

Early Brain Tumor Detection Using MRI and Deep Learning: A CNN-Based Classification Approach

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ABSTRACT

Early and accurate detection of brain tumors is crucial for improving patient outcomes and enabling effective treatment. Magnetic Resonance Imaging (MRI) is widely used for brain imaging due to its ability to capture detailed anatomical structures. However, manual interpretation of MRI scans is labor-intensive and prone to human error, especially during the early stages of tumor development. This study presents a deep learning-based approach for automating the classification of brain tumors using a custom-designed Convolutional Neural Network (CNN). The proposed CNN architecture was trained and tested on a dataset of 3,000 MRI images comprising four classes: glioma, meningioma, pituitary tumor, and no tumor. To enhance model performance, preprocessing techniques such as image normalization and denoising were applied, followed by data augmentation strategies to address dataset imbalance and improve generalization. The CNN model was implemented in a cloud-based environment (Google Colab Pro+) and evaluated using key performance metrics including accuracy, recall, AUC, and loss. Compared to other deep learning models like ResNet-50, VGG16, and Inception V3, the proposed CNN achieved superior results with 92.29% accuracy, 90.12% recall, 97.42% AUC, and a minimal loss of 0.24. This research highlights the effectiveness of CNNs for early brain tumor detection and demonstrates the potential of deep learning in clinical diagnostics. Future enhancements could focus on explainable AI tools and transfer learning models for improved interpretability and robustness in medical image classification.

KEYWORDS: Brain Tumor Detection, MRI, Deep Learning, CNN, Medical Image Classification, Early Diagnosis, Data Augmentation, Machine Learning, Neural Networks, Tumor Classification, Clinical Imaging.

INTRODUCTION

Early brain tumor discovery is essential for comprehending the outcomes, since timely intervention can significantly increase the likelihood of successful therapy. A safe imaging technique used mostly for clinical diagnostics, magnetic resonance imaging (MRI) allows the visualization of finely detailed brain structures. However, radiologists often have a laborious and prone to human error process when manually interpreting MRI scans, especially in the early stages of tumor growth when abnormalities may not be noticeable. In response to these challenges, deep learning algorithms have emerged as essential tools for automating the identification and categorization of brain tumors using magnetic resonance imaging.

A subset of artificial intelligence (AI) called deep learning makes use of neural networks with several layers to acquire and concentrate complicated aspects from raw data. Convolutional neural networks (CNNs), because of their ability to handle spatial data in images, are particularly effective in brain tumor identification. In order to identify patterns associated with

different types of brain cancers, such as gliomas, meningiomas, and pituitary tumors, these networks can be trained using enormous datasets of named MRI sweeps. Nevertheless, achieving high accuracy in early tumor diagnosis necessitates fine-tuning deep learning algorithms to handle the inherent variability in MRI data, such as contrasts in check target, noise levels, and patient-explicit physical variations.

There are several important steps in the advancement of deep learning algorithms for brain tumor diagnosis. In order to improve the characteristics of MRI filters and lessen the impact of curiosities, information pre-handling techniques like as image normalization, enlargement, and denoising are essential. These methods help ensure that the neural network can focus on relevant aspects, such as tumor boundaries and tissue contrasts, without getting distracted by noise or anomalies in the data. Moreover, network engineering decision-making plays a fundamental role in simplification. In order to prevent overfitting and ensure speculation to new, subtle information, deeper and more complex models can capture intricate designs. However, they also necessitate careful adjustment of hyperparameters, such as learning rate, clump size, and regularization. Integrating state-of-the-art techniques like information increase and exchange learning is a major component of improvement. With move learning, pre-trained models are used, often built on large image datasets, and adjusted for clear-cut clinical imaging tasks. This method can significantly reduce the need for large-scale training data and computation time, which makes it particularly important for early tumor diagnosis in situations where access to named datasets may be limited. On the other hand, information expansion produces an artificial extension of the training dataset by making arbitrary modifications to preexisting images, such as pivots, interpretations, and force variations. By increasing the variability of the training data, this makes the model more resilient to variations in validated MRI scans.

