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Artificial Intelligence for Brain Tumor Diagnosis: A Comprehensive Review

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ABSTRACT

Brain tumors are a mass of unregulated cells brought about by uncontrolled growth, or if a cell does not die when it should. Accurate segmentation of these brain tumors is difficult due to their size, shape, and location differences. Artificial intelligence is an expansive tool with tumor classification, segmentation, and feature extraction applications. The neural networks artificial intelligence models are based on are especially good at extracting meaning and definition from data by identifying deeper underlying patterns that may go unnoticed by humans. Brain tumors are volatile data, and deep learning neural networks and other machine learning algorithms excel in modeling highly variable data such as brain tumor location, size, and type.

keywords: image segmentation; brain modeling; brain tumor segmentation; convolutional neural networks; machine learning

1. INTRODUCTION

The brain is a major organ in the central nervous system that processes sensory information. One million Americans are living with a brain tumor, which can be classified as malignant or benign. Malignant means it is cancerous and can spread, while benign means it is non-cancerous and will not spread. According to the National Brain Tumor Society (NBTS), around 64.3% of people with brain tumors may die from a brain tumor. Machine learning has fundamentally changed how brain tumors are classified (Abd-Ellah et al., 2019a; Bhatele & Bhadauria, 2019). Neural networks encompass many different algorithm types, which all have one thing in common: Neural networks need large data sets, which are hard to obtain in brain scans. Data sets for brain tumors vary, with some using MRI scans, PET, CT, and MEG, among others. The most popular are MRI scans due to their varying contrast levels, allowing for efficient and accurate detection of brain tumors (Mudda et al., 2020; Sharif et al., 2020b; Deepa & Sam Emmanuel, 2019; Tandel et al., 2019; Zulpe & Pawar, 2017). BRATS is a challenging, commonly used public MRI dataset. In hospitals, MRI scans are manually analyzed by professionals such as radiologists. Machine learning models are capable of highly accurate segmentation and classification of tumors, which can surpass that of professionals in many fields. An example of an area where machine learning has done so is in complex games such as chess and Go. Machine learning also excels in pattern recognition, such as self-driving cars, which is invaluable in tumor classification and segmentation. There are various techniques and methodologies to define and establish the brain's segmentation, which are mentioned below.

Computed tomography (CT) is an important technique for visualizing the segmentation of the brain, and it works by rotating an X-ray beam around the patient. These generate cross-sectional images of the region. This allows for many different angles to visualize the organ or structure and, unlike a regular X-ray, does not just provide a single viewing angle of a singular plane. CT scans may also be ordered with contrast, such as dilute iodinated contrast, allowing the radiologist to identify veins and other circulatory structures if injected intravenously. This works by allowing such structures to deplete energy signals and be picked up by the X-rays.

Another important technique for brain segmentation is MRIs. It has great contrast and is a non-invasive way to visualize soft tissue. It uses magnetic resonance to energize nuclei from their equilibrium state to a higher energy state. Radiofrequency pulses are then applied; the machine measures the spin-lattice and spin-spin relaxation times. This relaxation time is compared to known longitudinal and magnetization decay times for malignant and healthy cells. Contrast can also be used to differentiate between certain tissues. Various body parts may be imaged using a series of gradient coils owing to different induced resonances. These signals are sent to a computer system that controls and optimizes pulse sequencing. The computer system takes the data from the MRI scan. It may use a direct reconstruction in the case of cartesian sampling using a Fast Fourier Transform or the more computationally complex iterative reconstruction when a direct solution is not practical or impossible. Iterative reconstruction may be used in the case of non-cartesian sampling, where a non-Cartesian Fourier transform may be applied. A final image is produced using these methods, which medical experts or neural networks may interpret.

Positron emission tomography is another technique for brain segmentation, and it uses radiotracers such as Dihydrotetrabenazine (DTBZ) and Fluorodeoxyglucose using Carbon-11 or Flourine-18 as a radioisotope. All radioisotopes used by PET scans have a short half-life so as not to cause excessive harm through annihilation radiation. The most common positron-emitting radioisotopes are Flourine-18, Carbon-11, Nitrogen-13, and Oxygen-15.

