# Brain Tumor Detection

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**Abstract:**

This research highlights the increasing global problem of brain tumors and how they affect public health in different ways. Brain tumor is the abnormal growth of tissues in the brain it affects many brain parts such as CNS which control many motor functions.The symptoms of brain tumor include headache , seizures and nausea. The methods studied, including both traditional imaging and advanced machine learning like **KSVM-SSD** and BraTs, help improve the accuracy of identifying these tumors. By combining different approaches, we can better understand and treat brain tumors. This presentation not only informs us about the current situation but also encourages future efforts to develop better methods for identifying and classifying brain tumors. The most used the dataset that was used the most was **BraTS(2015)** the braTS series of dataset gave the algorithms the highest efficiency rate.The highest results achieved was on the model FFNN which gave Training**: 99.93%**, Validation**: 98.63%,** Test**: 98.56%**, Overall**: 99.94%.**

**1.Introduction**

Brain tumors are abnormal growths of tissue in the brain that result from the uncontrolled multiplication of cells [[1](#a1)].Brain tumor first carried out by "Mr. Rickman J. Godlee officially acknowledged removal of a primary brain tumor on 1884. The medical and popular press of the time provided a detailed and comprehensive account of Godlee's "first" operation for a primary cerebral tumor. It also sparked discussions on the subject among professionals and laypeople, which both directly and indirectly led to additional cerebrum surgery and the development of modern neurosurgery [2].

Symptoms of brain tumor can be often be generalized into more than one sign. The symptoms include headache, altered mental status, and seizure, increased intracranial pressure, including papilledema, nausea, and vomiting [3]. There are primarily two types of brain tumors: benign and malignant. Benign tumors are those that are less dangerous to humans and do not include cancerous cells. On the other hand, a tumor that has cancerous cells and is more dangerous to people is referred to as malignant [4]. Cancerous tumors can be divided into primary tumors and secondary tumor, Primary tumors originate inside the brain, and secondary tumors that have spread from outside the brain are referred to as brain metastasis tumors [5].

The number of people dying due to brain tumor is increasing, with the World Health Organization estimating that nearly 251,329 people worldwide die from brain tumors each year [6]. In 2023, approximately 5,230 children under the age of 20 in the US will receive a CNS tumor diagnosis. Cancers such as melanoma, leukemia, lymphoma, and lung, kidney, and breast cancers can spread to other parts of the body and develop into secondary brain tumors. The principal brain tumors in adults are the subject of this guide. When it comes to the deaths of men and women, brain and CNS cancer comes in at number 10. It expected to end in 18,990 deaths in the United States in 2023, which compared to 251,329 deaths globally in 2020 [7]. Around 700,000 patients in the US have been diagnosed with primary brain tumors. Furthermore, in 2021 there were almost 85,000 new cases of brain tumors found in the United States alone. When treating a brain tumor on of the crucial aspect of the patients survival is its age. According to the study, patients between the ages of 55 and 64 had a one-year survival rate of 46.1%, whereas patients between the ages of 65 and 74 had a survival rate of 29.3%. The significance of early tumor discovery in raising the chance of survival is emphasized [8].

Brain tumors may be different significantly in size, shape, location, and appearance, diagnosing them can be challenging. Early brain tumor identification is extremely difficult due to the tumor's not being able to be accurately measured. However, the brain tumor is discovered, the appropriate treatment may begin, and it might even be treatable. As a result, treatments such as chemotherapy, radiation therapy, and surgery, are dependent on the tumor [9]. Imaging tests that could be carried out include CT and/or MRI scans, which utilize computers to provide precise images of the brain. To see the blood veins in the brain supplying a brain tumor with blood, a technique known as a brain angiography may also be performed [10].

In the early stages, radiotherapy can help a patient survive without surgery. When cancer is in its middle or advanced stages, it is very harmful and can only be treated with chemotherapy and radiation. For this reason, a qualified radiologist is required for the diagnosis. Image processing methods have been extremely successful in the medical area for the diagnosis of lung cancer, stomach cancer, skin cancer, blood cancer, and brain tumors. The best imaging methods for identifying brain tumor are CT scan and MRI pictures. Because MRI images are based on information about shape and texture, they are superior to CT scan images. With MRI, determining a tumor's size, location, and form is simple. These methods' disadvantages, meanwhile, are their expense and computation time [11].

Every year, new techniques for picture segmentation are developed that address the problems of earlier approaches. The deep learning-based segmentation and classification are thought to be the most effective techniques for locating and obtaining MRI image features. The brain and its neurons serve as the model for artificial neural networks (ANNs), which are networks of connected neurons that can perform certain calculations based on inputs. An ANN is employed as a classifier if the output layer generates the final classification category. One kind of deep neural network is the convolutional neural network (CNN). CNNs are very effective in picture segmentation and classification applications because they can extract features from the images [12].

Many machine learning-based classifiers, such as Support Vector Machine (SVM), Random Forest (RF), fuzzy C-mean (FCM), Convolutional Neural Network (CNN), Naïve Bayes (NB), K-Nearest Neighbors (KNN), Sequential Minimal Optimization (SMO), and Decision Tree (DT), have been used for the classification and detection of brain tumor. There is extremely little mathematical complexity involved with the CNN implementation. These classifiers, in general, raised   academic interest because of their modest training dataset requirements, low computing cost, and simplicity of use for non-expert users [13].

# 2.Literature Review

The article utilizes the BraTs 2015 dataset for its working using three algorithms CNN, MKK and KMC.By applying these some observations were made that are as follows the sensitivity, and accuracy of the method is evaluated using four algorithms PPV, NPV, FPR, FNR.To check the performance of this model it is compared with the old models and the accuracy that was obtained was 99% sensitivity obtained was 93.5% specificity obtained was 99.22% [14].

The article involves two individuals Siva Raja and Antony that used BraTS 2015 dataset. The algorithms used were Hybrid: Bayesian Fuzzy and Autoen coder these algorithms were segmented and classified based on certain brain tumors along the working there was a certain error that occurred which was called Mean square error (need to find solution). The accuracy obtained was 98.5% the sensitivity was 96% the specivity obtained was 99.54 [15].

