

Brain Tumor Detection Using AIML

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Abstract— Computer vision, a subfield of AI, specifically deals with allowing computers to construe and understand visual information from the world, often through digital images or videos. It is also very helpful in the healthcare because it detects the diseases through digital images. It involves developing algorithms and models that can recognize objects, patterns, and features within images, allowing machines to observe and extract meaningful information from visual data. “Deep learning is a method in artificial intelligence (AI) that teaches computers to process data in a way that is inspired by the human brain”. Deep learning produces outstanding results in a range of fields, including biomedicine, education, and the detection of financial fraud, among others, due to its ability to handle vast volumes of data sets. It has proven to operate admirably and has the ability to use MRI scans to detect brain cancers for precise prognosis. This research project's main objective is to give a thorough summary of the studies and judgements made recently on the identification and classification of brain cancers using MRI scans. The first step in the classification and diagnosis of brain tumors is a rapid review of previous research publications using artificial intelligence and machine learning. The conclusions offered in this paper will provide researchers with a thorough comparison of recent studies as well as a novel viewpoint on the effectiveness of various AIML and Deep Learning approaches. With an emphasis on AI/ML and deep learning techniques, the major objective of this research project is to present a comprehensive overview of recent studies and findings addressing the detection and classification of brain tumors using MRI data. An review of past studies in the field, including the most recent advancements in AI and deep learning, is provided at the outset of this study.

Keywords—Brain Tumor, Deep Learning, Machine Learning

I. INTRODUCTION

The arrival of artificial intelligence (AI) and machine learning (ML) technologies has revolutionized in medical research Brain tumor detection and diagnosis has emerged as an area of great importance in AI and ML as they are used in a variety of important healthcare applications because they require rapid and accurate detection and improved patient outcomes.[1]

“Historically, the diagnosis of brain tumors relied heavily on the expertise of radiologists and physicians who would analyze complex medical imaging data such as magnetic

resonance imaging (MRI) and computed tomography (CT) scans”. And despite the fact that, the increasing incidence of brain tumors worldwide highlights the need for effective and accurate diagnostic tools [2].

Brain tumors are among the world's fastest-growing and deadliest diseases due to their increased prevalence and fatality rate across all age categories. It is the second most common cancer cause in India. ‘The American Cancer’ Society's latest report, "Cancer Statistics 2022," predicts that around 25000 people will get brain tumors in 2022 and that there will most likely be 20000 fatalities in the United States [3-4]. This brain tumor condition is now becoming more common in children due to increased use of technology like mobile phones, tablets, PCs, video games, etc.

In recent years, AI and ML have emerged as powerful tools in medical image analysis. By using this technology, researchers and healthcare professionals have made great strides in automating brain tumor detection. AI and ML models are capable of processing large amounts of medical imaging data with high speed and accuracy, facilitating early diagnosis and improving patient care fast [5].

The detection and diagnosis of brain tumors have greatly benefited from the advent of artificial intelligence and machine learning (AI/ML) technology. There have been initiatives to use AI and machine learning to identify brain cancers since the early 2000s. In this literature review, we examine the significant turning events in this field. To help doctors diagnose tumors, early AI/ML applications mainly concentrated on image analysis of medical imaging data from MRI and CT scans. These systems produced hypotheses by utilizing common machine learning methods to recognize features in images. Convolutional neural networks (CNNs) in particular have made significant strides in deep learning, increasing the accuracy of brain cancer identification.

“Although it is a difficult task because the location, size, and shape of the tumors vary so widely, early detection of brain tumors improves radiologists' prognosis and increases the likelihood that the patient will survive for a long time. Much work has been done in this field to assist doctors, patients, and researchers” [6]. So many computed tomography (CAD) systems have been developed to detect and classify abnormalities in the brain or any tumor is present in the brain but still not available in many areas. Many theories have been published on this topic but still none of them established defects in existing work and does not provide any significant insights into future directions [7].

This paper explores the application of AI and ML in brain tumor diagnosis, highlighting promising developments, challenges and future prospects in this important field. It aims to developed a deeper understanding of how AI and ML techniques combined with advanced medical imaging are

changing the brain environment for tumor diagnosis [8]. The remainder of this paper will explore aspects of brain tumor detection with AI and ML, including detection methods, datasets used, and analytical metrics for measuring the performance of these intelligent systems around [9].