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They are used more than other isotopes as they can be substituted easily into biomolecules. For example, F-18 can be substituted into a hydroxyl group, which does not significantly impact body processing (Schlyer, 2004). After the tracer is administered, usually intravenously, the patient is laid in the PET scanner, which records energy emissions caused by the tracer. The resulting gamma rays from the tracer give a 3D hot-cold image of the area being studied. Thus, locations with abnormal nutrient usage can be identified and visualized. This works via positron decay; an antielectron is released from an unstable nucleus with too many protons and few neutrons to be stable, such as Sodium-22, which decays to Neon-22. When a positron encounters an electron, the most likely result is the production of 2 gamma photons through annihilation. The probability of more photons being created decreases with each photon, but producing just one is generally impossible. Regardless of the number of gamma photons, the result is ionizing radiation that can harm human health in large quantities. According to Nievelstein et al. (2012), the risk posed by the radiation produced by a PET scan is significant, and that, in the pediatric group, may lead to radiation-related death in .4% of males and .7% of females. This is why PET is usually limited and only ordered when necessary.

Besides these techniques, the segmentation of the brain can be divided into different categories, such as threshold-based segmentation, region-based segmentation, and edge-based segmentation. Threshold-based segmentation is a form of pre-processing that allows for greater contrast and pixel classification with a is the simplest process. This method is effective because the binary operation gives simple data for the AI. An intensity threshold is picked, and that threshold transforms the whole image. Ilhan et al. (2017) introduced this technique into the field. Threshold-based segmentation is amazing for removing noise from the image by only allowing values of a certain intensity to enter the AI. Tarhini et al. (2020) developed an algorithm for threshold-based segmentation and described methods such as Fuzzy C-Means (FCM) and SVM. T. Logeswari (2010) used double thresholding by first enhancing the MRI image and then converting it to greyscale. He increased the middle range and then performed a double threshold by removing unwanted pixels with a disk radius 3.

Similarly, region-based segmentation: This method uses pixel similarity to group regions. A specific method is a region growing where a seed pixel is picked, and neighboring pixels with similar properties are iteratively added. The properties may include proximity, color, texture, etc. The seed pixel is usually picked for its region's common properties so the computer can select the correct region accurately. Arce-Santana (2018) proposed a new method using a probability density function for each studied object, such as a different one for meningioma and skull base tumors. Arce-Santana also showed that active contours work well for region-based segmentation. These would be guided by regularization and external forces. These are calculated with an energy function that minimizes energy, not allowing the contour to get too convoluted. The contour evolves following the probability density function. Its accuracy is comparable to other functions having a DSC of >90%. An issue may be parameter tunning, such as finding the correct probability density function and setting the energy function parameters.

Subsequently, edge-based segmentation, in general, involves applying an edge filter, which may vary. The specifics may vary, and specifics such as Canny edge detection are discussed later in this paper. An edge filter can be utilized to identify tumor edges, which would be essential for tumor segmentation as it defines the problem.

2. MACHINE LEARNING FOR BRAIN SEGMENTATION.

Machine learning is a subfield of artificial intelligence founded by Alan Turing, who is also considered the father of modern computers and coding. Designed to mimic the way the human brain learns, machine learning models learn by changing the weight of the connection between their neurons. The problem of tumor detection, classification, segmentation, etc., currently is a problem that inherently lends itself to weak Artificial Intelligence (AI) problem-solving due to the limited range of inputs and outputs. The problem trying to be solved is not trying to replace any medical professionals but rather helping them, making it a computer vision problem. In classification, there are linear and non-linear. A non-linear classifier would be best for brain tumor detection as the dividing lines for tumor location and classification are not easily expressed, even for highly experienced doctors when training algorithms, a cost function can be employed to regressively change the weights and biases till the algorithm reaches a local minimum or global minimum if the cost function is convex (Muhamedyev, 2015). This is achieved by taking a partial derivative concerning each bias and weight, ideally for each data point, using the cost function with functions such as Mean Squared Error (MSE) in equation 1. The cost function takes in all the parameters, whether they be one or one million, and outputs a single "cost" of the perceived $\hat{y}$ From the correct y at each i. Using this function for a derivative usually makes the MSE better than its other version, the Mean Absolute Error (MAE), due to the absolute value function not being differentiable at all values.

$$\frac{1}{2m}\sum_{i=1}^{m}(\hat{y}^{i}-y^{i})^{2} \tag{1}$$

The ideal process is computationally burdensome but does yield a higher convergence rate for the iterative function. To reduce the computational load, a stochastic gradient descent may be calculated; due to its increased efficiency, a batch gradient descent may be used with a vectorization library. The question of how this descent is calculated requires only an understanding of multivariable calculus.

