A Systematic Literature Survey On Brain tumour Detection From MRI Images

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Abstract: *A brain tumour puts one's life in danger and interferes with the body's regular operations. Early identification and treatment planning are essential for a correct diagnosis of a brain tumour. Medical image analysis requires careful consideration of digital image processing. Separating pathological brain tissues from normal brain tissues is the process of segmenting a brain tumour. Researchers have previously suggested semi- and fully-automatic techniques for the detection and segmentation of brain tumours. The various segmentation strategies that are available have been discussed in this article. The study done in the past by numerous researchers to partially or completely automate the task of segmenting the brain tumour is the main subject of this article.*

KEYWORDS *- Brain tumour, Pre-processing, Segmentation, Deep learning, Machine learning, Convolution Neural Network*

I.INTRODUCTION

The creation of ground-breaking ideas and algorithms has been made possible by the revolution in machine learning and computer vision. It has demonstrated impressive performance and finds use in a variety of fields, including self-driving cars, health, education, and the Internet of Things (Internet of Things). Recently, academics have become increasingly interested in the biomedical uses of machine learning and artificial intelligence, especially the field of anomaly detection. Due to its rising prevalence and high fatality rate across all age groups, brain tumour is regarded as one of the worst diseases in the world. It is stated that it is India's second-leading cause of cancer. According to the American Cancer Society's most current publication, "Cancer Statistics 2020," approximately 24000 people will develop brain tumours while an estimated 19000 Americans will pass away. Due to an increase in the use of technology, such as cell phones and tablets, this disorder is now becoming more prevalent among children as well.

A total of 120 different forms of tumours have been identified to date, and because of the complicated structure of the brain, their appearance in various shapes and sizes makes detection more challenging. For many years, many medical imaging modalities, such as computed tomography (CT scan), positron emission tomography (PET scan), magnetoencephalography (MEG), and magnetic resonance imaging (MRI), have been used to identify brain anomalies. Due to its ability to distinguish between structure and tissue based on contrast levels, MRI multimodality imaging technology is the most well-known and effective method for the detection of brain tumours. Currently, the majority of MRI anomaly identification is manual, and it takes a lot of time for doctors to locate and segment tumours for surgical and therapeutic purposes. This manual method might endanger life and is also prone to mistakes. Studies have begun to concentrate on various machine learning and Deep Learning techniques for computer-based tumour identification and segmentation in order to address these problems.

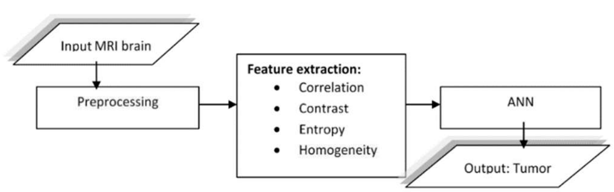
Since a few years ago, a machine learning area called deep learning has been extensively employed to create automatic, semiautomatic, or hybrid models like FAHS-SVM[1] and Levenberg Marquart optimization[2] that can accurately and quickly classify and segment tumours. Although early diagnosis of brain tumours aids radiologists in accurate prediction and increases the likelihood of long-term survival, it is still a difficult process because of the tumour's varying appearance, location, form, and size. Much effort has already been done in this field to support researchers, doctors, and patients.

Thus, the automatic detection and categorization of brain cancers using deep learning approaches where Almalki proposed a deep-feature-trained SVM which showed high efficiency[3] has attracted attention and some other methods like cascaded CNN[4] also comes in this list. These methods have also been used to segment brain tumours, and the medical world is paying close attention to this topic. The goal of segmentation is to alter how an image's various regions are represented, making it simpler to understand the various aspects of the image. Each of these distinct regions, which make up the image of the brain, is spatially contiguous. Due to the complexity of the issue, there are a number of frequent issues with manual diagnosis of brain tumours, including the lengthy time commitments and the potential for misclassifications. As a result, the identification and treatment of brain cancers can be greatly improved by the automatic segmentation of MRI images, particularly in situations where access to qualified specialists and radiologists is problematic. The most recent research in this field will be covered in this paper. Using a variety of deep learning approaches and architectures, research by 30 different authors has been discussed.

