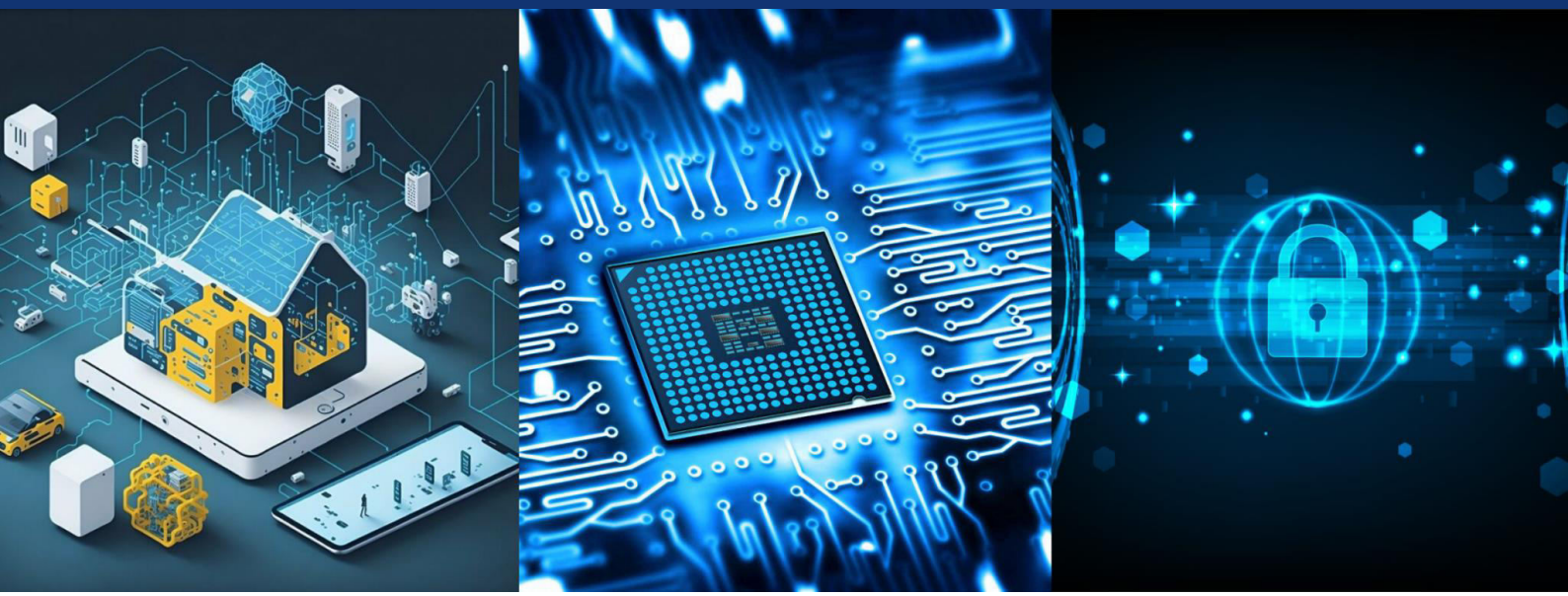
IJIRCCE

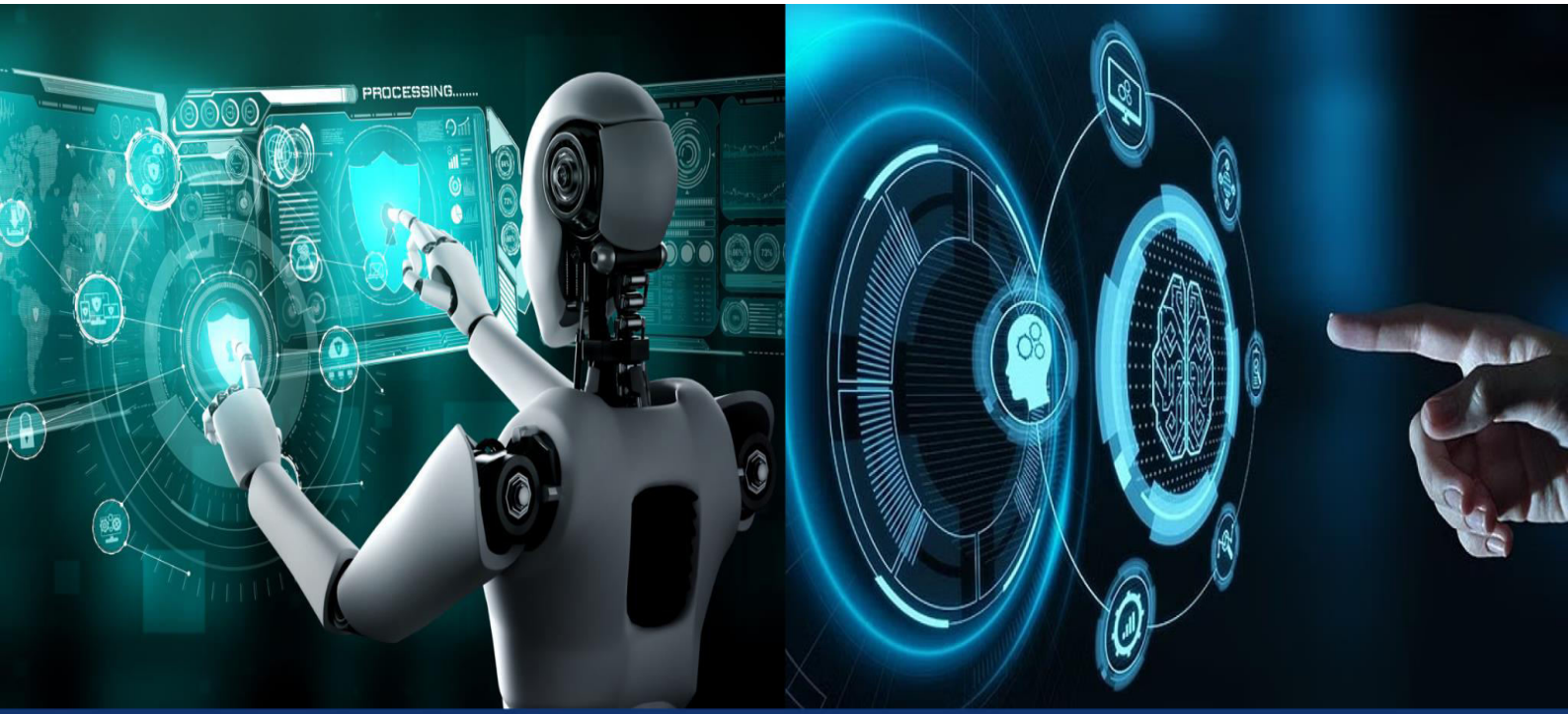
ISSN(O): 2320-9801

ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 9.927

Volume 14, Issue 10, October 2026

© 2026 IJIRCCE | Volume 14, Issue 10, October 2026 DOI: 10.15680/IJIRCCE.2026.1410043

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Brain Tumor Detection Using Convolutional Neural Network (CNN) and Medical Imaging

Mr. Dinesh Kumar M, Harshitha S A, Chirag M, Mizba Fathima, Gaurav

Department of Information Science and Engineering, Rajarajeshwari College of Engineering, Bengaluru, India

ABSTRACT: Finding a brain tumor early makes a major difference in how effectively doctors can plan treatment. Clinicians typically rely on Magnetic Resonance Imaging (MRI) to examine brain tissue and spot abnormal growth. Still, going through large batches of MRI scans by hand takes considerable time, and interpretations can vary from one specialist to another. To help address this challenge, our study presents an automated classification workflow built around the Xception Convolutional Neural Network (CNN). Using transfer learning, the network pulls useful visual patterns from brain MRI scans and sorts each image into one of four groups: glioma, meningioma, pituitary tumor, or healthy brain tissue (no tumor). Before feeding images into the network, we resize them to a single standard resolution and scale their pixel values, while also applying brightness adjustments during training so the model handles new scans more reliably. Because medical tools need to be transparent rather than acting as a closed box, we pair the classifier with Gradient-weighted Class Activation Mapping (Grad-CAM). This step generates color heatmaps over the scan to show which specific regions pushed the model toward its final answer. We also connected the trained network to a simple web interface where a user can upload an MRI slice and immediately view the predicted label, class confidence scores, and the Grad-CAM overlay. Our goal is to combine multi-class sorting with clear visual feedback as a supportive research and learning aid, rather than replacing a qualified doctor's judgment.