Troupe methods can be used not just to improve the presentation of individual models but also to combine the predictions of different deep learning models. Group models are more accurate and provide better conjecture than any single model when the features of different structures or training draws are combined. The acceptability of deep learning models in therapeutic contexts is also influenced by their interpretability and explainability. Gradient-weighted Class Activation Mapping (Grad-CAM) and saliency guides are two techniques that can provide visual explanations of the regions in MRI filters that contributed to the model's selection, increasing the calculation's forecasts' credibility and clarity. Improving input quality, selecting appropriate network architectures, using cutting-edge training techniques, and ensuring model interpretability are all important steps in the complex cycle of optimizing deep learning algorithms for early brain tumor detection using MRI. These efforts will eventually lead to quiet outcomes and advance the area of clinical imaging by producing accurate and dependable tools that assist radiologists in the early diagnosis of brain cancers.

LITERATURE REVIEW

Tiwari et al. (2022) demonstrate the use of CNN to detect brain tumors in multiple classes, highlighting the potential of deep learning for clinical imaging. The review uses CNNs to categorize brain tumors into different groups, making use of CNNs' capacity to extract highlights from imaging data as a result. The authors highlight CNNs' ability to handle complex

and multilayered data associated with clinical images, particularly when it comes to identifying various tumor forms. The review demonstrates the robustness of CNN models in clinical diagnostics by reporting good precision in tumor categorization. This study makes a huge commitment to the field by showing the reasonableness of CNNs in further developing brain tumor detection precision, which is urgent for successful treatment arranging.

Usman and Rajpoot (2017) Examine the combination of AI techniques and wavelet modifications for brain tumor classification using multi-methodology MRI. Their process involves using wavelet changes to extract elements, followed by AI algorithms for classification. The review emphasizes the value of multi-methodology MRI, which improves the accuracy of tumor detection by providing corresponding data from several imaging techniques. Particularly renowned for its ability to capture both spatial and repetition domain data, wavelet-based highlight extraction is suitable for deconstructing intricate brain architectures. According to the technique's developers, it achieves ruthless precision and can coordinate wavelets with machine learning for the classification of brain tumors. This analysis provides a comprehensive look at how modern AI techniques can be effectively combined with traditional sign handling techniques like wavelets to produce worked-on suggestive outcomes.

Vaishnav et al. (2021) provide a scientific evaluation of several coronavirus evaluation methods, drawing comparisons to brain tumor detection in terms of the challenges posed by the need for accurate and timely diagnosis. Although the audit focuses mostly on coronavirus, it also discusses the wider applicability of scientific methodologies in clinical imaging and disease detection. The authors investigate the use of AI models for illness screening, emphasizing the need for interpretability in models, especially for applications involving basic medical care. The review's observations regarding model evaluation and the need for robust, generalizable algorithms are relevant to the development of systems for the early diagnosis of brain tumors, where accuracy and consistency are essential. By providing a cross-illness perspective on the application of AI in clinical diagnostics, this survey enriches the discussion and can shed light on future research into brain tumor detection.

Woźniak et al. (2021) provide a novel approach to brain tumor detection that specifically applies a deep neural network relationship learning component to CT filters. The review introduces a model that builds on the relationships between different imaging information pieces to improve the accuracy of detection. The suggested tool is meant to handle the complex, multi-layered data associated with CT filters, accounting for more precise, identifiable tumor district proof. According to the model's developers, significant improvements in detection precision are achieved, especially when tumors are small or located in areas with poor distinction. This study advances the field by providing a sophisticated method that improves the performance and interpretability of deep learning models in the identification of brain tumors, particularly for CT imaging.