The following article uses the hakrabarty N (2019) data set for its working CNN algorithm was used. A generalized proposed framework was introduced for the detection of brain tumors this specified model used two different algorithms for two different tasks the benefit from this model was the ideal tumor detection the respective accuracies obtained was 90.62% from CNN, transfer Learning 93.75%, proposed framework gave 96.88% [16].

In the following article WebBrain data set and kaggle dataset was used both utilized the same algorithms CNN and DNN both had 1000 images in the data set after processing the result obtained were as follows the kaggle data set gave accuracies of 93.50,98.28 with DNN AND CNN respectively. However, the WebBrain gave accuracies of 97.40, 97.50 in WebBrain the DNN accuracy was improved. In kaggle, the CNN accuracy is better [17].

In the following article the BRATS series of data sets were used ranging from 2013 to 2018 the approach used was deep neural network with feature selection the accuracy obtained was 92% this was done by sharif et al. amin et the brats 2015 data set he used a different approach he used statistical feature and machine learning method the accuracy obtained by him was 97% [18].

In this article the brats data set was used which consisted a viable benchmark data set for performance evaluation this brat data set consisted of 2 classes which were representative for non-tumor and tumor MRI images 187 and 30 images respectively the images were passed through many methods like T1, T2, FLAIR the results obtained were superlative by splitting the dataset in 70 to 30 in training for CNN the accuracies obtained from CNN was 92.42% [19].

In this article the KSVM-SSD is used on brat datasets ranging from 2018-2020 the tool which is used for the analyzing is python programming language the brain tumor is being divided into two parts malignant and begnine tumor this precise division through segmentation and classifications is a superior method than existing old methods in overall accuracy recall, and, F1 score the accuracy achieved by the brat 2018-2020 was 99.2%, 99.36% and 99.15%, respectively [20].

In this article its explained that the higher the accuracy of an algorithm the higher will be the prediction rate Physio Net/CinC Challenge Dataset is a common dataset that worked on ANN,CNN,SVM and KNN which gave (97.89%)(97.35) (94.03%) (85.70%) respectively. The physio net/Cinc challenge data set that worked on RNN CNN AND SVM and gave accuracies of (94.82) (94.82) (88.60) respectively the GitHub PCG Dataset worked on SVM CNN they scored (97.00%)(85.89%) respectively these models achieved top prediction the Pascal Challenge Dataset Was worked on KNN CNN for the normal dataset and which gave the accuracy of 99% and 96.25 respectively but some private data sets were used which on using KNN , CNN ,SVM RNN AND ANN gave (97.00%), (96.30%), (90.18%), (90.11%) (89.40%) respectively [21].

In this article, the REMBRANDT dataset was used which consisted of 33 patients, with an average image rate of 20 images per patient this data set was posted by the NCI (National Cancer Institute) from the Cancer Imaging Archive (TCIA). SVM, KNN, LDA and RF models were used which gave an accuracy rate of 90%, 87%, 83% and 83% respectively [22].

In this article kaggle data base is used Dense Net, VGG16, and basic CNN algorithms for training the model we divide the data set into two parts the 1st 80% of the data set of MRI was used in training the algorithm and 20% was used in the testing phase the second fold cross validation method was normalized when the proposed model and some other models were being tested on the same MRI dataset an improvement in the algorithm accuracy was seen but the processing time was increased [23].

The study presented a hybrid method that included an SVM and CNN on brain MRI pictures to identify and classify the tumor as benign in addition to MT. The segmented characteristics of brain MRI pictures were fed into hybrid CNN and SVM algorithms, which produced a classification accuracy of 98.49% for brain MRI images, 72.55% for SVM alone, and 97.43% for CNN. In this article MO. Khairandish et al introduced a hybrid merged model made up of CNN and SVM which was based upon the brain MRI images that had the ability to detect and filter benign and malignant tumor these MRI images were classified by passing the segmented its features to the CNN which was a hybrid along with some SVM algorithms the results obtained were 98.49% classification CNN accuracy rate yet SVM got 72.55% and CNN got 97.43 individually [24].

In this article six models relating to CNN are used which are VGG16, Google Net, InceptionResNetV2, Xception, ResNet50, and EfficientNet-B0 each algorithms had its own depth and layer but with the same parameters the results of the algorithms are as follows the VGG16 had the precision,recall,F1 score, sensitivity specificity and accuracy of 98.5,99.1,99.1,98.8,98.5,98.6 respectively the inceptionRESNETV2 had the precision ,recall,F1 score, sensitivity specificity and accuracy of 97.7,97.6,96.4,97.6,97.4,97.5 respectively the Xception algorithm had precision ,recall,F1 score, sensitivity specificity and accuracy of 96.6 98.5 97.5,98.2,96.3,97.6 respectively The ResNet50 Had precision ,recall,F1 score, sensitivity specificity and accuracy of 97.6,98.2,97.9,98.2,96.3,97.6 respectively the InceptionRESv2 had precision ,recall,F1 score, sensitivity specificity and accuracy of 97.6,98.4,98.0,98.4,98.3,98.3 respectively [25].

In this article the MR dataset is used which consisted of 1924 images and the the data that was used to test consisted of 482 image samples the algorithm that was used for this dataset is called R-CNN which consisted of Stochastic Gradient Descent the algorithm was trained for 120 epochs with 1000 iterations per epoch the total time that took was 16 hours the accuracy that was calculated was 98.4% the problems The four components of the algorithm was RPN regression, RPN detection, R-CNN classifier and R-CNN box regression [26].

The classification of tumors of the pituitary, glioma, and meningioma types is done using artificial neural networks. The suggested network construction makes use of the efficient "Levenberg-Marquardt" training function. The specificity of this suggested approach is 95.4%, 94.58%, and 97.83%. This enhanced outcome is superior to other current detection methods in comparison. The use of ideal preprocessing procedures and an efficient training function are the fundamental causes of the outstanding results . [27].