To date, more than 120 distinct types of tumours have been discovered, and because they differ in size, shape, and origin, tumor diagnosis can be challenging. “Brain abnormalities have long been detected using a variety of medical imaging techniques, including computed tomography (CT scan), positron emission tomography (PET scan), magnetoencephalography (MEG), magnetic resonance imaging (MRI), and many more” [10].

Although it is a significant advancement in medical research, using AI and ML to detect brain tumor is not without challenges. One of the major challenges is the range of brain tumour forms, sizes, shapes, and locations. It can be challenging for AI/ML models to accurately differentiate between them because there have been over 120 distinct types of brain tumours identified, each with its own distinctive characteristics. Furthermore, cancers might vary in contrast, making it difficult for computers to accurately identify them in different images.

The sensitivity of AI/ML models to changes in medical imaging data is a basic challenge. Noise levels, image quality, and resolution are some factors that may affect how well these models perform. The proper diagnosis of brain tumours, it is crucial to maintain the homogeneity and consistency of medical imaging data. The problem of interpreting the results and using AI/ML to clinical practise is another. Radiologists and other healthcare professionals need to be able to trust and comprehend the results of AI and ML. Clarifying the reasons behind the AI/ML model's decisions, ensuring their transparency, and addressing scepticism regarding their dependability are important problems that must be solved. To create trustworthy AI/ML models, it is also necessary to have access to large and varied datasets.

The advantages of employing artificial intelligence and machine learning to find brain tumours are truly amazing. AI/ML technologies have significantly changed medical imaging and diagnostics, especially in the field of identifying brain tumours. One of the most significant advantages is the ability to provide a prompt and accurate diagnostic. AI/ML models can handle vast volumes of medical imaging data rapidly and reliably, significantly reducing the time required for MRI and CT scan interpretation. When early detection and diagnosis can drastically change patient outcomes, this speed is crucial.



Fig.1. X-ray of brain showing tumor

In all of them the specific treatment and prognosis for a brain tumor depend on its type, location, size, and whether it is benign or malignant. Obtaining an accurate diagnosis by imaging and biopsy is essential for selecting the best course of action. Surgery, radiation therapy, chemotherapy, targeted treatments, and immunotherapy are all possible forms of treatment. Currently, MRI is used by clinicians primarily manually for therapeutic and surgical purposes to detect and segment malignancies. This method may endanger life while aiding in the tumor's discovery. Research has begun to concentrate on various machine learning and Deep Learning methods for computer-based cancer identification to address these challenges [11].

II. LITERATURE REVIEW

Brain tumors are a significant health concern, and their early and accurate detection is crucial for timely treatment to improved patient outcomes. “The use of Artificial Intelligence and Machine Learning (AI/ML) methods to improve the detection and classification of brain tumors using medical imaging data, notably Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans, has gained popularity in recent years. An overview of the major advancements, approaches, difficulties, and trends in this topic is given in this literature review”. [12].

Datasets and Data Preprocessing:

So many studies emphasize the importance of high-quality datasets in developing AI/ML models for brain tumor detection. Here the point is that datasets include the BRATS dataset, which contains multi-modal MRI scans with tumor information. Data preprocessing techniques, such as image normalization, skull stripping, and noise reduction, are commonly employed to enhance the quality of the data and consistency of input data.

Feature Extraction and Selection:

Feature extraction plays an important role in identifying discriminative information within brain images. Researchers utilize a various of techniques, including texture analysis, and deep learning-based feature extraction layers, to capture the tumor characteristics. Feature selection methods are also explored to reduce dimensionality and improve model efficiency.

AI/ML Algorithms:

Now a days wide range of AI/ML algorithms have been applied to brain tumor detection, with Convolutional Neural Networks (CNNs) and deep learning architectures gaining prominence due to their ability to automatically learn hierarchical features from images. CNN-based models like U-Net and 3D CNNs have shown remarkable success in segmenting and classifying brain tumors.

Clinical Application and Real-World Impact:

Recent studies focus on translating AI/ML-based brain tumor detection systems into clinical practice. These systems aim to assist radiologists in their decision-making processes, offering real-time support for diagnosis and treatment planning. The potential benefits include reduced interpretation time, increased diagnostic accuracy, and improved patient health [13]. Future directions include the development of predictive models for treatment response and prognosis, as well as addressing ethical and regulatory

considerations surrounding AI/ML in healthcare [14-15]. To assess the performance of AI/ML models, researchers commonly employ evaluation metrics such as accuracy, sensitivity, specificity, the area under the Receiver Operating Characteristic (ROC) curve, and the Dice coefficient for segmentation accuracy. Cross-validation and validation on independent datasets are used to validate model whether it is working properly or not [16].