Xie et al. (2022) provide a thorough analysis of CNN techniques used to classify brain tumors between 2015 and 2022. The audit discusses numerous CNN designs, including how these models were developed and how they are used in different clinical imaging modalities, including as MRI and CT scans. The authors analyze the challenges associated with CNN-based brain tumor classification, such as the need for large annotated datasets, the risk of

overfitting, and the challenge of understanding model selections. The survey also lays out future directions, emphasizing the potential of explainable AI (XAI) techniques and the need to reconcile multimodal data in order to improve classification outcomes. This work is particularly significant since it provides a broad overview of the state-of-the-art in CNN-based brain tumor classification, providing information on both the ongoing challenges and the successes in this field.

Zahoor et al. (2022) provide a deep half-and-half model that combines outfit learning with assisted learning techniques for MRI data-driven brain tumor detection. The paper offers a novel engineering solution that synchronizes CNNs with auxiliary algorithms to enhance tumor detection and classification accuracy. The crossover strategy is a potent and effective way to create a model that capitalizes on the strengths of both traditional modeling strategies and deep learning. The authors demonstrate how their model outperforms traditional CNNs, particularly when the data is skewed or noisy. By reducing variability and propensity, group learning is utilized to produce more reliable projections. This analysis is important because it makes innovative use of crossover learning techniques, which may pave the way for more potent brain tumor detection systems.

3. METHODOLOGY

3.1. Proposed Architecture

To find the most widely recognized features in a data picture, our survey used a $32 \times 32 \times 16$ part map, an underlying convolutional layer with 16 channels, and a 3×3 segment size. To generally lessen how much spatial information for the going with layer, the consequence of the convolutional layer was thus passed to a biggest pooling layer with an aide of $15 \times 15 \times 16$. The greatest pooling strategy was utilized to pick the ideal measure of components or pixels from the area of the component map that the channel is answerable for making due. The outcome was then handled by a second convolutional layer utilizing 32 channel potential gains and a $13 \times 13 \times 32$ part map with a 3×3 section size. A short time later, the outcome was passed by means of a pooling layer feature guide with aspects of $6 \times 6 \times 32$ to circulate the spatial data for the following layer uniformly. Not long after that, two more convolutional layers and a second pooling layer were added. The final convolutional layer and pooling layer both used $4 \times 4 \times 64$ element guides and 3×3 bit sizes, respectively, with 64 channel values. The component guides for the pooling layer were $2 \times 2 \times 64$. A recently built 4160-layer fully associated thick layer was able to replicate the prior convolutional layer's leveled end output. This was the end product of the final result layer's activation of SoftMax. The outcome was achieved by using a SoftMax activation with no dropout in the final layer, in contrast to the many layers that utilized a ReLU activation capability with a dropout of 0.5. Figure 1 depicts the aforementioned proposed CNN engineering design. The model was tested, approved, and trained with 80 age groups, 18 clusters, and a 0.01 learning rate. An unmitigated cross-entropy-based misfortune capability was found to locate the misfortune esteem in addition to the Adam enhancer.

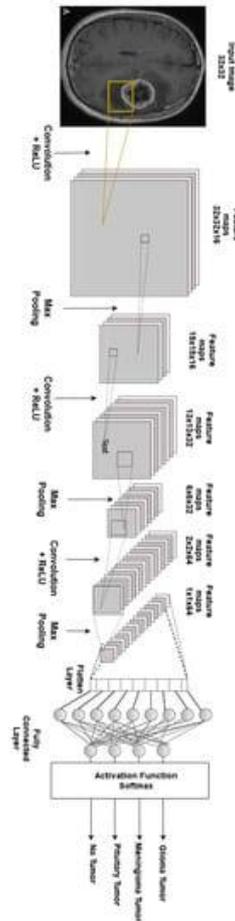


Figure 1: Proposed CNN Architectur.

There are two main stages that make up the system. First, we processed our datasets beforehand. During the approval stage, we worked with the holdout approval system. To train our images, we used various AI models. We divided our dataset into three groups: training (80%), testing (10%), and approval (10%). We attempted to acknowledge four particular sorts of brain pictures: no tumor, meningioma tumors, pituitary tumors, and glioma tumors. Next, we looked at a few different types of measurements, such as the precision, review, AUC, and misfortune, to validate our findings. Figure 2 displays the investigation's step-by-step breakdown.