Second, by combining the best features of the most well-liked and successful classifiers for image identification and classification—KNN and CNN—this hybrid CNN-KNN model was proposed. Finally, as decisions are made, the hybrid model's complexity is slightly raised. Out of all the models, including CNN, CNN-DISCR, CNN-SVM, CNN-NB, CNN-ESEMBLE, and CNN-TREE, the suggested CNN-KNN model yielded a 96.25 percent accuracy rate. [28].

In this article different KNN classifiers are used the models that are used are BNN (Back-propagation neural network) RBFN(Radial basis function neural network) DWT(Discrete wavelet transform) PCA-ANN(Principal component analysis) K-Nearest Neighbor (KNN) (Proposed method) these were the main classifiers used for detection the respective accuracies are 76.19 ,85.71 89.54 ,91.97 ,96.15 with respect to the algorithms above [29].

In this article the a data set of CT scan brain images were used using decision tree this process involves many methods such was pre-processing, edge detection, association rule mining and hybrid classification. Tree was mainly used to classify certain images from the dataset to perform various classification the algorithms used were SVM, Adaboost, CART, KNN, K-Means, chaos genetic algorithm, EM method, C4.5 out all these algorithms SVM and KNN gave the highest accuracy 97.15,96.94 respectively [30].

In this article some techniques are used the datasets used were BRATS2018 and BRATS2019 on these datasets some algorithms were used that include Entropy–Kurtosis-based High Feature Values (EKbHFV) which was based on mathematics. MGA had new proposed features both of these algorithms the EKbHFV and MGA-based features are fused together and the given output accuracy was 95% [31].

In this article the BRATS 2018 dataset is used from this dataset the 3D-MR images are used by applying the custom CNN algorithm we obtained the following result 98.14%, accuracy 98.26% using the Dense-Net classifier, and a DSC of 96.4%, an accuracy of 96.52% using the Dark-Net classifier. The Dense-Net classifier compared to the Dark-Net classifier this shows that the results obtained from CNN are high as compared to others achieved a higher level of accuracy [32].

In this article the  [Harris Hawks optimization](https://www.sciencedirect.com/topics/computer-science/harris-hawks-optimization) (WHHO) is used for the detection of brain tumor the segmentation of the data set is performed the algorithm that is used is deepCNN that was trained for a proposed WHHO this proposed WHHO algorithm is designed integrating another algorithm that is called HHO algorithm the deepCNN outperformed the models with a accuracy of 0.816, maximal specificity of 0.791, and maximal sensitivity of 0.974, respectively [33].

In this article a deep learning network was developed the purpose of its development is to divide the dataset into 2 parts the classification accuracies of the proposed model is 92.9% and 89.5% for a complete MRI mask abidwianda et al he presented a deep learning architecture for the sub-group categorizations of MRI images but the accuracy achieved was only 84.19% but when another study was studied it exhibited an accuracy rate of 95.56% [34].

In this article a technique of extreme learning machine for classification of brain tumor from 3d MRI images this proposed method achieved This method obtained an accuracy sensitivity specificity 93.2%, 91.6%, 97.8% respectively Sacdeva et al  
displayed a multiclass tumor classification a feature attraction performed using data set of 428 MRI images and performed segmentation they used ANN AND PCA-ANN algorithms and achieved an accuracy ranging from 77-91% [35].

In this article BraTS 2015 was used and passed through some algorithms called ALEX net and ISLES 2018 these algorithms gave an accuracy rate of 74.7% and this was achieved through google net when both of the models it was observed that the nearest k neighbors outperformed in every field this was compared to the other existing models where it was clear how better it was than others [36].

In this article, the working is based on the plans for the transfer of learning based tumor detection and segmentation via a technique called superpixels technique in this model the MRI images are classified into three parts called normal LGG and HGG. An accuracy rate achieved was 99.82 and 96.32 on VGG-19 at epoch-6 through training data.in testing phase the accuracy, specificity, sensitivity and Area Under Curve (AUC) was 99.30%, 100%, 97.81%,99% respectively [37].

In this article the brats 7(2016) dataset is used the methodology used here is called segmentation .This application is applied with respect to ground truth images. By applying segmentation the results achieved were 97% of sensitivity and the specificity rate of 98.2% and FPR FNR LPR LNR 0.93 0.27 0.93 0.15 respectively [38].

In this article some of the algorithms were applied on the Harvard dataset and more than one methods or algorithms were used these include F-KNN, Decision Tree, back propagation and SVM by applying all these algorithms some of the results were achieved for F-KNN Sensitivity, Accuracy was 91.19 92.23 for Decision tree Sensitivity Accuracy was 90.49, 92.90 for Svm Sensitivity Accuracy was 97.78, 98.88 for back propagation Sensitivity Accuracy was 93.21, 95.69 [39].

In this article there are many algorithms that are used for classification of brain tumor but one of the most used algorithm used for classification is CNN in this the tumor site is identified via MR segmentation another Tanique that is applied is dataset augmentation this is applied before CNN overall the accuracy achieved was 94.58% for classifying images [40].

The article uses the SVM algorithm the following results were obtained by applying these on braTS 2021 dataset the precision, recall, and f1 score for the test dataset obtained was 94.6%, 85.4%, and 89.7%.another algorithm had a very solid performance after training the dataset the results were obtained was 86.6%, 80%, and 82.8% Decision Tree (DT) model performed perfectly on the training dataset, achieving 100% accuracy for all evaluation parameters. However, when applied to the test dataset, the model's performance dropped, with precision, recall, and F1 score values of 88.5%, 73.3%, and 78.7%, respectively [41].

Depak et al used the MR images dataset and created a system that differentiates between 3 tumor types including meningioma glioma and pituraty tumor type’s .the algorithm used was known was google net that achieved a classification accuracy of 97.1% [42].

Using the utilized net model and resnet152 algorithms for segmentation of brain tumor ramasamy used the braTS2020 Dataset using these models he found the accuracy sensitivity and dice coefficient of of 99.2%, 76.62% 77.33% respectively for the tumor region [43].