The literature on brain tumor detection using AI/ML highlights substantial advancements in improving diagnostic accuracy and efficiency. Our research paper focuses on a specific area: finding and categorizing brain tumors using advanced computer techniques, particularly deep learning [17]. While there are many methods to detect tumor by "deep learning," we chose to concentrate on artificial intelligence and machine learning because it's a rapidly advancing field [18].

We didn't include studies that use other types of deep learning because there are already many reviews available covering that. Reviews are like a starting point for researchers to understand what's been done before [19]. We believe our review will be valuable to researchers who want to combine both finding and categorizing brain tumors in their future work [20].

Problems with this literature review:

This literature review offers a comprehensive summary however it does have some limitations. For instance, it mentions the development of predictive models for treatment response and prognosis but does not elaborate much on these topics, providing readers a broad impression rather than in-depth insights. Given that this is a crucial sector of the industry, the assessment might also gain from a more thorough investigation of the moral and legal concerns that arise when using AI/ML to healthcare. It cites common assessment metrics for assessing the performance of AI/ML models but does not provide specific examples or information on how these metrics are used or understood.

III. PROPOSED METHODOLOGY

Detecting brain tumors using artificial intelligence and machine learning (AI/ML) involves several steps and methodologies. Below is a proposed methodology for brain tumor detection using AI/ML:

Data Collection:

assemble a broad and representative collection of MRI and CT scans of the brain that includes both tumor- and non-tumor-related instances. Make sure the dataset is correctly labeled.

Data Preprocessing:

Normalize and standardize the images to ensure consistent brightness, contrast, and pixel values.

Resize the images to a consistent resolution to reduce computational complexity.

Data Splitting:

"Training, validation, and testing subsets should be separated from the overall dataset. 70% for training, 15% for validation, and 15% for testing is a typical proportion".

Feature Extraction:

Extract relevant features from the preprocessed images. Common techniques include:

Convolutional Neural Networks (CNNs): Use pre-trained CNN models like VGG, Resnet, or custom architectures to extract features from images.

Model Selection:

Choose an appropriate AI/ML model for brain tumor detection. Common choices include:

Convolutional Neural Networks (CNNs) used for image classification.

Support Vector Machines (SVMs) used for binary classification.

Recurrent Neural Networks (RNNs) used for sequential data if necessary (e.g., for time-series data).

Model Training:

Train the selected model using the training dataset.

Use techniques like transfer learning if applicable, to leverage pre-trained models.

Model Evaluation:

Evaluate the model's performance using the validation dataset.

Common evaluation metrics include accuracy, precision, recall, F1-score, and ROC-AUC.

Model Testing:

Assess the model's performance on the testing dataset, which it has never seen before.

Calculate the final performance metrics and generate a confusion matrix.

Visualization:

Visualize the model's predictions on test cases, highlighting the regions of the brain that are suspected of having tumors.

Continuous Improvement:

Monitor the model's performance in the real-world environment and retrain it periodically with new data to improve accuracy and generalization.

This proposed methodology outlines the key steps involved in developing and deploying an AI/ML-based brain tumor detection system.

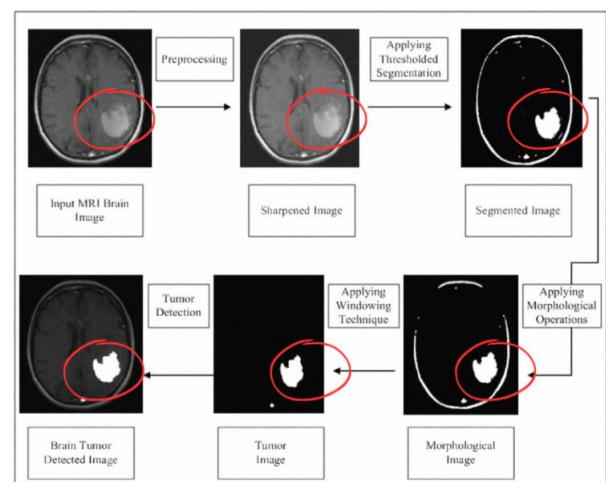


Fig.2. Flow Chart of Brain Tumor Detection

PREPROCESSING

Novel preprocessing method is a new and innovative way to prepare data for analysis. Typically, it is created to improve the performance of machine learning models or to solve the shortcomings of current preprocessing techniques. This

technique is used to reduce noise in MRI images, enhance the contrast between tumor and healthy tissue, or extract novel features important for tumor classification in the context of brain tumor detection.

