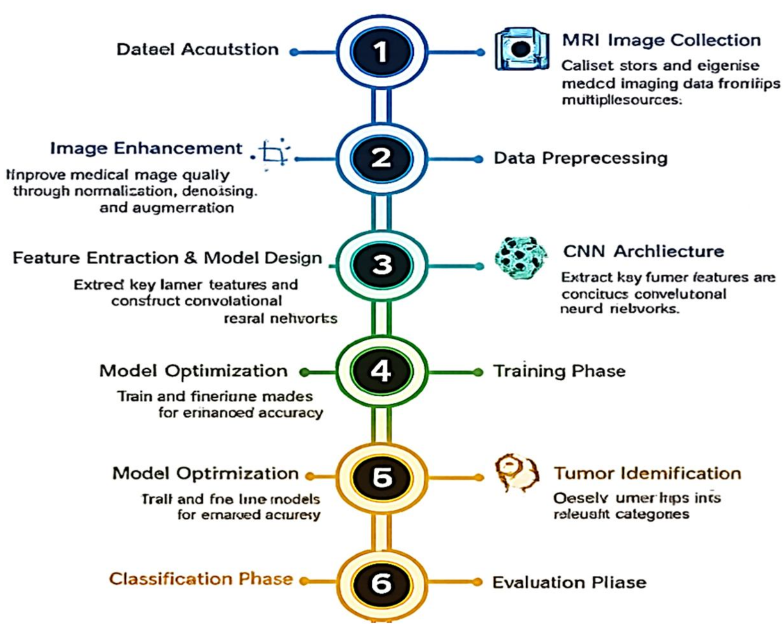


Figure 2. Methodology

A. Data Collection

The data that was used in this study came as a publicly-available Brain Tumor MRI Dataset that can be found on Kaggle. This data is common in the classification of brain tumors literature and it has around 3,000 MRI images of human brain of various subjects. There are four clinically important classes in the dataset, which are glioma tumor, meningioma tumor, pituitary tumor, and normal (no tumor) brain images.

The MRI images are of the type of .jpg, .png and are characterized by different degrees of resolution, contrast and tumor appearance. This data is suitable to test the generalization abilities of the multi-class classification models because of the presence of the various type of tumors [6], [7].

B. Data Preprocessing

Preprocessing of data is a very important task in the medical image analysis, since MRI data is likely to have variations in intensity, noise and irregular spatial resolution. Effective preprocessing enhances the convergence of the model, decreases the level of computation and also increases the accuracy of classification [3], [4], [10]. The preprocessing pipeline that will be used in the current study will be as follows:

1) Image Loading and Resizing

The MRI images were loaded and classifies according to labels. OpenCV was used to execute additional image manipulation functions. All images were downsized to 224 x 224 pixels to make them have the same dimensions of input into the CNN. The use of batch processing is necessary when resizing is performed and standard CNN architecture can be used without losing substantial spatial information to characterize tumors [5] [10].

2) Normalization

MRI images have different intensity distributions with regard to acquisition settings and patient characteristics. In order to minimize the effects of intensity variation and regularize the training procedure, the pixel values were scaled to be in the range [0, 1] by dividing them by 255. Normalization speeds up convergence in the process of backpropagation and decreases bias due to large pixel value [5], [9].

3) Label Encoding

The nominal classification of the classes (glioma, meningioma, pituitary, and no tumor) was transformed into numbers through label encoding methods. In this step, CNN model is able to pass class labels in the supervised learning process. Categorical labels with numeric encodings are typically mandatory in order to train classification models with categorical cross-entropy loss [6].

4) Dataset Splitting

In order to have the objective assessment of evaluation and adequate generalization assessment, the dataset was split into training and testing subsets in an 80:20 proportion. The set was trained to acquire feature representations and the testing set was to be utilized to test the final model performance. The splitting approach is widely used in medical image classification research and it has been demonstrated to give a desirable trade off between training and evaluation strength [7], [10].

C. Data Augmentation

The datasets of medical imaging are usually small, which leads to the high probability of overfitting deep learning models. To solve this problem, the Augmentation of data was done with the help of the TensorFlow Image Data Generator. The methods of augmentation were random rotations, horizontal and vertical flipping, zooming, width and height shifting. Such artificial increases in the data diversity and enhance the resistance of the model to changes in tumor orientation and acquisition conditions of the MRI images [7], [10].