II. LITERATURE SURVEY

Z. Jia et. al. in. [1] In order to identify and segment brain tumours, this research provides a segmentation method employing a support vector machine (FAHS-SVM). Our preliminary findings suggest that the suggested strategy will aid in promptly and precisely determining the precise location of the brain tumour. Therefore, the suggested approach is crucial for detecting brain tumours in MR images. The testing findings demonstrated the suggested technology's 98.51% accuracy in identifying diseased and normal tissues in magnetic resonance imaging. The conclusions follow from the data, which support the idea that the suggested strategy is adequate for including primary diagnostic and radiologist or clinical experts in support of clinical decision systems.

et. al. in. [2] Their experimental findings demonstrate that the suggested strategy can help with the precise localization of a brain tumour as well as its timely and accurate detection. The proposed method is important for detecting brain tumours using MR images. They suggested an automatic brain detection system in this chapter. MRI tumour finding. To identify brain tumours, they used preprocessing, feature extraction, and ANN. Levenberg Marquart (LM) nonlinear optimization technique was utilised to train the feed forward neural network with all the MRI slices obtained from the WBA after preprocessing, resulting in a higher recognition rate of 97.5%. I hope this work will help the doctor decide what course of action to take for the patient.



Almalki et. al. in. [3] This study describes a novel technique for using brain MRI scans to identify and classify brain cancers. Three multi-layer CNN models were designed to classify brain MRI images, but their classification performance was mediocre. The deep features of the created CNN models were generated using transfer learning and utilised to train the MLCs in order to improve classification accuracy. The 22-layer CNN deep-feature-trained SVM showed a high accuracy of 98% with a sufficient feature vector size when compared to other deep-feature-trained (19-layer, 25-layer, and pre-trained CNN) MLCs. The recommended model is a promising candidate for assisting doctors in the diagnosis of brain tumours due to its high testing accuracy of 97.2% for unknown brain MRI datasets.

et. al. in. [4] The characterization of the four MRI modalities has helped us create a new brain tumour segmentation architecture in this paper. It implies that each modality has distinctive qualities to effectively aid class distinction by the network. We have shown that a CNN model—the most popular deep learning architecture—can achieve performance that is comparable to human observers by focusing just on a region of the brain picture close to the tumour tissue. Additionally, a straightforward yet effective cascade CNN model has been presented to extract local and global features in two distinct methods with distinct extraction patch sizes. In their method, such patches are chosen to feed the network that the tumor's centre is located inside this area after extracting the tumor's predicted area utilising a potent preprocessing methodology. As a result of the preprocessing step's extensive removal of the clinical image's insignificant pixels, the computational time required to classify the clinical image is reduced, as is the capacity to make predictions quickly. When compared to state-of-the-art methods, extensive trials have demonstrated the effectiveness of the Distance-Wise Attention mechanism in our algorithm as well as the extraordinary capability of our overall model.

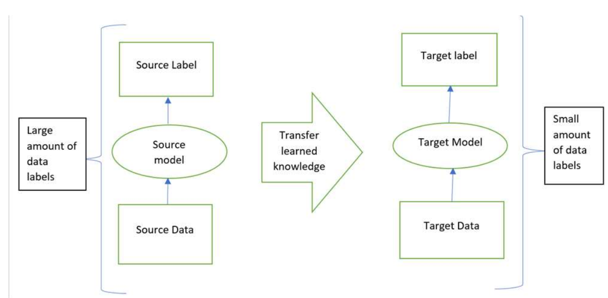
et. al. in. [5] This study presents a brand-new approach for identifying and categorising brain tumours. The main concept is to create a large dataset of synthetic MRI images from a small class-unbalanced dataset of acquired data, reflecting the normal pattern of brain MRI images. In order to train a deep model for detection and classification, the obtained dataset is next utilised, many models have been used for the above-mentioned procedures like generative model, deep learning model, transfer learning model. Segmentation has been implemented by segmenting medical volumes on basis of multi resolution analysis which converts small unbalanced datasets into large balanced dataset with best performance in accuracy, precision, recall, and F1 score of 96.88%