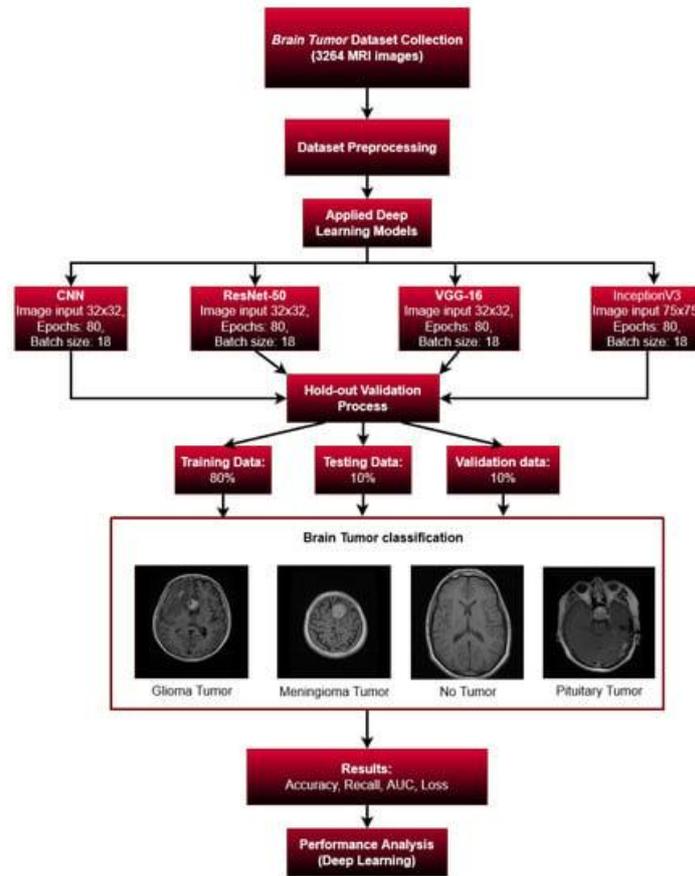


Figure 2: Overall Study.

3.2. Environment Setup

Our current arrangement is based on a cloud-based Google Colab Pro+ stage. Google's Colab Pro+ stage was assembled utilizing GPUs from NVIDIA, to be specific the K80, T4, and P100 series. It was at this stage when the 52 GB high-Smash runtime was also employed. A much enhanced stage allows for the training of AI models to be done more rapidly and efficiently.

3.3. Dataset Collection

We used information from kaggle.com to accumulate a dataset to perceive brain tumors using publically accessible web based sources. Attractive reverberation imaging (MRI) pictures were utilized to assemble the information base. We chose to use attractive reverberation imaging (MRI) for our solicitation since it is the greatest level for recognizing brain malignancies. Meningioma (871 photographs), no tumor (434 photos), pituitary tumor (834 photos), and glioma tumor (860 photos) were the four classes of brain tumor information that were utilized for our review. Our dataset incorporated an amount of 3,000 MRI inspects. Figure 3 shows the critical attractive reverberation pictures for the different kinds of brain tumors, and Table 1 shows the dataset's breakdown.