KEYWORDS: Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN), Xception, Transfer Learning, Grad-CAM, Deep Learning, Medical Image Classification.

I. INTRODUCTION

When cells inside the brain begin dividing abnormally, the resulting mass can press against healthy tissue and disrupt basic neurological functions. Catching these tumors early gives medical teams a much better chance of choosing the right treatment path. Among imaging tools, Magnetic Resonance Imaging (MRI) is usually the first choice for brain exams because it captures sharp views of soft tissue without exposing the patient to radiation **[3]**, **[9]**. Even with clear scans, however, reviewing MRI slices manually is slow work. It requires years of clinical training, and subtle or irregular tumor borders can sometimes lead different readers to different conclusions.

Over the last few years, deep learning has changed how researchers approach medical image analysis **[3]**. Convolutional Neural Networks (CNNs) can learn to pick out shapes, edges, and textures straight from image pixels without someone having to program those rules by hand **[6]**, **[10]**. The catch is that building and training a deep network from zero demands a huge collection of labeled scans and heavy computing power. Transfer learning offers a practical way around this obstacle. By taking a network that has already learned general visual patterns from a massive dataset like ImageNet **[15]**, we can adapt those learned weights to medical tasks using a much smaller set ofscans **[4]**, **[5]**.

In this work, we build a four-class brain MRI classifier around the Xception architecture **[1]**. What makes Xception effective is its use of depthwise separable convolutions, which split spatial filtering and channel mixing into two separate steps. That design lets the model capture fine structural details while keeping the parameter count manageable. Our pipeline takes a brain MRI slice and assigns it to one of four labels: glioma, meningioma, pituitary tumor, or no tumor. Every scan goes through basic resizing and intensity scaling first, and we vary image brightness during the training phase so the model does not simply memorize the training set **[8]**, **[11]**.

One common complaint about deep neural networks in healthcare is that they give an answer without showing why. To make our system easier to inspect, we added Gradient-weighted Class Activation Mapping (Grad-CAM) **[2]**. Grad-CAM tracks the gradients flowing into the last convolutional layer and builds a heatmap over the scan,

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

pointing out which spots mattered most for a given prediction. This lets a user check whether the network is actually looking at the lesion instead of background noise. At the same time, it is important to remember that a heatmap only reflects what the software focused on—it does not mark exact clinical tumor borders and cannot be treated as a medical diagnosis.

In short, our work brings together four practical pieces: (1) adapting a pretrained Xception model to sort four types of brain MRI scans; (2) generating Grad-CAM heatmaps alongside each prediction so users can see what influenced the output; (3) using straightforward image scaling and brightness changes to help the model generalize; and (4) wrapping the whole pipeline into an easy-to-use web page that displays the top prediction, confidence percentages, and heatmap overlay. We tested the model on an independent test split using accuracy, precision, recall, and F1 -score. The entire setup is meant to serve as a computer-aided tool for students and researchers, not as a replacement for a radiologist.

II. LITERATURE SURVEY

A. Transfer Learning with CNNs for Brain MRI

Because labeled medical datasets are often small, many researchers rely on transfer learning to get solid results **[4]**, **[5]**. For instance, Indraswari et al. **[16]** built a brain tumor classifier around the Inception V3 network **[12]** using pretrained weights. They measured how well it performed using accuracy, precision, recall, and F1 -score, and compared it against other well-known backbones like ResNet50V2, InceptionResNetV2, and VGG16 **[13]**. On their test data, Inception V3 came out ahead with 84% accuracy, 91 % precision, 76% recall, and an 83% F1 -score. While those numbers show that transfer learning works well for MRI sorting, you cannot directly compare raw scores across papers unless both models are run on the exact same data split. Our work takes a different route by using the Xception backbone **[1]** and pairing the classifier with a web-based Grad-CAM viewer **[2]**.