Niepceron B et. al. in. [6] They researched the creation of a novel technique to create a quick and light brain tumour detection system in order to overcome the drawbacks of the majority of deep learning techniques now used in the state-of-the-art. They first looked at the application of the PCNN model for computer vision in an effort to satisfy the demands revealed by healthcare providers in terms of cost effectiveness and explainability. While underlining the significance of fine-tuning its settings to improve the performance of the visual task to complete, we discussed how it may be applied to picture fusion. To develop a feature extraction technique and obtain a novel representation of a dataset of open-source brain images, a modified version of this model was also studied. They were able to demonstrate the effectiveness and efficiency of our method in performing a full tumour detection system by combining this model with the Selective Search algorithm, a region proposal algorithm. This also provided insight into how to improve the solution by repeating the process to predicted patches for multi-label brain tumour detection and by fine-tuning the fusion process. In order to optimise the medical image fusion and improve detection accuracy, they suggested using the differential evolution algorithm. Our results showed that the detection of complete tumours can be done without training a deep neural network and by tuning a simple spike-based model, encouraging the development of quick, light, and scalable medical image analysis systems. Although our method exposes some bases to build tumour detection system with PCNN and is perfectible.

et. al. in. [7] This study employed three transfer learning models to identify brain cancers using stunning resonance images (MRI). The suggested method reduces execution time and increases accuracy to 98%. The study integrates a number of technologies, including the CNN model, which is used to quickly and accurately locate the tumour in MRI image data, and the Alex Net efficient classification approach, which is used to accurately classify the location of the tumour that has been located. HOG and SVM were employed for item labelling, along with the wavelet transform for pre-processing and skull masking. As a result, this overall combination has a greater impact than individual modules or other combinations. The model's accuracy is exceptional and dependable when compared to earlier transfer learning strategies. The advantage of the suggested approach is that the model picks up information about the occurrences quickly, producing good accuracy during the initial epochs

Kurian, S.M. et. al. in. [8] In order to identify the tumour locations from the MRI images, this research suggested the LSFHS approach, a segmentation and classification algorithm for brain tumours. In order to identify the regions of interest, the MRI images are first preprocessed using the Lee sigma filter in the first hidden layer. The resultant preprocessed images are then segmented using a grey bimodal histogram segmentation in a second hidden layer, where the pixels providing different intensities are integrated. The third hidden layer is then used to extract the various attributes from the input segmented image, including texture, shape, grey level intensity, and colour. The output layer analyses the extracted information to perform classification and identify the tumour. An extensive simulation estimation is performed using data on brain tumours. The results of the experiments show that the LSFHS technique outperforms previous works with a 14% increase in tumour detection accuracy, a 58% decrease in error rate, and a 25% faster tumour identification time. The examination of the qualitative and quantitative results demonstrates that, when compared to other relevant work, the LSFHS technique performed better in terms of achieving higher brain tumour detection accuracy and reduced time consumption and error rate. Future research will expand the suggested LSFHS strategy to recognise tumour areas in MRI images using optimization-based deep learning techniques

P. Modiya et. al. in. [9] They used the EfficientNetB7 deep learning pre-trained models with the PCA strategy for feature extraction followed by feature reduction in this proposed methodology to categorise brain MRI pictures into normal or abnormal images. This model was tested using the 3000 MRI normal and abnormal pictures from the Kaggle brain tumour detection dataset. The most pertinent feature for more accurately identifying tumours can be produced by combining features obtained from the CNN EfficientNet model and PCA (Principal Component Analysis). Their findings demonstrate that the EfficientNetB7 model with PCA outperformed the VGG16 model with PCA in terms of training accuracy. Additionally, it has been found that the CNN model performs better than models without PCA when using dimensionality reduction techniques



et. al. in. [10] In this paper, they present their semantic segmentation method, which won the BraTS 2018 challenge, for segmenting volumetric 3D brain tumours from multimodal 3D MRIs. They use an asymmetrically large encoder to extract deep image features, and a decoder that reconstructs dense segmentation masks. This is similar to the encoder-decoder structure of CNN. In order to regularise the shared encoder, they additionally add the variational autoencoder (VAE) branch to the network, which reconstructs the input pictures together with segmentation. Only the primary segmentation encode-decoder component is employed at inference time. They were able to double the number of features compared to the V100 16GB version by using the NVIDIA Volta V100 32GB GPU. The additional VAE branch also assisted in regularising the shared encoder (in the case of sparse data), which not only enhanced efficiency but also made it possible to consistently achieve high training accuracy for any random initialization. Their BraTS 2018 testing dataset values for enhanced tumour core, whole tumour, and tumour core are 0.7664, 0.8839, and 0.8154 average dice, respectively