$$\alpha.\frac{\partial C}{\partial w_{ik}^{L}} \tag{2}$$

The value w_{ik}^{L} Determines the value of the parameter of weight as shown in equation 2. It is calculated by the partial derivative of the cost function concerning the weight of the connection at layer L with the index's connection with the neuron at layer L-1 at index k. It demonstrates the magnitude and direction of descent for the I know connection at layer L.'

$$\alpha.\frac{\partial C}{\partial b_{ik}^{L}} \tag{3}$$

where b_{ik}^{L} It is a partial derivative of the cost function concerning the bias for a neuron at layer L. The equation 3 for b_{ik}^{L} Which is very similar to the equation for w_{ik}^{L}. This is calculated as a summation of the partial derivatives for the change in the values that the neuron affects in layer L-1. The indices are ordered from the output layer; the descent is calculated backward regarding backpropagation. In reality, equation 1 and equation 3 are an average over the whole dataset or a portion of it. The learning parameter α determines, in many cases, whether the equations will converge or not. The learning rate is commonly adjusted as the vector decays to avoid oscillation. Equation 4 shows how descent is calculated from the weight and bias parameters for every index. which corresponds to every bias and weight in the architecture. The result of this formula is a vector that helps to reach the minimum by a magnitude of α via an iterative process whereby the formula is recalculated till a minimum is reached of cost function; the minimum can be modeled with min C (w_{ik}^{L} , b_{ik}^{L}).

$$\nabla C = \begin{bmatrix} w_1 \\ b_1 \\ \vdots \\ w_l \\ b_l \end{bmatrix} \tag{4}$$

Many more aspects go into training a powerful and accurate neural network, like the number of layers, pooling layers, and dropout regularization. However, AI training is not the focus of this paper and thus has been omitted from this brief overview.

2.1 Pre-Trained Models

Pre-trained AI models are transforming the field of medical imaging by revolutionizing brain tumor detection. They allow already proven architectures to be used, which ensures a certain level of ability for the model. They are often CNNs like VGG-16 and ResNet-50, which are trained on a large dataset of general images, allowing for the foundation of image processing to be built. The models are then retrained to fit the problem the researchers are trying to solve. Many times, the pre-trained models pay little attention to the background in brain tumor images. This is because CNNs are just not as efficient as utilizing the background cerebral structure as other forms of neural networks. That is why CapsNet considers background features more than CNN-based models. CapsNet works with capsules, which are bundles of neurons, but this sensitivity to the background is also a drawback of the model, and many times, the tumor must be given to the model. Chelghoum et al. (2020) showed that the ability of such models is comparable to state-of-the-art models, reaching an accuracy of 98.71% for classification. In 2014, google researchers developed a new CNN architecture with the new inception module, which allowed for multi-level feature extraction and is now called GoogLeNet (Inception v1). GoogLeNet has much potential and may even surpass the more commonly used ResNet-50. GoogLeNet has more recently been able to beat more common models, like in Chetan Swarup et al. (2023), showing that GoogLeNet had an accuracy of 99.45% compared to the lower accuracy of AlexNet at 98.95%. They also pointed out that a benefit of GoogLeNet is that it takes significantly fewer parameters than AlexNet. Both models were trained on Radhamadhab Dalai, "Brain Tumor Dataset" (2021). Hassan A. Khan et al. (2020) made a CNN from scratch and compared it to VGG-16, ResNet-50, and Inception-v3 models. The scratched CNN performed at 100% accuracy on their limited dataset, while ResNet-50, VGG-16, and Inception-V3 achieved 96%, 89%, and 75%, respectively. This could be due to overfitting but may also highlight the value of having a model that does not have redundant pre-trained general computer vision features.

2.2 Evaluation Metrics in Medical Image Segmentation

There are many methods to evaluate image segmentation. One commonly used metric is the dice similarity coefficient (DSC). The DSC of a neural network is a harmonic mean, generally measuring the similarity of two samples. In the case of brain tumor segmentation, it can be used to tell how correctly a neural network identifies each pixel as either tumorous or non-tumorous. This can be modified to prioritize precision, the accuracy of positive pixels, or recall, the proportion of positive pixels identified. The Jaccard index or Intersection over Union (IoU) is the correctly identified positive pixels over the incorrectly identified pixels and correctly identified pixels.