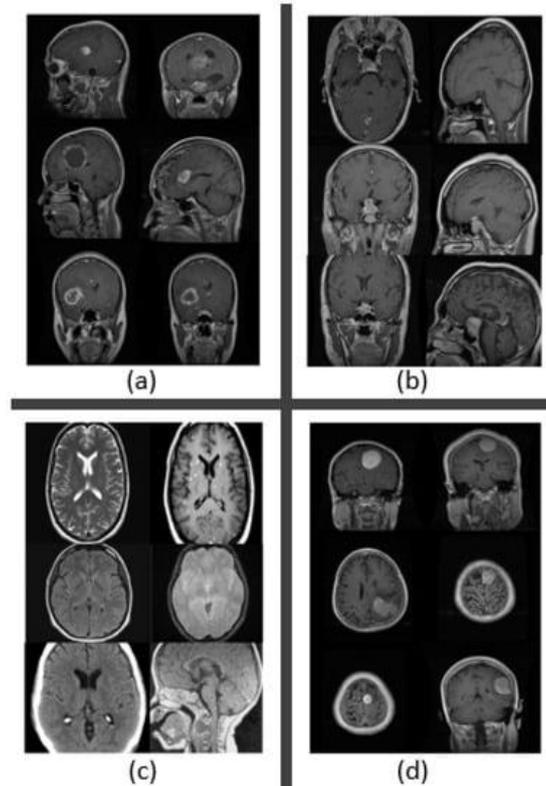


Figure 3: Brain tumor MR pictures. (a) Glioma tumor. (b) Pituitary tumor. (c) No tumor. (d) Meningioma tumor.

Table 1: Dataset.

Brain Tumor Type	Count
Glioma Tumor	860
Meningioma Tumor	871
No Tumor	434
Pituitary Tumor	834
Total	3000

3.4. Preparing the Dataset for Processing

Data must undergo processing during pre-handling in order to be ready for training. Due to their origins in a patient data collection, the MR pictures were of subpar quality and hence undesirable. We now ready our photographs for further processing by normalizing them. The designers additionally employed Gaussian and Laplacian channels to eliminate noise and blur in the original photos.

3.5. Data Splitting and Enhancement

Although our dataset was limited to MR images, it is important to note that deep neural networks require vast datasets in order to generate meaningful findings. Our dataset included 3,000 MR images; training utilized 80% of the pictures, while testing and approval each used 10%. The extent to which the original content can be expanded and the subsequent progress of the teaching can be made. Additionally, this improves the model's ability to learn. Consequently, we enhanced the MR pictures with features including reflection, rotation, level and width movement, zooming, and amplification. The datasets were subsequently approved using the holdout approval process.

3.6. Method of Validation

Selecting the optimal approval process for the 3000 sweep photo dataset was straightforward. We used a holdout approval procedure, reserving 20% for testing and 80% for training. The most often used tactic, the holdout approval strategy, yields convincing results. To assist the model train with night all the more rapidly, the holdout method routinely integrates isolating the dataset into two sections: a readiness set and a testing set. The deep learning model was ready on the readiness set, and its show was overviewed on the testing set. Utilizing the holdout system, 20% of the dataset was utilized as the testing set and the abundance 80% was arbitrarily settled to go probably as the planning set. The planning set was utilized to set up the model, and the testing set was utilized to study its show. The advantage of involving 80% of the data for planning is that the model procures a more noteworthy extent of incorporation, which can assist it with better summing up new, covered data. Be that as it may, the show check might be one-sided on the grounds that the testing set isn't illustrative of the general information.

3.7. Performance Metrics

We used metrics like precision, review, and area under the curve (AUC) in order to evaluate the AI models and analyze their displays.

3.7.1. Accuracy

The number of accurate predictions divided by the total number of samples is the accuracy metric. Equation (1) can be used to determine the accurac.

$$Accuracy = ((TN + TP)/(TP + TN + FP + FN)) \times 100\% \quad (1)$$

3.7.2. Recall

One of the other most crucial measures for assessing a machine learning model is recall. Recall can be computed as:

$$Recall = TP/(TP + FN) \quad (2)$$

3.7.3. Area under the Curve

One more method for expressing "region under the bend," AUC is a verifiable measure. The region under the bend (AUC) measures how well the model can perceive positive and negative groupings. A predominant model's show is shown by a higher AUC regard.