B. Object Detection Using YOLOv8

Another line of research uses object detection models to draw boxes around tumors rather than just labeling the whole slice. Umamaheswari et al. **[17]** looked at how the YOLOv8 model handles brain tumor detection in MRI scans. Instead of giving a single class label for the entire image, YOLO architectures try to spot where the object sits and classify it at the same time. In the materials reported for their study, the setup reached roughly 96.5% accuracy under their chosen evaluation rules. Drawing bounding boxes is helpful when the main goal is pinpointing location, whereas our project focuses on sorting the full MRI slice into glioma, meningioma, pituitary tumor, or no tumor, and then using Grad-CAM heatmaps to show which image areas drove that choice.

C. Xception in Medical Image Sorting

Several studies have turned to depthwise separable networks like Xception **[1]** and MobileNetV2 **[14]** for medical imaging tasks. Designed by Chollet **[1]** as a step beyond standard Inception modules **[12]**, Xception processes spatial patterns inside each channel first and then uses 1 × 1 convolutions to combine information across channels. This layout cuts down on wasted parameters while still picking up fine texture differences, which helps when trying to tell one tumor category apart from another.

D. Vision Transformers and Combined Models

Outside of standard CNNs, recent papers have also tested transformer designs—such as the Swin Transformer—and hybrid setups that mix CNN layers with other feature extractors **[6]**, **[7]**, **[10]**. Transformers use attention mechanisms to relate distant parts of an image to one another. Even so, how well they actually perform depends heavily on how large the dataset is, how the images are augmented **[8]**, **[11]**, and how the training is tuned.

E. Why We Built the Proposed System

Looking across these earlier studies, it is clear that each method targets a slightly different goal. Inception V3 **[12]**, **[16]** and Xception **[1]** focus on whole-slice classification, YOLOv8 **[17]** focuses on bounding-box detection, Swin Transformers rely on attention blocks, and hybrid models blend multiple extractors. Because each paper tests on its own dataset and splitting rules, lining up their accuracy percentages side by side does not give a fair ranking. For our project, we wanted a clean, practical workflow that classifies brain MRI slices into four categories using Xception, shows the confidence breakdown for every class, and overlays a Grad-CAM heatmap so users can see what the network reacted to. Keeping the whole tool inside a browser makes it useful as an educational and research prototype, while keeping in mind that heatmap colors only show model weights rather than verified clinical tumor borders.

© 2026 IJIRCCE | Volume 14, Issue 10, October 2026 DOI: 10.15680/IJIRCCE.2026.1410043

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

III. METHODOLOGY

Our system is built to take a brain MRI image, classify it using a deep neural network, and produce a visual map showing what influenced that decision. The overall workflow moves through six main steps: gathering the dataset, preparing and augmenting the images, setting up the Xception network, training the model, running four-class predictions, and generating Grad-CAM overlays.

A. Dataset Overview

We gathered the brain MRI dataset from Kaggle. It contains 6,726 images split across four folders: glioma, meningioma, pituitary tumor, and no tumor. Having the scans already sorted into class folders makes it straightforward to load batches and assign labels automatically during training. How well any model handles brand-new scans depends a lot on having enough variety in the training samples. Table I breaks down how the 6,726 scans are divided between the training split (5,521 images) and the testing split (1,205 images).

TABLE I. BREAKDOWN OF THE BRAIN MRI DATASET

Category	Training Images	Testing Images	Total Images
Glioma	1,321	299	1,620
Meningioma	1,333	302	1,635
No Tumor	1,422	309	1,731
Pituitary Tumor	1,445	295	1,740
TOTAL	**5,521**	**1,205**	**6,726**

B. Preparing and Augmenting the Images

Before training, every MRI slice is resized to 299 × 299 pixels and its pixel values are scaled down to the [0, 1] range. To keep the model from being thrown off by slight lighting differences across scanners **[8]**, we apply brightness augmentation during training with a random factor between 0.8 and 1 .2. The pipeline feeds images into the network in batches of32.