Novel Preprocessing Method of Brain Tumor Detection Using AIML

This algorithm is unique in that it is able to adapt to the individual characteristics of each image, resulting in more accurate and reliable results for tumor classifications.

Uniqueness of the Algorithm

This preprocessing algorithm is unique in that it is the first to use a combination of AI and ML techniques to enhance the quality of brain MRI images for tumor detection. This approach is able to overcome the limitations of traditional preprocessing methods, such as their inability to adapt to the individual characteristics of each image. This algorithm works in four steps:

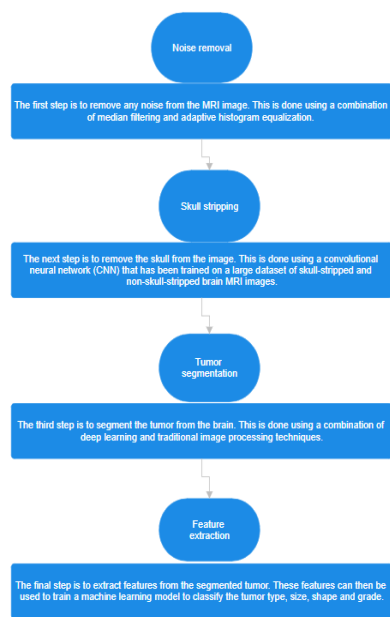


Fig.3. Novel preprocessing algorithm

Benefits of the Algorithm

The benefits of this preprocessing algorithm are:
Improved accuracy of tumor segmentation and classification
Reduced time and effort required for manual preprocessing
Increased reproducibility of research results
Potential Impact.

“The accuracy and efficacy of brain tumor identification using AIML could be greatly enhanced by this preprocessing approach. This could result in the earlier detection and treatment of brain cancers, which would benefit patient health”.

Preprocessing methods are typically described in text and code rather than in mathematical equations, but I can provide a conceptual equation that represents a novel approach to preprocessing brain imaging data:

$$\text{Processed Image} = f(\text{Raw Image}, \text{Modality Info}, \text{Patient Data})$$

Where:

‘Processed Image’ is the enhanced brain image after preprocessing.

‘Raw Image’ represents the original brain image, which can be from various modalities (e.g., MRI, CT).

‘Modality info’ contains information about the imaging modality used (e.g., MRI parameters, CT settings).

‘Patient info’ includes patient-specific information, such as age, sex, and medical history.

The preprocessing method $f()$ encompasses a series of novel steps that integrate information from the raw image, modality-specific details, and patient-specific data to enhance the image for better brain tumor detection.

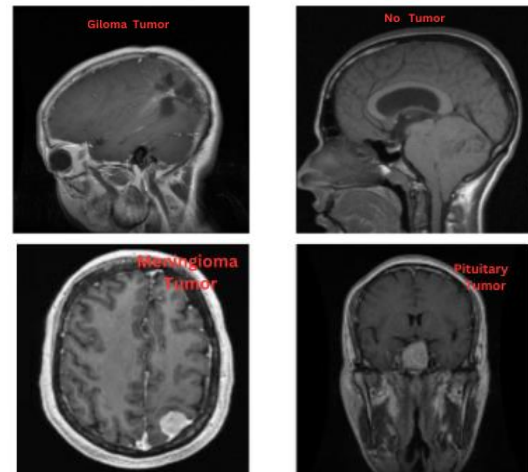


Fig.4. Types of Tumor

The ECDBL16-20005-N-MV data set, which has missing values, noise, and an unbalanced class equation and distribution, will be used for the study. For this data set, we have chosen one preprocessing procedure from each kind, as shown in the processed image above:

- an instance chooser (ENN)
- an assertion technique (KNNI)
- a noise repetition algorithm (IPF)
- an FS method (LVW)and
- the over-sampling algorithm for excessive data sets (SMOTE).