et. al. in. [11] In this study, we employed a hybrid PSO-SVM model to classify different types of brain tumors. With the aid of bio-inspired algorithms called PSO, we choose the smallest set of features that are necessary as opposed to taking all the features. PSO increases the classification accuracy by using fewer features, but just the most crucial ones. Including key characteristics will only boost efficiency and cut down on computing time. If all 14 features are included, the PSO-SVM classification model achieves an accuracy of 95.23 percent, compared to the standard SVM classifier's 86.82 percent. Similar to sensitivity, specificity is 100% and 94.8.

et. al. in. [12] In this work, a 3D DNN-based architecture is developed for tumor type classification and tumor extraction. Using a suggested 3D CNN architecture, the tumor is retrieved from MRI scans, then transfer learning is used to classify the data. A pre-trained CNN model, VGG19, is used to extract features, and the suggested CbFNN technique is then used to choose the best feature. Through FNN, the chosen features are verified. We draw the conclusion that the proposed 3D CNN model segments the tumor with high precision and a low error rate from the findings. Additionally, the proposed architecture accurately separates the tumor from MRI scans with low contrast. Additionally, when a pretrained model is trained using extracted tumor pictures, the classification accuracy of the tumor type is improved; however, the classification time takes more time than when the pretrained model is taught using original MRI scans.

Zahid Ullah et. al. in. [13] The feed-forward NN, wavelet transform, colour moments, CLAHE, and median filter were used to develop this system. The proposed approach achieves astonishing classification accuracy for benign and malignant MRI images. The key benefit of this strategy is that the doctor may make the final decision based on this methodology without any second thoughts.The outcomes of the experiment show that this approach is effective for categorizing benign and cancerous brain MRIs. The proposed system has sensitivity and specificity rates of 96.0% and 95.65%, respectively. The similar outcomes are produced using SOM and SVM [40,24]. We also contrasted our findings with newly released findings based on identical MRI T2-W images. This technique can produce accurate classification on T1-W, T2-W, and proton density MRI images.

Ullah, F et. al. in. [14] Training the deep learning model for automatic brain tumour segmentation requires pre-processing the input training data. In the current study, several preprocessing techniques, including bias field correction, intensity normalisation, histogram equalisation, and Gibbs ringing artefact removal, were used to examine the effects of preprocessing techniques and identify the best preprocessing technique (sequence-6) for training the 3D U-Net deep network. Additionally, we looked into whether bias field correction and Gibbs ringing artefact removal led to better segmentation outcomes. It was concluded that the results of removing Gibbs ringing artefacts as a preprocessing method are encouraging in terms of increasing segmentation accuracy. As a result, it is highly advised to utilise Gibbs ringing artefact removal as a pre-processing technique. Additionally, segmentation outcomes are improved when Gibbs ringing artefact removal is followed by bias field correction (N4ITK). In order to train the model, different pre-processing approaches were used in conjunction with the Gibbs ringing artefact removal on brain MR data

Mohammad Havaei et. al. in. [15] They introduced a deep convolutional neural network-based automatic brain tumour segmentation technique in this research. Results from the BRATS 2013 online evaluation system show that they were able to outperform the recently published state-of-the-art method in terms of accuracy and speed with their best model, as demonstrated in MICCAI 2013. A innovative two-pathway architecture, which can represent both local details and global context, as well as modelling local label dependencies by stacking two CNNs, are responsible for the outstanding performance. They've discovered that using a two-phase training process makes it possible to train CNNs effectively even when the distribution of labels is unequal. The resulting segmentation system is extremely quick due to the models' convolutional nature and the effective GPU implementation used. With each of these CNN architectures, it takes between 25 and 3 minutes to segment a complete brain, making them useful segmentation techniques