The authors T. Kalaiselvi and S. T. Padmapriya have formulated six convolutional neural network models (CNN) to classify brain tumors (Kalaiselvi et al., 2020). All the models in their research paper mainly have different layers. In 2 of the CNNs, a drop-out layer was utilized. An additional 2 have batch normalization and stopping criteria. All 6 were trained on BRATS and tested on the World Brain Atlas. Model 6 yielded the most optimum results with a 96% accuracy rate. Authors Kurup et al. (2020) found that data pre-processing makes the convolutional neural network smaller in required size. The pre-processing methods used were rotation and patch extraction. These were applied to 3064 images, which produced a larger data set with greater variance. The images were resized, which reduced the input values for the neural network, thus reducing the size. Capsule-net was used to test the results of the pre-processing. The network classified the tumor images as either glioma, meningioma, or a pituitary tumor, and the network greatly increased in its effectiveness due to pre-processing.

Begum and Lakshmi (2020) showed a new algorithm for brain tumor categorization and segmentation using statistical characteristics. This algorithm removes noise and uses run-length texture features with a GLCM matrix. It is cut down using an Opositional Gravitational Search Algorithm (OGSA), and the data is given to an RNN, which states whether it is a tumor. Then, the data is sent for ROI segmentation. This algorithm gave 96% accuracy on the given dataset. Raj et al. (2020) gave another new algorithm to analyze MRI images called BRAINnet. The first BRAINnet consists of checking if something is a tumor and then BRAINnet 2 segments it to classify the type of tumor. It has 98% accuracy in determining whether something is a tumor and 99% accuracy in classifying it. Islam et al. (2020) use MRI scans to show whether a tumor is cancerous. They utilize multi-level segmentation for more effective categorization and feature extraction. They start by pre-processing the data and then segment it by thresholding it and using a morphological operation with a watershed algorithm. Features are extracted through CNN so that K-SVM can classify the tumor as cancerous. This algorithm has an overall 87.4% accuracy.

In a study by Megha et al. (2020), the Kaggle MRI dataset is used. It uses a convolutional neural network to complete pre-processing and input processing, including feature extraction. It takes an MRI image and classifies it as either tumorous or non-tumorous. A Graphical User Interface (GUI) was also developed for medical professionals ease of use. This emphasizes the practical value of such a neural network. The CNN had a 90-99% accuracy on Kaggle. Abdelaziz Ismael et. Al (2020) showed the significance of data pre-processing in Resnt-50 architecture training and testing. The processes worked to increase the generalization of the data and decrease the gradient vanishing problem in RNN models when using gradient descent and backpropagation. The data was fitted and cropped to remove parts that did not affect the analysis or background areas. The efficacy of the model was 98%. Pankaj et al. (2013) explained the value of an edge detection algorithm. The most common is John F. Canny, who developed the Canny Edge Detection Algorithm. The main advantage of the Canny Edge Detection Algorithm is that it depends highly on the value of σ (standard deviation of the Gaussian filter), which changes based on the desired blurring. A major drawback of the algorithm is that it is computationally time-consuming. Another edge detection method is the Prewitt filter, a gradient-based algorithm. This reliance on a gradient makes it sensitive to noise, which cannot be fixed as the coefficients are fixed and are not dependent on a tunable σ. Thus, Prewitt cannot be changed for data with high background noise. As such, the Canny Edge Detection Algorithm performs the best of the other edge detection software available.

Amin et al. (2020) convey the significance of pre-processing and segmentation. Before giving information to a deep learning algorithm, they sharpen the images and smooth the noise by applying median filtering. Subsequently, they use region growing to segment the tumor area and provide it to a fine-tuned stacked sparse autoencoder model (SSAE). They tested it on 2012, 2013, 2014, and 2015 BRATS, proving it improved accuracy and responsiveness. Amin et al. (2020) also propose an interesting method where they combine four MRI modalities using DWT technology for one MRI image, creating one MRI sequence for every patient. The corresponding CNN model is more capable of detecting tumors in fused images. In 2019, Amin et al. published a paper about using pre-trained models such as Googlenet and Alexnet to classify the tumor. The MRI images are pre-processed using linear and log transformations, followed by thresholding and morphological operations to segment the tumor region. Using this processed image as input increases the accuracy of classifying the tumor as malignant or benign. Antony et al. (2018) do something novel: They classify the tumor type into three distinct types: necrosis, enhancing, and non-enhancing. They used CNN to classify and segment tumors and NI4TK for preprocessing. They did intensity normalization and bias field correction and used data augmentation to solve overfitting. This demonstrates that it can classify brain tumors accurately.