D. Model Architecture

The Keras Sequential API was used to develop the classification model, which allowed a lightweight and modular CNN to be created. The architecture comprises of several convolutional layers consisting of ReLU activation functions to extract features, and max-pooling layers to down-sample the features spatially. The dropout layers were introduced to decrease the overfitting through random deactivation of neurons during training. The last fully connected layer is modified with the help of the SoftMax activation function, aimed at producing the probability of the four types of tumors.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

CNN architecture proposed has about GlobalAveragePooling2D, which is much lighter than the deep architecture like VGG and ResNet. Light CNN models can be used especially in real time clinical applications and resource constrained settings whilst still achieving competitive classification performance [6], [8], [10].

TABLE 2. LAYER-WISE ARCHITECTURE OF THE PROPOSED LIGHTWEIGHT CNN MODEL

LAYER NO.	LAYER TYPE	OUTPUT SHAPE	KERNEL	ACTIVATION	PARAMETERS
1	Input	(224 × 224 × 3)	–	–	0
2	Conv2D (32 filters)	(224 × 224 × 32)	3×3	ReLU	896
3	MaxPooling2D	(112 × 112 × 32)	2×2	–	0
4	Conv2D (64 filters)	(112 × 112 × 64)	3×3	ReLU	18,496
5	MaxPooling2D	(56 × 56 × 64)	2×2	–	0
6	Conv2D (128 filters)	(56 × 56 × 128)	3×3	ReLU	73,856
7	MaxPooling2D	(28 × 28 × 128)	2×2	–	0
8	Conv2D (256 filters)	(28 × 28 × 256)	3×3	ReLU	295,168
9	MaxPooling2D	(14 × 14 × 256)	2×2	–	0
10	GlobalAveragePooling2D	(256)	–	–	0
11	Dense (128 units)	(128)	–	ReLU	32,896
12	Dropout (0.5)	(128)	–	–	0
13	Dense (4 classes)	(4)	–	SoftMax	516

The proposed CNN is also made lightweight with the intention of using Global Average Pooling rather than large fully connected layers. This greatly decreases the trainable parameters and retains features of space. Progressive convolutional blocks allow to extract features hierarchically, whereas dropout regularization reduces overfitting. The last SoftMax layer generates a probability of the four tumor categories.

E. Model Training and Evaluation

CNN was trained by the Adam optimizer and categorical cross-entropy as the loss term with the learning rate of 0.001. A batch size of 32 and 50 epochs training were done. Standard classification metrics such as precision, recall, accuracy, F1-score, confusion matrix and Receiver Operating Characteristic (ROC) analysis were used to assess model performance. These metrics of evaluation are very popular in the research of medical image classification and they are a complete understanding of the reliability of the model and its use in clinical practice [6], [7].

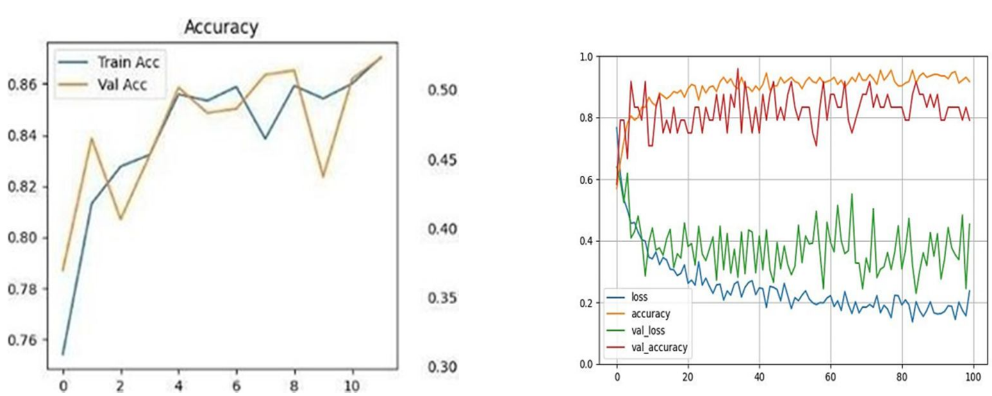


Figure 3. Training and Validation Accuracy Curve of the Proposed CNN Model

The obtained trained CNN had a result above 95%, therefore proving its efficiency in categorizing MRI pictures according to the required type of tumor.