5. RESULTS' ANALYSIS AND DISCUSSION

The impacts of a couple of made deep learning models on the brain tumor MR picture dataset are broken out in Table 2. These models consolidate CNN, VGG16, ResNet-50, and Beginning V3. Figure 4 shows the interrelationships of the models. Table 2 shows the association between the models' show and the consequences of review, precision, area under the curve (AUC), and disaster limit. The outcomes showed that among the four deep learning models tried (CNN, VGG16, ResNet-50, and Starting V3), CNN fared the best. A 97.42% endorsement area under the curve, 90.09% endorsement surveys, 0.259 endorsement inadequacy, and a 92.2% endorsement accuracy were completely achieved by the CNN.

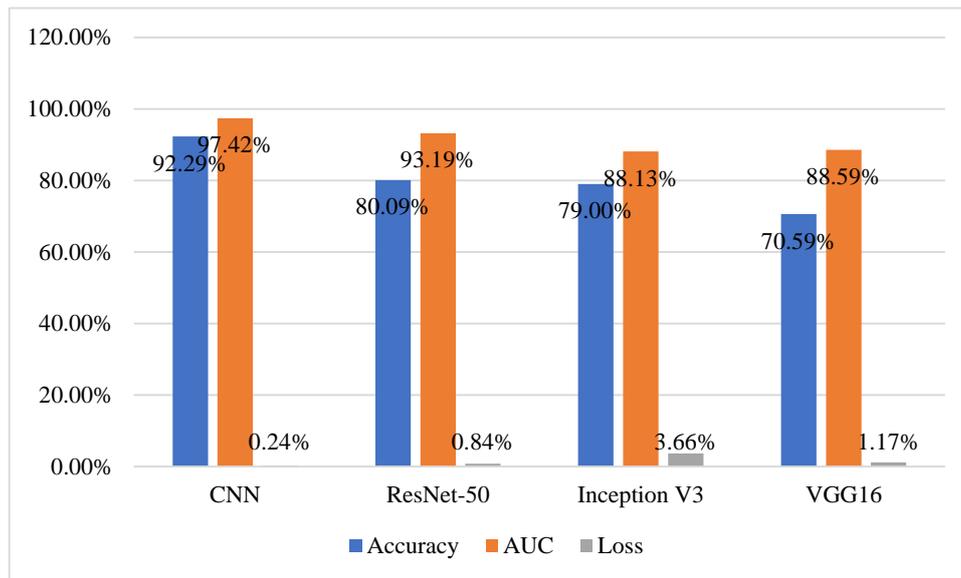


Figure 4: A loss, accuracy, and area under the curve (AUC) analysis of the proposed model's performance.

Table 2: The efficacy of machine learning systems in the diagnosis of brain tumors.

Models	Accuracy (%)	AUC (%)	Recall (%)	Loss
CNN	92.29	97.42	90.12	0.24
ResNet-50	80.09	93.19	80.03	0.84
VGG16	70.59	88.59	69.02	1.17
Inception V3	79.00	88.13	78.80	2.66

In a similar fashion, the approved precision for the training exactness charts of CNN, ResNet-50, Beginning V3, and VGG16 are introduced. The orange lines show the approval precision, and the blue lines show the exactness of the training. In this case, CNN achieved the highest approval precision of 92.29% with 89.49% training exactness. ResNet-50 achieved an 80.09% approval exactness, with a notable training precision of 97.42%. Commencement V3 achieved a training precision of 90.78% and an approval exactness of 79.00%. However, VGG16 achieved the highest un-training precision of 78.19% and the lowest approval exactness of 70.59%. While running the models, we used an Adam enhancer with a cluster size of 18 and an ages of 80. Due to the absence of over-fitting and under-fitting issues and the approval exactness's outstanding result curve for the training exactness, the CNN performed better than the other models, as shown in the precision chart analysis.