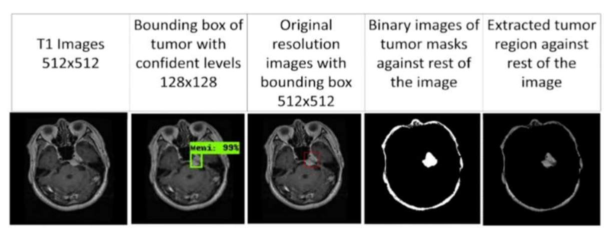
et. al. in. [16] In this study, a deep- and machine-learning model is proposed for feature extraction and brain tumour classification. Due of their advantages, Inception-v3 and Xception were utilised for feature extraction. The following methods were used for classification: softmax, SVM, RF, KNN, and ensemble. To use machine learning for therapeutic applications linked to brain tumours, the Inception-v3 model with softmax was merged with additional models such as Inception-v3-SVM, Inception-v3-RF, Inception-v3-KNN, and ensemble. Similar to this, the Xception model and its connection with other models like the ensemble technique, Xception-SVM, Xception-RF, and Xception-KNN were investigated. In the classification of brain tumours, the performance of the suggested models was examined and contrasted with the models already in use. The models built using the ensemble technique outperform the current models and achieve the highest testing accuracy. The clinical applications of brain tumour analysis may benefit from this work.

et. al. in. [17] Deep learning network models have shown success in the field of medical image analysis recently. We executed the necessary steps in this model, including feature extraction using a deep wavelet auto-encoder model, image sharpening, high pass filter, thresholding segmentation, growing seed technique, and classification. The databases from BRATS2012, BRAT-S2013, BRATS2014, 2015 challenge, and Brats 2015 are combined for the proposed model testing and training. The average accuracy is 99.3 percent, while the average sensitivity, specificity, and precision are 95.6 percent, 96.9 percent, 97.4 percent, 96.5 percent, and 93.33 percent, respectively. They draw the conclusion that the suggested model outperformed the 21 other models that have been published in prestigious journals based on the results of the overall experiment, segmentation, classification, and performance of the DWAE model.

Yin et. al. in. [18] The three primary stages of the suggested method are background removal, feature extraction, and classification using a multilayer perceptron neural network. There, a modified version of the whale optimization algorithm based on chaos theory and logistic mapping is used to pick the characteristics and classification stages most effectively. The provided method's performance analysis is contrasted with those of several other approaches already in use. Final results demonstrated that the suggested method outperformed other comparable methods when CDR, FAR, and FRR were analysed as testifying indices

Kaplan et. al. in. [19] Using MRI data, they presented a new classification system for three different forms of brain tumours, including meningiomas, gliomas, and pituitary tumours. Images are first given a pre-processed treatment. LBP, nLBP, and LBP feature extraction techniques were used to extract LBP information from the photos. The suggested LBP approaches are fundamental, workable, and inexpensive solutions. After that, feature matrices and histograms of the produced LBP, nLBP, and alphaLBP tumour images were created. K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN), Random Forest (RF), A1DE, and Linear Discriminant Analysis (LDA) classifiers were used in the classification process along with the acquired feature metrics. With the nLBPd=1 feature extraction approach and KNN model, the classification of brain tumours with the best success rate was 95.56%.

H. N. T. K. Kaldera et. al. in. [20] The segmentation and classification of brain tumors from T1 weighted MR images using an innovative mechanism based on CNN is demonstrated in this study. For all classifiers, the proposed system has an average accuracy of 94%. Furthermore, a Neurologist's ground truth demarcations are used to confirm the segmentation method' accuracy. The tumor region extraction's average confidence interval is 94.6%, which is a noteworthy performance level. Generalizing the automated approach for T2- and Flair-weighted MR images of various planes, including as sagittal and coronal plane slices, is a potential future direction. As a result, the suggested method would give medical facilities with a shortage of skilled personnel and resources greater diagnostic support



Varuna Shree, N et. al. in. [21] Brain MR images segmented into normal brain tissue (unaffected) and malignant tumour tissue were employed in this study (infected). Preprocessing is used to eliminate noise from the image and smooth it, which enhances the signal-to-noise ratio. The images were then divided up using a discrete wavelet transform, and textural features were taken out of the gray-level co-occurrence matrix (GLCM), which was done after the morphological operation. Brain MRI scans are utilized to classify cancers using a probabilistic neural network (PNN) classifier. When compared to manual brain tumor identification performed by clinical specialists, the observation results make it evident that the detection of brain tumors is quick and accurate. The performance elements that were assessed additionally demonstrate that it improves PSNR and MSE parameters to produce superior results. Because the statistical textural features were retrieved from the LL and HL subbands wavelet decomposition, accuracy of nearly 100% was obtained for the trained dataset and 95% for the tested dataset in the identification and classification of normal and abnormal tumors from brain MR images. Based on the above mentioned findings, they draw the conclusion that their suggested method clearly separates the tumor into normal and abnormal, which aids clinical specialists in making accurate diagnosis decisions.