The FFNN model operates at a very high level when the R-value is near to unity. The results of the FFNN algorithm on the brain tumor dataset are shown in Figure 16 over different phases. 99.93% of the regression values were reached during the training phase, 98.63% during the validation phase, 98.56% during the test phase, and 99.94% over the full phase [44].

By using the Bag of Words (BoW) model on the tumor region and tumor boundary independently, retrieval performance was improved and a mean Average Precision (mAP) of 91.0% was attained. By using brain tumors as a region of interest (ROI) in the region partition learning method, Huang et al. enhanced the mAP to 91.8% in a follow-up investigation [45].

Our training and testing datasets came from an 8-bit JPEG dataset of 7022 T1-weighted contrast-enhanced MR brain tumor pictures that was made available to the public on Kaggle . Glioma, Meningioma, Pituitary, and No-tumor are the classifications assigned to the photos. There are 5712 photos in the training set, comprising 1457 pituitary samples, 1321 glioma, 1339 meningioma, and 1595 no tumor images. Thirteen11 pictures total from 405 No-tumor, 300 Glioma, 306 Meningioma, and 300 Pituitary cases make up the test set. To the best of the authors' knowledge, this study is the first to demonstrate the use of fully automated graph-feature-based classifiers for end-to-end brain tumor detection. Overall classification accuracy, according to the results, is 94.89% [46].

A method involving a classification network that separates input MRI images into two categories—tumor containing and tumor-free—was presented by Anil et al. Transfer learning is used to retrain the classifier to identify brain tumors. With an accuracy rate of 95.78%, VGG-19 is the most successful architecture among those examined. Muhammad Sajed et al. presented a unique CNN model for brain tumor classification in a different method. Their process starts with the segmentation of tumor spots from MRI images and ends with dataset expansion. Next, the proposed CNN is utilized for classification, yielding a 94.58% accuracy rate [47].

Rehman et al. (2016) augmented their dataset using image-processing technology to enhance the model's performance. They applied affine transformations to the image data of DCNNs, including AlexNet, GoogleNet, and VGG16. As a result, the classifiers achieved impressive accuracy rates of 97.39 percent, 98.04 percent, and 98.69 percent, respectively [48].

Alrashedy et al. (2022) generated and classified MRI brain pictures using a variety of deep learning models, such as CNN, ResNet152V2, and MobileNetV2. To create the images, DCGAN and Vanilla GAN were used. These images were used as training data for deep transfer models. An authentic set of MRI brain images was used as the test set for evaluating the model's performance. Remarkably, based on the MRI brain pictures, ResNet152V2 was the best-performing model, obtaining remarkable results with 99.09% accuracy, 99.51% AUC, 99.08% recall, 99.12% precision, and a loss of 0.196 [49].

A dataset consisting of 33 benign and 65 malignant lesions from 98 women who were judged to be at high risk of developing breast cancer was subjected to EST-NET analysis. Multiple two-dimensional slices with different axial planes were included in each patient's data, creating a dataset of 2245 slices total. ESF-NET showed a diagnosis accuracy of 85.61% at the slice level and 89.66% at the patient level in cases when sequence information was unavailable. When compared to the use of a single sequence, this signifies a noteworthy improvement of 8.39% [50].

To categorize input MRI images as either normal or pathological, features are derived from the segmented area of brain tumors through grayscale co-occurrence matrices (GLCM) and the Support Vector Machine (SVM). K-means clustering is employed to differentiate the brain tumor from other brain regions. 64 photos are analyzed in this study, with 42 featuring benign and malignant brain tumors and 22 representing normal images. The approach achieves an overall classification accuracy of 99.28% when applied to the Brain Tumor Segmentation (BraTS) 2015 datasets [51].

Jun Cheng et al. developed a method for tumor classification comprising two phases: offline database construction and online retrieval. In the offline phase, brain tumor images undergo sequential processing, including tumor segmentation, feature extraction, and distance metric learning. During online retrieval, input brain images are processed similarly, and their extracted features are compared with the learned distance metrics stored in the online database. Despite not employing a neural network approach, this method achieves a classification accuracy of 94.68% [52].

For classifying gliomas, the scientists developed a system that combines SVM and KNN. This approach achieved an accuracy of 88% for binary classification and 85% for multiclassification. Using Wavelet Transform (DWT), PCA, and ANN-KNN for image classification, a different method for brain tumor identification is provided in a different study, with results ranging from 97% to 98%. Cheng and colleagues proposed a method that enlarges the tumor area using picture dilatation and subdivides it into regions to improve the classification performance of brain tumors. For feature extraction, they used three different techniques: BOW, GLCM, and intensity histograms. The method combines tumor region augmentation with ring shape segmentation, yielding an amazing accuracy of 91.28% [53].

A method for integrating k-Mean clustering-based processes for tumor localization was proposed by Rinesh et al. The firefly method is an optimization strategy that determines the value of k. Methods such as k-nearest neighbor and k-means clustering are utilized. They additionally identify the discovered brain regions using a multilayer feedforward neural network. When compared to other methods like parallel k-means clustering and hybrid k-means clustering, the suggested method performs better with a lower mean absolute error and a higher peak signal-to-noise ratio. Results showed that the proposed model has a 96.47% overall accuracy, a 98.24% specificity, and a 96.32% sensitivity [54].

With a small CNN architecture, the authors were able to attain an 84.19% classification accuracy. A further suggested approach that used transfer learning to facilitate block-wise fine-tuning produced noticeably higher categorization accuracy. Another method achieved an outstanding classification accuracy for brain MR image classification using transfer learning and a pre-trained GoogleNet [55].

In 2019, Hossam H. Sultan et al. proposed a model centered on convolutional neural networks for brain tumors, comprising 16 layers. The model demonstrated a peak accuracy of 96.13% in detecting malignant tumors. The authors successfully identified tumors in the first phase and further categorized a tumor into three distinct subtypes in the second phase. Notably, they achieved 100% accuracy for two subtypes and 95% accuracy for the remaining subtype in the second part of their model [56].