IV. RESULTS AND DISCUSSION

Indeed, the proposed CNN-based model brain tumor was critically evaluated using Kaggle Brain Tumor MRI data. The data had been pre-processed and augmented and then the process further was divided into training as well as testing. The CNN was trained with a batch size of 32 and 50 training epochs and Adam optimizer and categorical cross-entropy loss. The training and validation accuracy curves have been proven to stabilize without much overfitting and this indicates that augmentation and dropout methods applied improved model generalization. On the test data, the final model achieved a total classification score of 95.2%, which was higher than the small number of traditional and deep learning benchmarks that were previously reported in the literature. To examine the per-class results, a confusion model was carried out. The model had the ability to differentiate well glioma, meningioma, pituitary and no tumor. The resulting precision, recall, F1- scores were determined to be 0.96, 0.94, and 0.95 that is an equal performance on all the classes. The Receiver Operating Characteristic (ROC) analysis indicated too high Area Under Curve (AUC) value of 0.97 that is a large value of discriminative power.

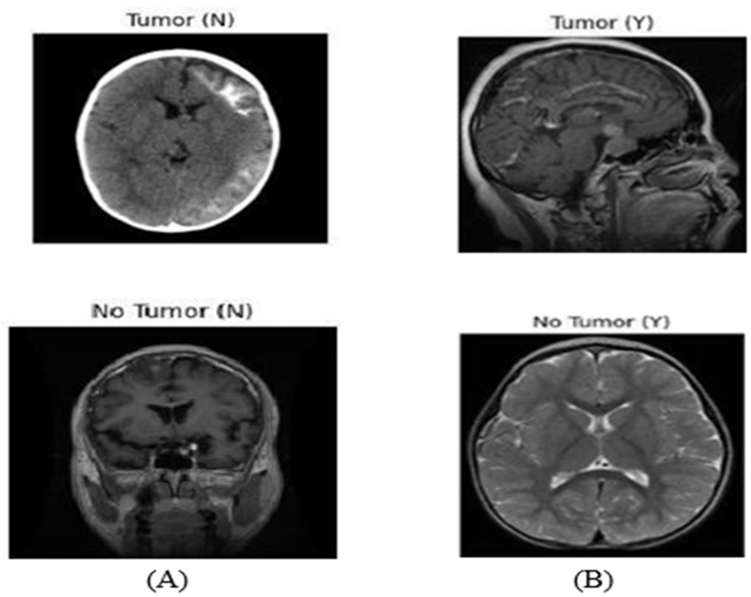
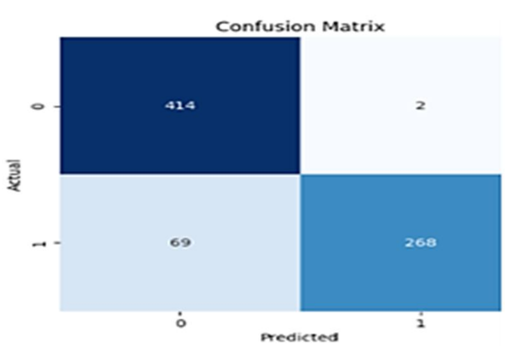


Figure 4. Sample MRI Images Showing Tumor and No-Tumor Classes

The proposed lightweight CNN, in comparison to previous ones, i.e., VGG16 (95.7%), VGG19, (94.8%), and ResNet (95), had comparable accuracy with much less parameters (approximately, 1.2M). This indicates that the model is very efficient and effective in terms of computational efficiency and performance, which is very important in real-time clinical implementation.