Pereira et al. (2016) had a proposed model with 3 steps. Pre-processing, glioma classification via a CNN, and then post-processing filters results under a certain volumetric threshold. The CNN was trained using the commonly utilized stochastic gradient descent. A small 3x3 kernel reduces overfitting due to fewer weights required with a smaller kernel. It is hypothesized that a deeper architecture is achieved using a smaller kernel. This is because it forces the network to notice more generalizable features and ensures unrelated details are not emphasized. The CNN produced won first place in many sections in the BRATS 2013 dataset, thus supporting the underlying ideas of the paper and stressing the importance of kernel size selection in CNN model training. Joshi et al. (2019) proposed an algorithm using CNN with eight layers for better classification with 98% accuracy. The algorithm tries to figure out whether something is a tumor or non-tumor via a private dataset; if it detects a tumor, it segments the image and applies global thresholding for binarization and uses a watershed algorithm followed by morphological operations to abstract the tumor and also calculate the area of the tumor. Gutsche et al. (2023) use amino acid PET scans for the training and testing dataset. The neural network used was a type of CNN made to yield highly precise segmentation and be trained faster. The model was trained on 476 scans. An average of 91% of scans with abnormal uptakes were recognized, with 92% for increased uptake lesions and 85% for lesions with hypometabolic uptake.

Sundar et al. (2022) worked with a nnU-Net version of the U-net architecture neural network. This is achieved by iteratively changing the data's augmentation to increase the network's performance. They used many different datasets of PET scans to train their model on many different body areas, including 13 abdominal organs, 20 bone segments, subcutaneous fat, and other parts of the body, including the brain. They used F-FDG PET/ MRI scans for cerebral imaging. They achieved a DSC of over .9 for 92% of noncerebral tissues, yet their DSC for 60% of brain regions stayed in the 0.8 to 0.89 range. Only 29% of brain segments had a median DSC of over 0.9. It was shown that large datasets are not required to train accurate neural networks; rather, unique patterns in the images are required. A larger data sample leads to more capturing of the natural variance in how tumors appear. This is great as obtaining a large dataset is cumbersome, expensive, and requires medical professional analysis. Tatsat Patel et al. (2020) compare the efficacy of 2 multi-resolution CNNs to detect brain aneurysms. The two types of architectures used are U-net and DeepMedic. Vasculature can be difficult to discern from brain images so that AI could add enormous value to the field. The DeepMedic had a DSC of 0.94±0.02. This was trained on 100 human-segmented digital subtraction angiography images. This was better than U-net, which performed with a DSC of 0.92±0.02. This makes sense when considering the types of problems U-net was made to solve compared to DeepMedic. Li et al. (2019) emphasize the magnitude of multimodalities in brain MRI images by using fused multimodal information, which increases the accuracy of the results when tested with 2018 BRATS. Contrast adjustment and grey-level normalization pre-processed the images and augmented them with conventional techniques. These images were then given to 3D CNN for classification, and instant normalization was utilized to accelerate the convergence, along with a modified loss function. They achieved a dice score of 92% by using multiple fused modalities.

Pan et al. (2015) presented a single-layered CNN model to grade brain tumors. First, they take images from 2014 BRATS and pre-process them using data from the middle. Then, they take more rotated versions of the tumor region and compare these results with a state-of-the-art neural network model with 67% specificity and accuracy. Xiao et al. (2013) presented a method for approximating features from the connection between tumors and LaVs of brains with four steps. The first would be preprocessing, feature extraction and segmentation, and classification. This helped to segment and classify brain tumor MRI images. Pranjal Agrawal et al. (2022) use 3D deep learning to segment and classify brain tumors. It uses the MRI Kaggle dataset to train its deep CNN 3D U-net model. It was found to have a 90% accuracy. The 3D U-net model is an image registration model that merges the 3D image slices and corrects for misalignment when the data is fed into the model, ensuring information is not lost. The output of the model is an image that has gone through the down and up-convolution cycle. The second CNN takes subsections as well. It then returns the classification of the tumor. D Filatov (2022) uses a CNN with the same basis as ResNet with identity mapping as the base instead of the random sampling that was used originally. Residual block ameliorates the vanishing or exploding gradient, creating deeper models. The basis is that any model with n% accuracy at L number of layers can be matched at L+a layers with identity mapping. Keeping the default as identity mapping removes the need to learn the identity function. They found EfficientNet models to be the most effective of all the models they were comparing.