Table Literature Review

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Reference** | **Dataset** | **Model** | **Accuracy** | **Limitations** |
| **[14]** | BraTs 2015 | CNN,MKK ,KMC | Accuracy 99% sensitivity 93.5% specificity 99.22% | This dataset while widely used may not fully represent the diversity of cases and imaging conditions in real world clinical settings. |
| **[15]** | BraTS 2015 | Hybrid: Bayesian Fuzzy and Autoen | Accuracy 98.5% Sensitivity 96% Specificity 99.54% | The presence of MSE indicates an error in the model's predictive performance, and although the accuracy, sensitivity, and specificity |
| **[16]** | Hakrabarty N (2019) | CNN  Transfer Learning  framework | 90.62%  93.75%  96.88% | N/A |
| **[17]** | WebBrain | CNN and DNN both had 1000 images | Accuracies of 93.50%, 98.28% with DNN AND CNN respectively. However, the WebBrain gave accuracies of 97.40%, 97.50% in WebBrain the DNN accuracy was improved | While comparing accuracies of CNN and DNN on Kaggle and WebBrain datasets, it is essential to note that dataset characteristics, such as size, diversity, and complexity, can affect model performance. |
| **[18]** | BRATS 2013 to 2018  brats 2015 | Deep neural network  machine learning | Accuracy 92%  Accuracy 97% | The article lacks a thorough analysis, making it difficult to fully understand challenges and compare the performance of deep neural network and statistical feature-based methods on BRATS datasets. |
| **[19]** | brats  benchmark | CNN | Accuracy 92.42% | Limited diversity in the dataset and potential bias due to imbalanced class distribution, raising concerns about generalizability to broader populations. |
| **[20]** | brat 2018-2020 | KSVM-SSD | Accuracy 99.2%, sensitivity 99.36% specivity 99.15% | The article lacks exploration of potential challenges or drawbacks associated with KSVM-SSD, limiting a comprehensive understanding of its applicability and potential shortcomings in brain tumor classification. |
| **[21]** | Physio Net/CinC Challenge | ANN | RNN  CNN | CNN  SVM | AND  KNN | SVM | 97.89% |94.82  97.35% | 94.82%  94.03% | 88.62%  85.70% | ------ | The article lacks detailed insights into specific challenges or intricacies associated with the evaluated algorithms on various datasets, limiting a comprehensive understanding of their performance variations. |
| **[22]** | REMBRANDT | SVM  KNN  LDA  RF | Accuracy 90%,  87%  83%  83% | The study is constrained by the small sample size of the REMBRANDT dataset and lacks detailed exploration of model-specific challenges, limiting broader generalizability. |
| **[23]** | Dense Net | VGG16, CNN | N/A | The study lacks detailed exploration of the increased processing time associated with the proposed model, affecting practical implementation considerations. |
| **[24]** | hybrid technique | CNN  SVM | 98.49%  72.55%  CNN got 97.43 individually | The study lacks exploration of challenges or drawbacks associated with the hybrid CNN-SVM model, limiting insights into potential issues or areas for improvement in tumor classification accuracy. |
| **[25]** | Six CNN Models | VGG16, InceptionResNetV2, Xception, ResNet50, EfficientNet-B0 |  | -The study lacks exploration of potential challenges or weaknesses associated with the evaluated CNN models, hindering a comprehensive understanding of their limitations in various performance metrics. |
| **[26]** | MRI dataset | Four Component of algorithm  RPN regression,  RPN detection,  R-CNN classifier  and R-CNN box regression | Accuracy 98.4% | The study fails to address or discuss specific challenges or drawbacks encountered during the application of the R-CNN algorithm on the MR dataset, leaving gaps in understanding potential limitations. |
| **[27]** |  | Artificial neural network | specificity 95.4%,  94.58%  97.83% | Limitation: The study fails to address or discuss specific challenges or drawbacks encountered during the application of the R-CNN algorithm on the MR dataset, leaving gaps in understanding potential limitations. |
| **[28]** | Hybrid CNN-KNN | CNN, KNN | 96.25% | The paragraph lacks specific details regarding potential challenges or drawbacks associated with the proposed hybrid CNN-KNN model, limiting a comprehensive understanding of its performance nuances. |
| **[29]** | KNN classifiers | BNN  RBFN  DWT  PCA-ANN  KNN | 76.19%  85.71%  89.54%  91.97%  96.15% | -The paragraph lacks specific insights into challenges or comparative aspects of different KNN classifiers, limiting a comprehensive understanding of their performance. |
| **[30]** | Dataset of CT scan brain images | SVM, Adaboost, CART, KNN, K-Means, chaos genetic algorithm, EM method, C4.5 | SVM and KNN gave the highest accuracy 97.15, 96.94. | The paragraph lacks specific details on the challenges or drawbacks associated with the mentioned methods, limiting a comprehensive understanding of their effectiveness. |
| **[31]** | BRATS2018 BRATS2019 | EKbHFV  MGA | Together 95% | The paragraph lacks clarity on specific challenges or insights into the potential drawbacks associated with the EKbHFV and MGA-based approaches, limiting a comprehensive evaluation of their effectiveness. |
| **[32]** | BRATS 2018 Dataset used 3D-MR images | CNN  Dense-Net classifier, DSC  Dark-Net classifier | 98.14%  98.26%  96.4%  96.52% | The paragraph lacks information on specific challenges or potential drawbacks associated with the custom CNN algorithm, hindering a comprehensive understanding of its performance in diverse scenarios. |
| **[33]** | [Harris Hawks optimization](https://www.sciencedirect.com/topics/computer-science/harris-hawks-optimization) (WHHO) | deepCNN | accuracy 81.6%  specificity 79.1%  sensitivity 97.4% | The paragraph lacks details on potential challenges or shortcomings of the WHHO algorithm and its integration with deepCNN, limiting a thorough assessment of its applicability and robustness in diverse scenarios. |
| **[34]** | Deep learning network was divide the dataset into 2 parts normal and abnormal | Normal  Abnormal  MRI images  Another Study | 92.9%  89.5%  84.19%  95.56% | The paragraph lacks clarity on the factors contributing to variations in accuracy between different studies, hindering a clear understanding of the model's consistency and reliability across datasets. |
| **[35]** | 3D MRI images | 428 MRI images  ANN PCA-ANN | Accuracy 93.2% Sensitivity 91.6% Specificity 97.8%  77-91% | The paragraph lacks specific details regarding potential challenges or shortcomings of the extreme learning machine technique, diminishing a comprehensive assessment of its performance and applicability in comparison to other algorithms. |