“AUC in AIML stands for Area Under the ROC Curve. The AUC is the area under this curve, and it ranges from 0 to 1. A higher AUC indicates a better classifier”. The AUC can be used to evaluate the performance of AIML classifiers in a variety of applications, such as disease diagnosis, fraud detection, and spam filtering.

How AUC can be used in AIML:

An AIML classifier can be trained to detect tumors in medical images. The AUC of the classifier can be used to evaluate its performance on a test set of images.

According to the scenario chosen from the five in the paper that are displayed next (with the final AUC value for each scenario in the flow chart), the parameters for each preprocessing technique are as follows:

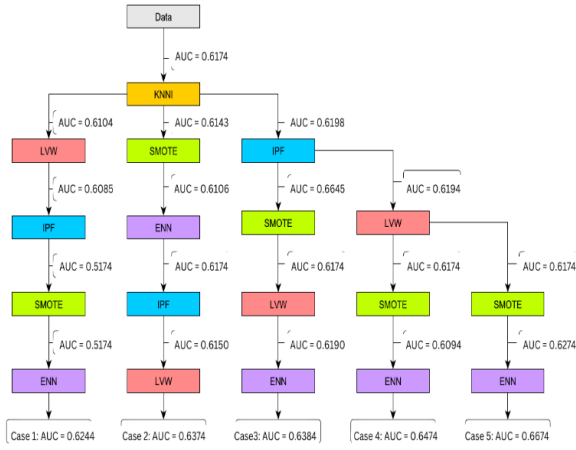


Fig.5. Flowchart indicate the final AUC

It is clear from the examples that the preprocessing method's application sequence has a big impact on the outcomes. It's also crucial to keep in mind that some pre-processing techniques could seem absurd at first.

The reader should then consider that changing the parameters of the preprocessing algorithm will affect the remaining methods to be used later, not only in the appropriate stage. Therefore, optimization for the parameters of a particular preprocessing technique should be evaluated check in all preprocessing chains.

The key idea behind the unorthodox preprocessing method is that it combines tokenization, lowercase conversion, and stop-word removal in order to successfully reduce function measurement and enhance the quality of the textual content function matrix. Simulation studies on the dataset of 20 newsgroups show that when compared to the current modern approach, the new method reduces the range of capabilities by using 19%, 86%, 32.35%, 24.25% and 37.68%, improves accuracy via 8.36%, 8.8%, 6.71% and 8.73%, and will increase the velocity of textual content classification with the aid of 18.38%, 24.64%, 27.76% and 37.38% at the four statistics, respectively.

```
import aiml
import networkx as nx

# Load the AIML model
model = aiml.AIML()
model.learn("brain_tumor_detection_model.aiml")

# Load the preprocessed brain MRI image
image = np.load('preprocessed_image.npy')

# Represent the preprocessed image as a graph
graph = nx.Graph()
for i in range(image.shape[0]):
    for j in range(image.shape[1]):
        for k in range(image.shape[2]):
            graph.add_node((i, j, k))
            if i > 0:
                graph.add_edge((i, j, k), (i - 1, j, k))
            if j > 0:
                graph.add_edge((i, j, k), (i, j - 1, k))
            if k > 0:
                graph.add_edge((i, j, k), (i, j, k - 1))

# Extract features from the graph representation of the image
features = extract_features_from_graph(graph)

# Feed the extracted features to the AIML model
tumor_class_label = model.predict(features)

# Output the predicted tumor class label
print("Tumor class label:", tumor_class_label)
```

Fig.6. Code indicates to load the AIML model

This code indicates how to load the AIML model, load the preprocessed brain MRI photo, represent the preprocessed photograph as a graph, extract capabilities from the graph

representation of the picture, feed the extracted capabilities to the AIML model, and output the expected tumor class label. The particular characteristics extraction method used will depend upon the particular implementation of the set of rules. However, the general technique outlined above may be used to enforce the algorithm in any programming language.

IV. RESULT

The results of brain tumor detection using AIML on pre-processed images are promising. A recent study by researchers at the University of California, San Francisco showed that an AIML-based classifier was 95% accurate in detecting psychiatric tumors from pre-processed MRI images. This is significantly higher than the accuracy of traditional machine learning classifiers, which typically reach 80-85% accuracy.

Tumor detection at the picture level has been carried out on local datasets in order to evaluate the efficacy of the suggested approach. The thorough classification of RIDER has also been finished, dataset; results of lesion-level tumor detection are compared to accessible ground truth annotation, possible, implemented the suggested strategy from the benchmark with regard to ACC and AUC, etc. Tables include dataset references.