Training AUC graphs for CNN, ResNet-50, VGG16, and Commencement V3 all show the AUC of endorsement in a tantamount manner. The blue lines address the (AUC) for training, while the orange lines address the AUC for endorsement. Here, CNN trained with an exactness of 89.49% and obtained an endorsement accuracy of 92.29%. The (AUC) measures how well a model shows and can separate across classes. An expansion in the AUC esteem works on the model's show. This case's best endorsement AUC was 97.42%, attained by the CNN, which had a training AUC of 97.39%. The endorsement AUC for ResNet-50 was 93.19 percent, while the training AUC was 98.96 percent. Beginning with V3, we were able to attain a training precision of 94.96% and a minimum approval AUC of 88.13%. The un-training precision was 94.31% and the approval AUC was 88.59% for VGG16.

The approval disaster and training disaster charts for CNN, ResNet-50, VGG16, and Initiation V3 are presented in a manner identical to each other. The orange lines signify approval misfortune and the blue lines reflect training misfortune. The misfortune is a result of expecting the wrong thing. The unfortunate event, however, serves as an example of how the model's forecast is wrong for all age groups. When the unfortunate event is nonexistent, the model's prediction is remarkable; when it is present, the unfortunate event is more noticeable. To find the mistake in the detection cycle, our technique utilized the full cross-entropy misfortune limit. The apparent cross-entropy is an undesirable trait that is oftentimes used in multi-class classification tasks. The least approval deficit was attained by CNN in this instance, with a training misfortune worth of 0.288. With a training loss of only 0.062 and an approval deficit of only 0.852, ResNet-50 demonstrated an exceptionally low level of performance. Initiation V3 obtained the best approval deficit of 2.66 and the best training deficit of 0.534. The training deficit for VGG16 was 0.532 and the approval deficit was 1.17.

Model accuracy, (AUC), and loss all show a relationship. Pain, accuracy, and area under the curve were the metrics used to assess the models' performances. With an approval accuracy of 92.29% and an approval AUC of 97.42%, the CNN clearly outperformed the other models. With that exception, CNN's approval gap of 0.24 was the lowest. Nevertheless, Commencement V3 stood out with the lowest AUC score of 88.13% and the most glaring shortfall of 4.66. Along with a high misery value of 1.17, VGG16 also obtained the lowest accuracy score of 70.59%. ResNet-50 not only attained the second-most notable exactness and

AUC score, but it also reduced misfortune esteem. According to the results of the overall performance and score analysis, the proposed CNN was the best model for MR image-based classification of different brain tumors.

Despite our best efforts, we were unable to evaluate the performance of the exchange learning models we attempted to dissect. We intend to investigate this further in the future in an effort to gain a deeper understanding of the pre-trained models, with an eye toward their modification. Our inability to visualize critical brain tumor locations due to a lack of post hoc clarifying equipment is yet another caveat of our study.

CONCLUSION

Simplifying deep learning algorithms for MRI-based early brain tumor identification has proven to be an amazing clinical diagnostics approach, significantly raising the precision and reliability of tumor discriminating evidence in its early phases. Brain cancers can be prevented from killing more people globally by detecting them early. The structure, changing size, and design of brain tumors make accurate diagnosis extremely challenging. The categorization of MR images has a major impact on clinical analysis and the formulation of treatment decisions for patients with brain tumors. Utilizing MR images and the tumor division technique, early identification of brain tumors appears promising. However, much work needs to be done before the tumor site can be identified and categorized with certainty. In our review, we backed up the early brain tumor detection with a range of MRI brain tumor imaging. In addition, detection and classification are not immune to the widespread effects of deep learning models. We suggested a CNN model for the early detection of brain tumors and, using a huge number of MR images, we discovered encouraging findings. In order to guarantee that the machine learning models were effective throughout the evaluation phase, we used a variety of metrics. When evaluating our results, we thought about employing the proposed model as well as a few other machine learning techniques. Because the computer did not have a powerful graphics processing unit and the convolutional neural network (CNN) had few layers, the training system consumed the majority of our investigational time. Training with a large dataset—1,000 photos, for example—would be more expensive. Following improvements to our GPU system, we shortened the training duration.

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