| **[36]** | BraTS 2015 | ALEX net  ISLES 2018 | 74.7% | The paragraph lacks specific insights into the reasons behind the observed superiority of the nearest k neighbors, leaving the reader without a clear understanding of the factors contributing to its better performance. |
| **[37]** | superpixels technique | VGG-19 at epoch-6 | accuracy, 99.30%  specificity, 100% sensitivity 97.81% Area Under Curve 99% | The paragraph lacks a clear acknowledgment or exploration of potential challenges or drawbacks associated with the transfer learning-based tumor detection and segmentation using the superpixels technique, providing limited insights into the model's limitations |
| **[38]** | brats 7(2016) | FPR  FNR  LPR  LNR | Sensitivity 97%  specificity 98.2%  0.93  0.27  0.93  0.15 | The paragraph lacks a thorough exploration of challenges or nuances related to the segmentation methodology, hindering a complete understanding of its limitations and potential impact on the reported results. |
| **[39]** | Harvard dataset | F-KNN  Decision Tree  SVM | Sensitivity91.1%  Accuracy 92.23%  Sensitivity90.49,Accuracy 92.90  Sensitivity97.78Accuracy 98.88  Sensitivity 93.21 Accuracy 95.69 | The paragraph lacks specific details on the challenges or shortcomings associated with the applied algorithms on the Harvard dataset, limiting a comprehensive understanding of their effectiveness and potential drawbacks. |
| **[40]** | MRI Dataset | CNN | 94.58% | The paragraph lacks specific insights into the challenges or drawbacks associated with the employed algorithms, MR segmentation, and dataset augmentation, limiting a nuanced understanding of their impact on the achieved accuracy of 94.58%. |
| **[41]** | braTS 2021 | SVM  Decision Tree (DT) | Precision: 94.6%, Recall: 85.4%, F1 Score: 89.7%  Precision: 86.6%, Recall: 80%, F1 Score: 82.8% | SVM algorithm, potential Decision Tree model overfitting, and lack of comprehensive comparative metrics pose limitations in the presented results. |
| **[42]** | MR Images | GoogleNet | Accuracy: 97.1% | overfitting issues, leaving uncertainties about the algorithm's reliability and generalization beyond the specific dataset used. |
| **[43]** | braTS 2020 | Utilized Net and ResNet152 | Accuracy: 99.2%, Sensitivity: 76.62%, Dice Coefficient: 77.33% | lacks information on potential segmentation challenges or errors encountered using the specified net model and ResNet152 algorithms on the BraTS2020 dataset. |
| **[44]** | Brain Tumor Dataset | FFNN | Training: 99.93%, Validation: 98.63%, Test: 98.56%, Overall: 99.94% | lack of information on potential overfitting issues or generalization challenges faced by the FFNN model when applied to the brain tumor dataset. |
| **[45]** | Brain Tumor Images | BoW Model | mAP: 91.0% | Limited information on potential drawbacks or challenges hinders a comprehensive assessment of the effectiveness of the Bag of Words (BoW) model and region partition learning method in brain tumor retrieval. |
| **[46]** | Kaggle Dataset | Various Deep Learning Models (ResNet152V2, MobileNetV2, etc.) | 94/89% | Limitations include potential dataset biases and a lack of information on diversity, impacting the generalizability of the fully-automated graph-feature-based classifiers for brain tumor detection. |
| **[47]** | Kaggle Dataset | CNN (VGG-19) | Accuracy: 95.78% | comparative evaluation metrics or details on potential challenges, making it difficult to assess the robustness and generalizability of the presented classification methods. |
| **[48]** | Various DCNNs | AlexNet, GoogleNet, VGG16 | Accuracy: 97.39%, 98.04%, 98.69% | challenges related to dataset augmentation using affine transformations, impacting the generalizability of the classifiers. |
| **[49]** | Kaggle Dataset | Deep Learning Models (CNN, ResNet152V2, MobileNetV2) | ResNet152V2 Accuracy: 99.09%, AUC: 99.51%, Recall: 99.08%, Precision: 99.12%, Loss: 0.196 | MRI brain images, impacting the real-world applicability and generalizability of the ResNet152V2 model. |
| **[50]** | High-risk Breast Cancer | EST-NET | Diagnosis Accuracy: 85.61% (Slice), 89.66% (Patient) | external validation, impacting the broader generalizability of EST-NET's improved diagnostic accuracy. |
| **[51]** | BraTS 2015 | SVM | Overall Classification Accuracy: 99.28% | small sample size (64 photos) and lack of external validation, impacting the robustness and generalizability of the proposed method. |
| **[52]** | Glioma Classification  Brain Tumor Identification | SVM and KNN  Wavelet Transform (DWT), PCA, ANN-KNN | Binary Classification: 88%,Multiclassification: 85%  Accuracy: 97-98% | e lack of clarity regarding the specific techniques used in tumor segmentation, feature extraction, and distance metric learning, making it difficult to replicate or compare the method. |
| **[53]** | Tumor Area Enlargement | Enlargement BOW, GLCM, Intensity Histograms | Accuracy: 91.28r4 | he significance of the achieved accuracy, questioning the method's competitiveness in the broader field of brain tumor classification. |
| **[54]** | Brain Tumor Segmentation (BraTS) 2015 | SVM and KNN | Accuracy: 96.47%, Specificity: 98.24%, Sensitivity: 96.32% | lacks insights into computational efficiency, scalability, and the potential impact of variations in imaging conditions on the model's performance, limiting its broader utility in clinical scenarios. |
| **[55]** | Various Methods | Small CNN Architecture | Classification Accuracy: 84.19% | lacks specific details on the dataset used, making it difficult to assess the generalizability of the models |
| **[56]** | Brain Tumors | Convolutional Neural Networks (16 Layers) | Peak Accuracy: 96.13% | achieving 100% accuracy may indicate potential overfitting or bias, requiring validation on larger and more diverse datasets for a comprehensive assessment. |

**2.2 Contribution**

**By going through almost 250+ papers we selected a fair total of 56 papers on which our litrerature**

**2.1Summary**

The articles utilize diverse datasets such as BraTS, WebBrain, Kaggle, and more, employing algorithms like CNN, SVM, KNN, and hybrid models for brain tumor detection and classification. Different studies assess the accuracy, sensitivity, specificity, and other metrics of their proposed models. Some projects involve the application of deep learning models, including CNN, ResNet, and GoogleNet, while others focus on traditional machine learning techniques.