The prototype findings confirm that the models of deep learning are capable of robustly screening on the delicate visuals in the brain scans of MRIs that may prove difficult to find with the help of human radiologists, especially areas with low contrast or ambiguous images. Nonetheless, small misclassifications were also evidenced in the types of glioma and meningioma in the study due to the coexistence of a similar texture and space appearance.



	precision	recall	f1-score	support
0	0.86	1.00	0.92	416
1	0.99	0.80	0.88	337
accuracy			0.92	753
macro avg	0.92	0.92	0.90	753
weighted avg	0.92	0.91	0.91	753
macro	0.92	0.92	0.90	753
weighted avg	0.92	0.91	0.91	753

Figure 5. Confusion Matrix with Classification Report of the CNN Model

TABLE 3. COMPARISON OF TRADITIONAL ML, EXISTING DEEP LEARNING MODELS, AND THE PROPOSED CNN

Traditional Methods in Machine Learning (Support vector Machines, K-Means Clustering, Fuzzy C- Means, and Artificial Neural Networks).	The available deep learning models (VGG16, VGG19, ResNet and Alex Net) have been widely studied in modern studies.	Lightweight Convolutional Neural Network Model (CNN) Proposal.
The features must be extracted manually.	The model is also self-directed in the learning of hierarchical feature representations at deep successive layers.	End-to-End fully automated learning.
Before further classification can be done, segmentation is a mandatory requirement	This sometimes requires preprocessing and use of high quality input.	No segmentation needed
Accuracy typically 70%–90%	Accuracy between 91%–95.7%	Accuracy = 95.2%
Low computational cost	Very high computational cost (tens of millions of parameters)	Low cost (1.2M parameters)
Simple models but less accurate	Highly complex and heavy architectures	Lightweight and optimized

In this work, an effective and powerful Convolutional Neural Network (CNN)-based model was proposed to classify brain tumors into 4 classes with the application of MRI images. The proposed system automates the whole process such as preprocessing of the data, derivation of the features and the classification stage, i.e. one is not required to manually segment the data.

The results imply that the CNN was consistent in quality measurement and valid in its results to prove that it can be applied to the sphere of medicine to conduct diagnostic test. The research paper contributes to the development of lightweight, interpretable and deployable AI-based neuro imaging by reducing the need to rely on manual functionality and simplifying the architecture of the model to the number of parameters. In addition, the ability to distinguish the glioma and meningioma, pituitary and normal scan of the model will allow radiologists to diagnose and plan on the treatment of the patient earlier and improve their outcome. The findings affirm that deep learning and CNNs in particular, can be an effective decision- support system of the medical practitioners in the under- resourced health care settings.

REFERENCES

[1] Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., & Bray, F. (2021). Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians, 71(3), 209-249.

[2] Jordan, J. T., & Gerstner, E. R. (2023). Imaging of brain tumors. CONTINUUM: Lifelong Learning in Neurology, 29(1), 171-193.

[3] Bauer, S., Wiest, R., Nolte, L. P., & Reyes, M. (2013). A survey of MRI-based medical image analysis for brain tumor studies. Physics in medicine and biology, 58(13), R97-R129.

[4] Gordillo, N., Montseny, E., & Sobrevilla, P. (2013). State of the art survey on MRI brain tumor segmentation. Magnetic resonance imaging, 31(8), 1426-1438.

[5] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. nature, 521(7553), 436-444.

[6] Swati, Z. N. K., Zhao, Q., Kabir, M., Ali, F., Ali, Z., Ahmed, S., & Lu, J. (2019). Brain tumor classification for MR images using transfer learning and fine-tuning. Computerized Medical Imaging and Graphics, 75, 34-46.

[7] Sajjad, M., Khan, S., Muhammad, K., Wu, W., Ullah, A., & Baik, S. W. (2019). Multi-grade brain tumor classification using deep CNN with extensive data augmentation. Journal of computational science, 30, 174-182.

[8] Khan MA, Hussain MZ, Mehmood S, Khan MF, Ahmad M, Mazhar T, Shahzad T, Saeed MM. Transfer learning for accurate brain tumor classification in MRI: a step forward in medical diagnostics. Discov Oncol. 2025 Jun 9;16(1):1040. doi: 10.1007/s12672-025-02671-4. PMID: 40490586; PMCID: PMC12149374.

[9] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25.

[10] [10] D. M. Barode, R. S. Awhad, V. D. Dhangar, and S. S. Kawathekar, “Comparative Analysis of SVM and CNN Techniques for Brain Tumor Detection,” International Journal of Innovative Technology and Exploring Engineering (IJITEE), vol. 13, no. 7, pp. 27–33, Jun. 2024, doi: 10.35940/ijitee.G9908.13070624.