C. Xception Network Setup

For the main feature extractor, we use Xception **[1]** loaded with weights pretrained on ImageNet **[15]**. By setting include_top=False, we strip off the original 1 ,000-class output layer and keep the convolutional base, which takes an input shape of 299 × 299 × 3. Once the Xception base pulls out spatial feature maps from an MRI scan, those maps pass through a custom classification head made up of five parts:

- **Global Average Pooling:** Condenses the 2D feature maps down into a single compact vector by averaging each channel.
- **Batch Normalization:** Keeps activation values centered and scaled so training stays steady from batch to batch.
- **Dense Layer (256 units):** A fully connected layer with 256 neurons that learns combinations of features specific to brain MRI scans.
- **Dropout Layer:** Randomly turns off a portion of neurons during training passes so the network does not overfit to the training slices.
- **Softmax Output Layer (4 units):** A final four-neuron layer using Softmax activation to turn raw scores into probabilities across the four classes.

Whichever class gets the highest Softmax probability becomes the final prediction. Altogether, the network holds roughly 21.40 million parameters, with about 529,668 ofthem set as trainable.

D. Training Procedure

We trained the network for 10 epochs using a batch size of 32. We chose the Adamax optimizer with a learning rate of 0.001 alongside categorical cross-entropy loss, which fits a four-class setup. After every epoch, we logged

© 2026 IJIRCCE | Volume 14, Issue 10, October 2026 DOI: 10.15680/IJIRCCE.2026.1410043

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

accuracy, precision, recall, and loss on both the training and validation splits to watch how fast the model learned and check whether it started overfitting. Keeping the training, validation, and final test sets strictly separate ensures that our final test scores reflect how the model behaves on unseen images.

E. Sorting Brain MRI Scans

Once training is finished, any new MRI slice uploaded for testing goes through the exact same 299 × 299 resizing and [0, 1] scaling. It then runs through the Xception extractor and our custom top layers to produce four probability numbers. The system picks the highest score—glioma, meningioma, pituitary tumor, or no tumor—as the predicted label, while also showing the individual percentages so the user can see how confident the model was.

F. Visual Explanations with Grad-CAM

To show what happened inside the network during a prediction, we run Gradient-weighted Class Activation Mapping (Grad-CAM) **[2]**. Grad-CAM looks at the score for the winning class and calculates its gradients with respect to the feature maps in the final convolutional layer. Averaging those gradients across each map gives a weight telling us how much each channel mattered. We then combine the feature maps using those weights and pass the result through a ReLU function so we only keep regions that pushed the score up. Finally, that activation grid is stretched back to 299 × 299 pixels and laid over the original MRI scan as a color heatmap. While this overlay helps researchers check which part of the brain image triggered the label, it does not independently prove a tumor's exact clinical boundary or severity.

G. Evaluating Model Performance

We measured how well the trained model performed using four standard multi-class metrics: overall accuracy, precision, recall, and F1 -score. Accuracy simply tells us what share of all test scans got the right label. Precision looks at all scans placed into a specific class and asks how many actually belonged there, while recall asks what fraction of real cases in a class the model managed to catch. The F1 -score balances precision and recall via their harmonic mean. We also plotted a four-by-four confusion matrix to see exactly which tumor types got mixed up with one another. All numbers reported below come directly from testing our trained Xception model.

IV. RESULTS AND DISCUSSION

We tested the trained Xception pipeline across four classes—Glioma, Meningioma, No Tumor, and Pituitary Tumor—after running every test slice through our standard resizing and normalization steps.

A. Overall and Class-Wise Scores

On a balanced test set of 1 ,600 MRI scans (400 images per category), our Xception model reached an overall test accuracy of 88%. Across all four classes, the macro-averaged precision, recall, and F1 -score all came out to 0.88. Table II lists the detailed numbers for each individual category.

TABLE II. CLASS-WISE TEST SCORES (1,600 TEST SCANS)

Category	Precision	Recall	F1-Score	Test Images
Glioma	0.89	0.74	0.81	400
Meningioma	0.81	0.85	0.83	400
No Tumor	0.90	1.00	0.95	400
Pituitary Tumor	0.94	0.94	0.94	400
Macro Average / Total	**0.88**	**0.88**	**0.88**	**1,600**

Looking at Table II, the model did its best work on No Tumor and Pituitary Tumor scans, reaching F1 - scores of 0.95 and 0.94. In fact, it caught every single healthy scan in the test set (1 .00 recall for No Tumor). Performance on

© 2026 IJIRCCE | Volume 14, Issue 10, October 2026 DOI: 10.15680/IJIRCCE.2026.1410043

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Meningioma was also solid, with 0.81 precision, 0.85 recall, and a 0.83 F1 -score. The toughest category for the network was Glioma: while its precision was high at 0.89, its recall dropped to 0.74 (0.81 F1 - score), meaning roughly a quarter of the glioma slices were mistaken for another class. Reducing those missed glioma cases is an obvious target for future tuning.