Notable achievements include a hybrid CNN-SVM model with a 98.49% classification accuracy, a CNN model achieving 99.2% accuracy on the BraTS 2018-2020 dataset, and a proposed CNN-KNN model outperforming other architectures with a 96.25% accuracy. Various datasets, such as Kaggle, REMBRANDT, and Physio Net/CinC Challenge, are used to evaluate different algorithms like ANN, CNN, SVM, and KNN.

Furthermore, research shows that improving model performance requires preprocessing actions, data augmentation, and transfer learning. Further, the research analyzes the use of various segmentation methods optimization techniques, and feature extraction methodologies. Some articles use a variety of algorithms for a careful examination, while others concentrate on a single method, such as Bag of Words (BoW) or Extreme Learning Machine (ELM).

**3.Methodology:**

**3.1Dataset:**

Identify and obtain the related datasets used in each article, such as BraTs 2015, Web Brain, Hakrabarty N (2019), BRATS series, REMBRANDT, Physio Net/CinC, MR Dataset, etc.

Preprocess the data by standardizing image sizes, normalizing pixel values, keeping in mind of any missing data.

**3.2Algorithm Selection and Implementation:**

For each article, clearly define the algorithms used (e.g., CNN, MKK, KMC, Hybrid: Bayesian Fuzzy, Auto encoder, KSVM-SSD, R-CNN, Levenberg-Marquardt, CNN-KNN hybrid, Extreme Learning Machine, ALEX Net, ISLES 2018, VGG16, Google Net, Dense Net, etc.).

Implement the listed algorithms using relevant libraries and tools, specifically marking parameters and configurations as mentioned in the respective articles.

**3.3Training and Testing:**

Divide the dataset into training and testing sets, following the described splits.

Train the models on the training set, specifying the number of epochs, iterations, and any specific training functions mentioned (e.g., Stochastic Gradient Descent, Levenberg-Marquardt).

Evaluate the models on the testing set to obtain accuracy, sensitivity, specificity, precision, recall, F1 score, and any other relevant parameters required.

**3.4Brain MRI Dataset:**

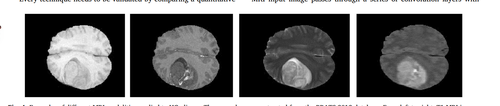


Figure : Glioblastoma (GBM)/HG glioma and LG glioma

The BRATS 2013 dataset, originating from the MICCAI 2013 Challenge, is a valuable resource for advancing the field of medical image analysis, particularly in the context of brain tumor segmentation. This dataset offers a diverse range of imaging modalities, including T1-weighted, T1-weighted with Gadolinium contrast (T1Gd), T2-weighted (T2), and T2 FLAIR (Fluid Attenuated Inversion Recovery). These modalities provide complementary perspectives on brain structures and pathology, enhancing the capabilities of algorithms in tumor segmentation. The dataset is specifically curated for Glioblastoma (GBM)/High-Grade (HG) glioma and Low-Grade (LG) glioma, covering a spectrum of tumor aggressiveness. With 65 3D images, each representing a unique patient, the dataset allows for a comprehensive exploration of the complexities in brain anatomy. Researchers and practitioners leverage this dataset to develop and evaluate innovative algorithms aimed at enhancing the accuracy and efficiency of brain tumor segmentation and classification.

Table Overview of Brats 2013 Dataset

|  |  |
| --- | --- |
| **Dataset Name** | **BRATS 2013** |
| Challenge | MICCAI 2013 |
| Modalities | T1, T1Gd, T2, T2 FLAIR |
| Image Type | Glioblastoma (GBM)/HG glioma and LG glioma |
| No. of Images | 65 (3D) |
| No. of Patients | 65 |

We utilized an open-source brain tumor dataset for the evaluation and analysis of our model, developed through various CNN architectures, as illustrated in Figure 2. This dataset is a combination of three sources: figshare, SARTAJ dataset, and Br35H. It encompasses four classes, specifically glioma, meningioma, pituitary, and healthy individuals, with 1623, 1627, 1769, and 2002 images, respectively. In total, our dataset comprises 7021 MRI images, openly available on Kaggle. Each file is a 512 × 512 JPEG, labeled to denote the type of brain tumor.For the classification and characterization of brain tumors using MRI images from this dataset, we initially processed three distinct models: a standard CNN architecture, VGG16Net architecture, and DenseNet architecture.

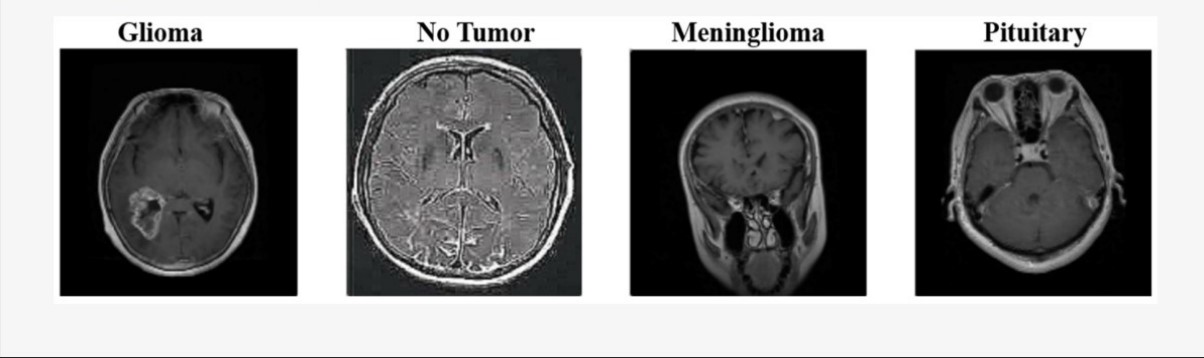


Figure :classes, specifically glioma, meningioma, pituitary with 1623, 1627, 1769, and 2002 images respectively

We then compared the performance of these models with a subsequently modified model. The examination involved assessing key metrics, with the initial models achieving the following regression values: 99.93% for the standard CNN architecture, 98.63% for VGG16Net, and 98.56% for DenseNet.