3. AVAILABLE RESULTS AND DISCUSSION

AI is very versatile in this new frontier that we are entering, but it has many complications. Though AI is gaining popularity, it hasn't been heavily invested in inside hospitals, so it would be hard to implement it there on a large scale. Data security would also hinder hospitals from sharing data from one clinic to another, which would make it harder to make a large dataset to train the AI.

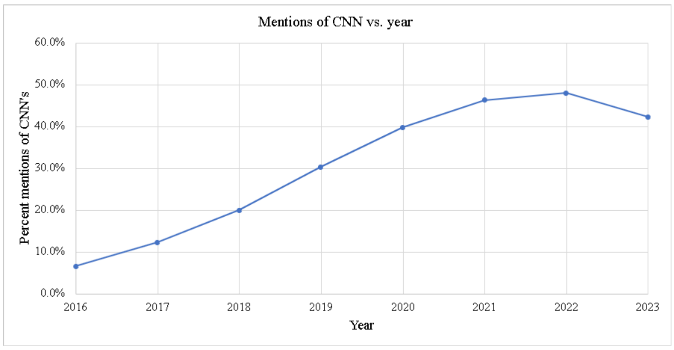

Fig. 1 Ratio of mentions of Convolutional Neural Networks out of total by year using Google Scholar.

In recent years, convolutional Neural Networks have become exceedingly popular for tumor detection and classification. They are logical choices as CNNs lend themselves well to the segmentation of tumors and are the primary network architecture for visual processing. The ratio of papers mentioning CNN has a maximum in 2022. Figure 1 shows a dip in ratio in the year 2023 from 48% to 42%. The increased interest in the field may explain this and, thus, the resulting increase in model types. As more researchers saturate the field of study, so does the variance increase. Recently, in 2023, there has been increased interest in Bayesian models, with the method developed by MIT being used more often called Deep Evidential Regression. Others may use a form of CNN, such as the paper by Gutsche et al. (2023), which uses a model called JuST_BrainPET, a nnU-Net. It is based on the convolutional neural network developed by the Comp Sci Department of the University of Freiburg for biomedical imaging called U-Net. The paper never mentions CNN and thus would not be picked up in Figure 1. This is a limitation of the data collection method, where it underrepresents the CNN dataset. It can be assumed that many papers that use a CNN model would mention the name, and thus, the data is adequate for understanding trends in the subject.

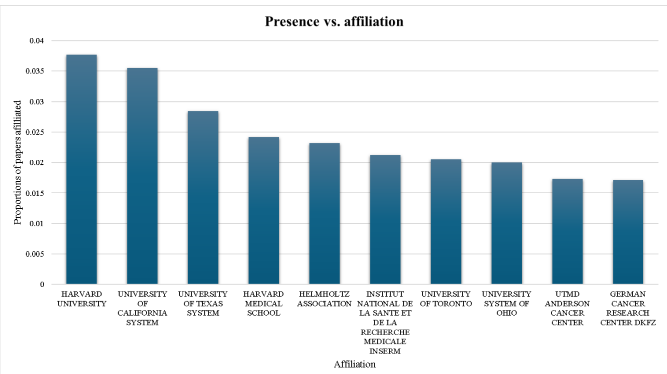

Fig. 2 Top 10 affiliations of paper in tumor detection, classification, segmentation, etc., using neural networks by proportion over the last 10 years based on data from The Web of Science.

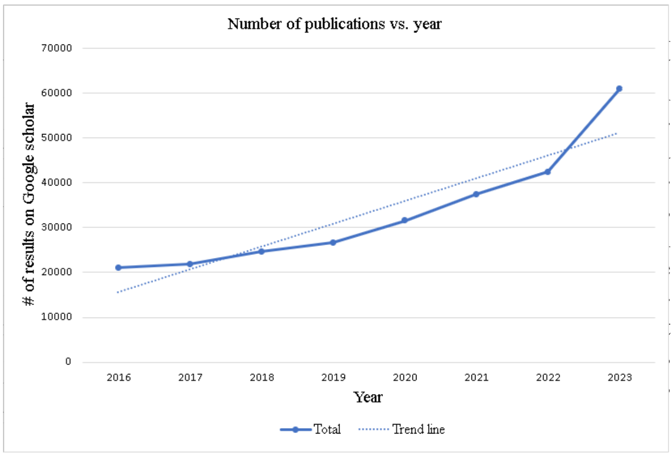

Fig. 3 Number of publications in tumor detection, classification, segmentation, etc. using neural networks