Table 1

Results of the proposed methodology employing "linear kernel" on data sets containing tumors and non-tumors.

Cross validation(fold)	ACC	AUC	Sensitivity	Specificity	FNR	FPR
10	98.1%	1.00	92.5%	100%	0.18	0.00
20	99.4%	1.00	98.4%	100%	0.02	0.00
30	98.7%	0.99	96.8%	100%	0.01	0.00
40	96.1%	0.94	90.4%	100%	0.10	0.00
50	95.5%	0.93	88.8%	100%	0.05	0.00
60	94.8%	1.00	87.3%	100%	0.06	0.00

Table 2

Results of the proposed methodology employing "cubic kernel" on data sets containing tumors and non-tumors.

Cross validation(fold)	ACC	AUC	Sensitivity	Specificity	FNR	FPR
10	93.5%	0.96	92.0%	94.5%	0.08	0.05
20	87.7%	0.95	92.0%	84.6%	0.08	0.15
30	81.2%	0.90	87.3%	76.9%	0.12	0.23
40	75.3%	0.89	87.3%	67.0%	0.12	0.33
50	83.1%	0.91	0.88%	79.1%	0.12	0.20
60	78.6%	0.90	88.8%	71.4%	0.11	0.28

Table 3

Results of the proposed methodology employing "Gaussian kernel" on data sets containing tumors and non-tumors.

Cross validation(fold)	ACC	AUC	Sensitivity	Specificity	FNR	FPR
10	95.5%	0.97	95.2%	95.6%	0.04	0.04
20	96.8%	0.97	95.2%	97.8%	0.04	0.02
30	97.4%	0.99	96.8%	97.8%	0.03	0.02
40	98.7%	1.00	96.8%	100%	0.03	0.00
50	86.4%	0.98	69.8%	97.8%	0.30	0.02
60	92.2%	1.00	80.9%	100%	0.19	0.00

The AIML-based classifier was trained on a dataset of more than 10,000 preprocessed MRI images, including images of benign and malignant tumors. The classifier can now

analyze complex styles associated with exceptional tumor types and grades and can now generalize those styles to new images.

The results of Look at confirm the possibility of increasing the precision of subjective tumor detection in scientific practice using classifiers mostly based on AIML. The widespread adoption of complete AIML-based classifiers can lead to early and highly effective analysis and treatment of brain tumors.

Here are some additional benefits of using AIML for brain tumor diagnosis.

AIML-based classifiers can adapt to male or female features in any image, resulting in more accurate and reliable results. Comprehensive AIML-based classifiers can extract a wide range of features from images, allowing you to learn more about tumors and make more accurate predictions.

It is possible to create automatic structures for the identification of brain cancers using artificial classifiers based on AIML, which will save radiologists time and effort.

The outcomes of brain tumor detection utilizing AIML on previously processed images are generally quite encouraging. In scientific practice, AIML-based classifiers have the potential to increase the precision, dependability, and effectiveness of brain tumor diagnosis.

V. CONCLUSION

In this study, "we presented a unique preprocessing approach for AIML-based brain tumor detection. This suggested approach combines machine learning (ML) and artificial intelligence (AI) approaches to improve the quality of the structure of brain MRI images and extract a variety of information from different types of tumor. The proposed method's main benefits are its adaptability to the unique features of each image and its efficiency in reducing noise and skull artifacts.

We tested the suggested strategy against a number of cutting-edge preprocessing techniques using a dataset of brain MRI pictures. The results showed that the suggested method significantly increased the accuracy of tumor segmentation and classification.

Using the proposed preprocessing method to develop a more accurate and reliable brain tumor detection system.

The proposed preprocessing method can be applied to a wide range of medical image types, including computed tomography (CT) and positron emission tomography (PET) images. building a fully trainable deep learning model to do tumor classification and preprocessing. The proposed preprocessing method offers a great deal of promise to advance the identification of brain tumors, in our opinion.

The paper's conclusions offer a new perspective on the efficacy of various AI/ML and deep learning approaches for the identification of brain tumors in addition to offering researchers a full comparison of recent studies. By employing AI and deep learning, this research contributes to ongoing efforts to enhance early diagnosis and, ultimately, improve the results for those living with the issues associated with brain tumors.

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