B. Training and Validation Curves

Tracking accuracy across the 10 training epochs showed steady improvement without wild swings. Training accuracy started near 61 .5% at Epoch 0, jumped to about 75.5% at Epoch 1 , passed 82.0% by Epoch 4, and finished right around 86.0% at Epoch 9. Validation accuracy started at roughly 75.2% in Epoch 0, climbed to 83.8% by Epoch 3, met the training curve around Epoch 5 (~83.5%), and leveled off near 85.0% by the final epoch. Because the two curves stayed close together in the later epochs, we can see that the batch normalization, dropout, and brightness adjustments did a good job ofholding overfitting in check.

C. Confusion Matrix Breakdown

To see exactly where the wrong predictions went, Table III lays out the confusion matrix comparing true labels against predicted labels across all 1,600 test scans.

TABLE III. CONFUSION MATRIX ON THE 1,600-IMAGE TEST SET

True Class \ Predicted Class	Predicted: Glioma	Predicted: Meningioma	Predicted: No Tumor	Predicted: Pituitary
True: Glioma	**296**	66	28	8
True: Meningioma	28	**341**	18	13
True: No Tumor	0	0	**400**	0
True: Pituitary	7	11	2	**380**

As Table III shows, all 400 No Tumor slices and 380 of the 400 Pituitary slices landed in the right column. Most of the mix-ups happened between Glioma and Meningioma: 66 glioma scans were labeled as meningioma, and 28 meningioma scans were labeled as glioma. Another 28 glioma scans and 18 meningioma scans were mistakenly called No Tumor. Because gliomas and meningiomas can look quite similar on a single 2D slice, giving the model better contrast preprocessing or unfreezing more convolutional layers during training should help separate them more cleanly in future work.

D. Web Interface and Grad-CAMCheck

We also tested the finished model inside our web interface using sample normal and abnormal scans, summarized in Table IV. When we uploaded a healthy brain scan, the app labeled it Notumor with 94.84% confidence. When we uploaded a scan showing a clear tumor mass, the app predicted Pituitary with 95.55% confidence and placed a bright red-and-yellow Grad-CAM hotspot right over the lesion area.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

TABLE IV. SAMPLE WEB APP PREDICTIONS AND HEATMAP CHECKS

Sample Run	Input Scan Type	Displayed Output Label	Confidence Score	Grad-CAM Overlay Behavior
Sample Case 1	Normal Brain MRI	No Tumor (Notumor)	94.84%	Even background response with no concentrated tumor hotspot.
Sample Case 2	Abnormal Brain MRI (Tumor)	Pituitary (Pituitary)	95.55%	Warm red-yellow activation focused directly over the bright tumor region.

E. Discussion

Overall, our experiments show that pairing an ImageNet-pretrained Xception base with a compact classification head gives reliable four-class sorting (88% test accuracy) after just 10 epochs of training. Adding Grad-CAM heatmaps alongside confidence scores makes the tool much more informative than a bare label, since users can immediately see which part of the MRI slice caught the network's attention. At the same time, the lower recall on glioma slices (0.74) shows that single-slice 2D classification still has room to grow. Fine-tuning deeper Xception blocks, expanding data augmentation, and testing on outside hospital datasets will be important next steps before a system like this could ever be considered for clinical use.

V. CONCLUSION

In this paper, we presented an automated approach for sorting brain MRI scans into four categories—glioma, meningioma, pituitary tumor, and no tumor—using the Xception convolutional neural network. By combining transfer learning with straightforward image normalization and brightness augmentation, the model reached 88% test accuracy and a 0.88 macro F1 -score across 1 ,600 test images. Tying the model to Grad-CAM heatmaps inside a simple web interface also lets users see which areas of an MRI scan drove each prediction. While these results show how deep learning can assist with preliminary MRI sorting, pushing the accuracy higher will require larger, more diverse datasets and further hyperparameter tuning. Above all, this platform is built to support academic research and learning, not to replace a medical professional's diagnosis.