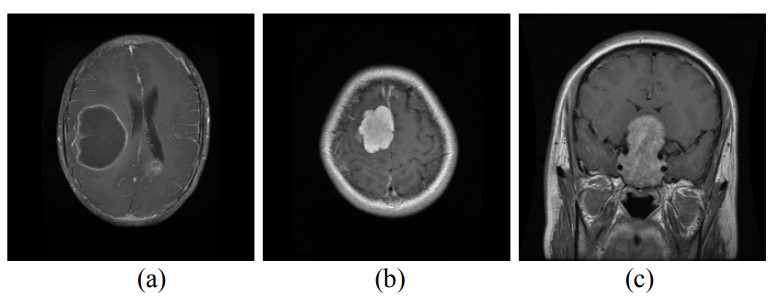
The dataset for our proposed work was created using the collection of MR images from 233 patients, originally compiled by Jun Cheng et al.. This tumor image dataset, accessible online includes type and boundary details provided by radiologists and is stored in MATLAB format (.mat file). As part of the preprocessing, each image undergoes normalization using the min-max method.

Figure T1-weighted contrast-enhanced MR images

The dataset comprises 2406 slices of T1-weighted contrast-enhanced MR images, featuring three classes: glioma, meningioma, and pituitary tumors. Specifically, there are 805 slices of glioma, 694 slices of meningioma, and 907 slices of pituitary tumors.. For model training and testing, 80% of the samples were allocated for training, while the remaining samples were reserved for testing.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Glioma | Meningioma | Pituitary tumors | Total No. of Samples |
| Training  Samples | 638 | 551 | 735 | 1924 |
| Testing  Samples | 167 | 143 | 172 | 482 |

**4. Results :**

In this comprehensive overview of brain tumor prediction studies, various datasets and algorithms have been explored, shedding light on the evolving landscape of machine learning in medical imaging. The studies primarily utilize datasets like BraTS 2015, Hakrabarty N (2019), WebBrain, Kaggle, Physio Net/CinC Challenge, REMBRANDT, and more. A diverse range of algorithms, including CNN, DNN, SVM, KNN, and hybrid models, have been applied to these datasets, demonstrating their efficacy in accurate brain tumor classification.

The performance metrics employed across these studies showcase the robustness of the models. Metrics such as accuracy, sensitivity, specificity, precision, and F1-score provide a comprehensive evaluation of algorithmic efficiency. For instance, in studies using BraTS 2015, CNN, MKK, and KMC achieve an impressive accuracy of 99%, while in the Physio Net/CinC Challenge dataset, CNN outperforms with an accuracy of 97.35%. These metrics collectively emphasize the significance of machine learning in advancing brain tumor prediction capabilities.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Datasets | Model | Precision | Specificity | Sensitivity | Recall | F1-score | Loss |
| [41] braTs 2021 | SVM  Decision Tree | 94.6%  86.6% | N/A | N/A | 85.4%  80% | 89.7%  82.8% |  |
| [49] kaggle dataset | Deep Learning Models (CNN, ResNet152V2, MobileNetV2) | 99.12% | N/A | N/A | 99.08% |  | 0.196 |
| 3D MRI | 428 MRI ANN-PCA-ANN | 93.2% | 97.8% | 91.6% |  |  |  |
| Harris Hawks optimization (WHHO) | deepCNN | 81.6% | 79.1% | 97.4% |  |  |  |
| braTs | Utilized Net and ResNet152 | 99.2% | 77.33 | 76.62% |  |  |  |
| Kaggle | Deep Learning | 99.09% |  |  |  |  |  |

**5. Performance Measure :**

**Precision (Positive Predictive Value-PPV):**

**. Definition:** Ratio of correctly classified positive sample to the total actual positive samples.

.Formula: Precision = \_\_\_\_\_True Positives\_\_\_\_\_\_\_\_ (1)  
 True Positives + False Positives

**Recall (Sensitivity):**

**. Definition:** Ratio of true positive to the sum of true positive and false Negatives.

.Formula Recall = \_\_\_\_\_True Positives\_\_\_\_\_\_\_ (2)  
True Positives + False Negatives

**Accuracy:**

**.Definition:** Closeness of predicted values of two true values.

.Formula: Accuracy = Correct Predictions (3)  
Total Predictions

**F1 Score:**

**. Definition:** Weighted harmonic meanof precision and recall.

.Formula: F1 Score = 2 \* Precision \* Recall   
Precision + Recall

**False Negative Rate (FNR-Miss Rate):**

. Definition: Ratio of the false Negative to the true Positive and false Negative

. Formula: FNR = False Negatives / True Positives + False Negatives

These Matric collectively provide insight into the effectively of the KSVM –SSD method in classifying MRI data for brain tumor segmentation, considering aspects like precision, recall, accuracy , F1 score, and false negative rate

**Conclusion:**

Brain tumor detection was a major problem in early times and the problem of its detection took many lives. We went through almost 250+ articles on brain tumor detection and found the following results the algorithm that has the highest efficiency rate was on **CNN** with the accuracy rate of **99%** on average the dataset that was used the most was **BraTS(2015)** the braTS series of dataset gave the algorithms the highest efficiency rate.The highest results achieved was on the model FFNN which gave Training**: 99.93%**, Validation**: 98.63%,** Test**: 98.56%**, Overall**: 99.94%**

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