This is an ever-growing field. As shown in Figure 3, the number of publications tripled from 2016 to 2023 and doubled over the last 3 years. The growth is exponential rather than linear, as shown by the r-squared score for the linear and exponential models in Figure 4, and as such, is projected to grow even more in the future. As interest grows, so will the amount of information; thus, a compilation of the current available information is required. Tumor detection using neural networks is the culmination of hundreds of years of human research and requires extensive knowledge of biology and computer science disciplines. His graph must not be an accumulative graph of all publications but rather a discrete number of publications each year. The data was pulled without regard for time in the year as the trends meant to be extracted are larger scale and not annual.

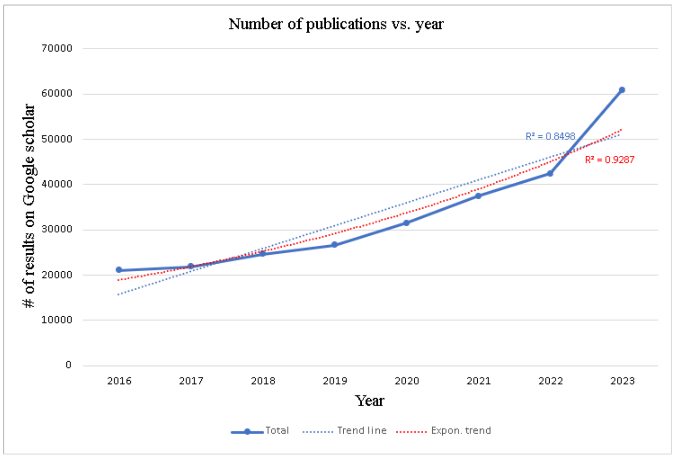

Fig. 4 shows the exponential regression vs linear regression model for the data.

4. CONCLUSION

Brain tumor detection remains a difficult and commonly studied field. Despite recent breakthroughs, the variable and volatile patterns of consistent brain tumor detection, classification, and segmentation remain elusive. Throughout human civilization, we have always dealt with problems such as brain tumors. However, advancements in modern surgery have led to a longer prognosis for many types of tumors. As we try to help the lives of those ailed with brain tumors, it has become exceedingly obvious that early detection is crucial in the treatment of all tumors. Currently, the only way to ensure that a tumor has been detected is via the time-intensive process of radiologist review. It is only fitting that the invention designed to mimic the human mind helps save the mind. Time is of the essence when dealing with tumors that grow every second; thus, the emphasis is on early detection, and we must look to any advancement that can aid in speeding up tumor detection. Neural networks may not replace radiologists due to their great insight and understanding, but networks most definitely will help play a role in quickening the detection process. This application of neural networks is necessary rather than just an intellectual endeavor.

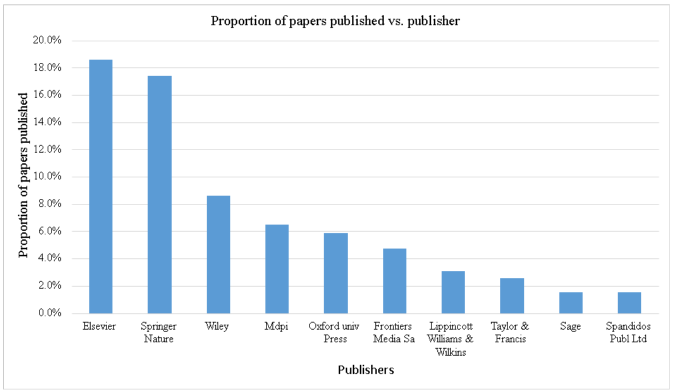

Fig. 6 Proportion of publications based on publishers.

This data shows how many research papers publishers published on brain tumors regarding AI in the last ten years. It shows that Elsevier has published the most publications on this topic, which aligns with the fact that it often publishes medical and scientific ideas and research. According to data from the Web of Science, Elsevier and Springer Nature combined have almost 40% of all papers published in this field. Fewer possible academic publishers may explain this in the world than affiliations in the case of Figure 6. Publishing with larger publishers also leads to more citations for a paper, which leads to more exposure for the researchers involved. Due to this, larger publishers may get more papers, thus propagating the positive feedback loop.

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