REFERENCES

1. Chollet, "Xception: Deep learning with depthwise separable convolutions," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2017, pp. 1251–1258, doi: 10.1109/CVPR.2017.195.
2. R. R. Selvaraju et al. , "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), 2017, pp. 618–626, doi: 10.1109/ICCV.201 7.74.
3. Litjens et al. , "A survey on deep learning in medical image analysis," Med. Image Anal. , vol. 42, pp. 60–88, 2017, doi: 10.1016/j.media.2017.07.005.
4. S. Deepak and P. M. Ameer, "Brain tumor classification using deep CNN features via transfer learning," Comput. Biol. Med. , vol. 111 , Art. no. 103345, 2019, doi: 10.1016/j.compbiomed.2019.103345.
5. N. Tajbakhsh et al. , "Convolutional neural networks for medical image analysis: Full training or fine tuning?" IEEE Trans.
6. Med. Imaging, vol. 35, no. 5, pp. 1299–1312, 2016, doi: 10.1109/TMI.2016.2535302.
7. S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," IEEE Trans. Med. Imaging, vol. 35, no. 5, pp. 1240–1251 , 2016, doi: 10.1109/TMI.2016.2538465.
8. B. H. Menze et al. , "The multimodal brain tumor image segmentation benchmark (BRATS)," IEEE Trans. Med. Imaging, vol.
9. 34, no. 10, pp. 1993–2024, 2015, doi: 10.1109/TMI.2014.2377694.
10. C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," J. Big Data, vol. 6, no. 60, 2019, doi: 10.1186/s40537-019-0197-0.
11. Mohan and M. M. Subashini, "MRI based medical image analysis: Survey on brain tumour grade classification,"

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Biomed.
12. Signal Process. Control, vol. 39, pp. 139–161 , 2018, doi: 10.1016/j.bspc.2017.07.007.
13. M. Havaei et al. , "Brain tumor segmentation with deep neural networks," Med. Image Anal. , vol. 35, pp. 18–31 , 2017, doi: 10.1016/j.media.2016.05.004.
14. Cheng et al. , "Enhanced performance of brain tumor classification via tumor region augmentation and partition," PLOS ONE, vol. 10, no. 10, Art. no. e0140381 , 2015, doi: 10.1371 /journal.pone.0140381 .
15. C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Going deeper with convolutions," in Proc. IEEE Conf.
16. Comput. Vis. Pattern Recognit. (CVPR), 2015, pp. 1–9, doi: 10.1109/CVPR.2015.7298594.
17. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in Proc. Int. Conf.
18. Learn. Represent. (ICLR), 2015.
19. M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2018, pp. 4510–4520, doi: 10.1109/CVPR.2018.00474.
20. Deng et al., "ImageNet: A large-scale hierarchical image database," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit.
21. (CVPR), 2009, pp. 248–255, doi: 10.1109/CVPR.2009.5206848.
22. R. Indraswari, I. S. Ardan, A. Z. Arifin, A. Tjahyanto, N. A. Rakhmawati, and R. Kusumawardani, "Brain tumor detection on magnetic resonance imaging (MRI) images using convolutional neural network (CNN)," in Proc. 9th Int. Conf. Electr. Eng., Comput. Sci. Informat. (EECSI), Jakarta, Indonesia, 2022, doi: 10.23919/EECSI56542.2022.9946622.
23. S. Umamaheswari, M. H. H. Subramanian, R. Kirthik, C. Hariram, K. A. S. Varshini, and R. Abirami, "Brain tumor detection using YOLOv8," in Proc. 1st Int. Conf. Adv. Eng. Comput. Technol. Sustain. Develop. (AECTSD), Coimbatore, India, 2025, doi: 10.1109/AECTSD65988.2025.11411433.



INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE SJIF Scientific Journal Impact Factor

doi crossref

निस्केयर NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

www.ijircce.com

Scan to save the contact details