Referene numbers	Models/ Architectures	Algorithms	Advantages	Disadvantage
[22]	Triple Cascaded Frameworks	Pre Processing: dice loss function Segmentation: anisotropic convolution, dilated convolution, and multi-scale prediction.	convert the multi-class segmentation problem to three cascaded binary segmentation problems, and use three networks to segment the whole tumor,	cascade is not end-to-end and requires longer time for training and testing compared with its multi-class counterparts using similar structures.
[23]	Multiview fuzzy clustering for Multiview data (MVD)	Clustering: CoFKM, Fuzzy C-means clustering algo Mean filtering, median filtering, custom filtering, CombKM, coclustering. IMV-FCM	considering the defects of MRI medical images, this study uses an improved multiview FCM clustering algorithm (IMV-FCM) to improve the algorithm's segmentation accuracy of brain images.	
[24]		Pre processing – median filter Segmentation – MM0 (Mathematical morphological operation), spatial fuzzy c – means Feature extraction: statistical features, textural features Classificatio: SVM with GRB kernel		One limitation is that the proposed solution has not been tested up to the evaluation stage, to compare with current best solution. Proposed solution has not been tested in a large data set with an abundance of variations.
[25]	CNN	Training: Adam optimization algorithm	Rather than dividing the images into multiple sections, by downsampling it when necessary to get high memory demand of 3-D image. 2.other than relative scarcity of MRI image, 3D CNN are able to	Class imbalance because of having many empty spaces in image reduced

			achieve better result quality	
[26]	Convolution neural network	Image Processing Algorithm	Firstly activation function then information split to give the overall accuracy rate of 98%. 2.the validation accuracy of ensembled feature is 95.5 and with one feature only it's around 91.1	Not introduced proper method to handle the images with noise
[27]	active contour model, Markov random field (MRF) model, RELM classifier model	PCA, unsupervised learning, grid search, segmentation: fuzzy c-means, Classifier: RELM	The percentage in classification accuracy performance got increased from 91.54 to 94.23 for random holdout technique.	Change in illumination and shadowing in images leads to affecting the image segmentation. For other biomedical problem the classification not succeeded yet
[28]	Gaussian mixture model, PNN classifier model	Automatic reading algorithms, Classifier: NB, SVM, PNN	algorithm grows the precise reading of MR Images faster and segment abnormal image area to classify as GBM or not.	Not applicable for automated detection of the tumor because during noise reduction tumor gets eliminated unintentionally
[29]	Classification model, class prediction models,decision tree model	k-means algorithm, SVM classification algorithm	1.resampling and feature selection exihhibit better performance using SVM 2.Feature selection with SVM classifier is best choice for imbalanced biomedical data learni ng	
[30]	Gaussian mixture model,	Feature extraction :genetic algorithm (GA) Classification:SVM algorithm	The proposed DNN-based CFIC method gives significantly better results in terms of sensitivity, and accuracy than the best existing techniques, namely CNN-ML and DTL	this study can only be applied to gray images. Further work could employ color images for the same problems.

III. CONCLUSION

This article presents the idea of detecting and segmenting brain tumours as well as highlighting and contrasting some of the essential features of cutting-edge techniques applied to this field. Some of the often-employed methods include machine learning (ML) methods like Fuzzy K-means clustering and Random Forests, as well as CNN architectures. So, this article makes an effort to review some of the important current research papers on the segmentation and detection of brain tumours. The automation of brain tumour detection and segmentation from brain MR images is one of the most active study topics, and significant research has been done in this area for many years, according to our examination of the literature. However, no automated procedure is currently approved by the medical community

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