Journal of Innovative Image Processing (ISSN: 2582-4252)
www.irojournals.com/iroiip/

Segmentation of a Brain Tumour using Modified LinkNet Architecture from MRI Images

Mrs. T. Ruba[1], Dr. R. Tamilselvi[2], Dr. M. Parisa Beham[3], M. Gayathri[4]

[1]Assistant Professor, Department of ECE, Sethu Institute of Technology, Kariyapatti, Tamilnadu, India.
[2,3]Professor, Department of ECE, Sethu Institute of Technology, Kariyapatti, Tamilnadu, India.

[4]PG Student, Department of ECE, Sethu Institute of Technology, Kariapatti, Tamilnadu, India.

E-mail: [1]ruba@sethu.ac.in, [2]tamilselvi@sethu.ac.in, [3]parisabeham@sethu.ac.in, [4]mohanadhanam123@gmail.com

Abstract

Brain tumour segmentation is one of the most significant tasks in medical image processing. It is believed that early diagnosis of brain tumours is essential for enhancing treatment options and raising patient survival rates. The manual segmentation is dependent on radiotherapist involvement and expertise. MRI scans are often speedy and an excellent diagnostic tool for medical professionals. As a result, in an emergency, doctors advise getting an MRI scan. However, there is a chance for inaccuracy because there is a lot of MRI data. This has made automatic brain tumor segmentation a feasible process. Currently, machine learning methods are in use for segmentation. This research proposes segmentation of brain tumour using modified LinkNet architecture from MRI images.

Keywords: Segmentation, Machine learning, LinkNet, Convolutional Network

1. Introduction

DOI: https://doi.org/10.36548/jiip.2023.2.007
Received: 01.05.2023, received in revised form: 01.06.2023, accepted: 11.06.2023, published: 21.06.2023

Along with some conventional techniques, Magnetic Resonance Imaging (MRI) is used to diagnose tumours and section them. The major objective is to identify whether the brain has a brain tumour or is healthy. For the purpose of enhancing performance and streamlining the segmentation process of medical images, the proposed system has been researched based on LinkNet Architecture and machine learning classifier. A lump or collection of aberrant brain cells is known as a tumour. The incredibly tough skull shields the brain from external harm. Any growth within this constrained space will lead to issues. Malignant (cancerous) or benign (non-cancerous) brain tumours are both possible. The pressure inside the bones rises when benign or malignant tumours develop, possibly leading to brain injury [1].

MRI and CT scans are low- risk procedures. Both provide vital information to assist the doctor in making an accurate diagnosis. In general, MRI scans are quick, especially in an emergency. Creating a precise delineation of brain tumor sections is the aim of brain tumor segmentation. In recent years, deep learning techniques have showed promise in addressing a range of computer vision issues, including semantic segmentation, object identification, and image categorization. Finding brain cancers and segmenting them is the main goal of brain tumor detection. It can identify tumors from images and report whether they are positive or negative, making it useful in instances when it is needed to know whether a tumor is present or absent. [2][3]. Tumour segmentation transforms the original medical image into an extractable image, making it a crucial stage in radiomics research. An automatic brain tumour detection is presented in this work.

2. Related Works

Ardhendu Sekhar et al., [43] (2021): According to the field of healthcare research, Internet of Medical Things (IoMT) is transforming the healthcare system into the internet of the future. Computer-Aided Diagnostic (CAD) systems with IoMT support keep track of patient health data online and provide reassuring information. In the work, a transfer learning model was used to separate glioma, meningioma, and pituitary tumours into three categories. The features of the brain MRI images were recovered using a pre-trained CNN called GoogleNet.

Kapil Kumar Gupta et al., [3] (2019): The review of tumor-containing CT and MR image segmentation is the main topic of the study. The algorithm obtained 89.7% accuracy over the unseen data on a dataset with 155 scans (105 train, 50 test). A model with an accuracy of 88.2% was created using solely texture features. These findings offer fresh perspectives on brain lesion identification, segmentation, and prediction in radiomics.

Yogita K Dubey et al., [11] (2019) proposed algorithms for brain tumour identification, and the tumour was divided into meningioma and glioma. Using the watershed approach and the Self-Organizing Map (SOM), brain tumours were segmented. The proposed algorithm reported a classification accuracy of 95% using the dataset of actual hospitalised brain images.

Md. Rezwanul Islam et al., [17] (2018) in brain tumour identification, the tumour was divided into meningioma and glioma. Using the watershed approach and the SOM, brain tumours were segmented. The magnetic resonance image data base BRATS was used. The method has successfully detected 86.84 of the time.

HussnaElnoor Mohammed Abdalla et al., [22] (2018) examined and explained the processes and strategies utilised in the identification of brain tumours utilising MRI and Artificial Neural Network (ANN) approaches; After gathering the image data (MRI), the first step is to improve and post-process the MRI images to make them more acceptable for analysis. The following step is to utilise threshold to segment the MRI images by using mean grey scales. Finally, the findings were shown. The network's performance was effectively analysed and tested, yielding the best results with accuracy and sensitivity of 99% and 97.9%, respectively.

3. Proposed Solution

The aforementioned issue has been addressed via a novel CNN-based approach. It can be difficult to train a CNN from scratch because it may take weeks or months to get the right results for a dataset without being overfitted or underfitted. As a result, the suggested architecture first uses a light deep neural network to segment brain images, then integrates the resulting semantic segmentation results with a CNN made up of Link Net layers [5][7]. Brain tumor segmentation is performed using a modified LinkNet architecture. The proposed method's detailed description has been discussed in the following chapters, along with its results and performance analysis of the existing method. This method achieves better segmentation results.

3.1. Design of Proposed System

The results of the literature analysis make it abundantly evident that the detection methods still need to be significantly improved. Techniques for machine learning are also challenging. Most Deep Learning methods simply employ computationally difficult segmentation [4]. This study proposes the use of a Convolutional Neural Network (CNN) method to conduct semantic segmentation of brain tumours in MRI images. Machine learning algorithms like the CNN algorithm use a cascade of several layers of nonlinear processing units to extract and transform features [6]. CNN provides higher levels of accuracy, allowing consumer electronics to meet user expectations, and there have been recent advances in CNN to improve it.

Each pixel in an image is classified using semantic segmentation, and the categorised pixels are then transformed into meaningful classes of objects [8]. Because each pixel is classified, semantic segmentation is also known as dense prediction. Semantic segmentation is widely employed in a variety of industries, such as autonomous driving, medical image analysis, and satellite image analysis. Important portions of medical scans are identified via semantic segmentation. For these applications, algorithm accuracy and low recall are critical [9][10]. It is particularly useful for detecting abnormalities such as tumour. The previous section discussed the solutions to the identified problems [11]. Based on this, a new method for brain tumors segmentation using modified Light has been proposed. The Light Deep Neural Semantic Segmentation Network is used in the suggested design to first segment brain images.

Steps in segmentation are,

Step 1: To perform segmentation, the training data (images) are analysed.

Step 2: A network is built for the segmentation process.

Step 3: Corresponding Network for the segmentation process is trained.

Step 4: The segmentation network is evaluated.

Step 5: After evaluation, the segmented results are examined.

Step 6: The pixel labelled dataset is imported to perform additional functions.

Step 7: After importing the datasets, the final step is to segment the images using a segmentation function based on a modified Link Net Architecture (Fig.1). Finally, a few performance indicators are employed to assess how well the Link Net semantic segmentation performs.

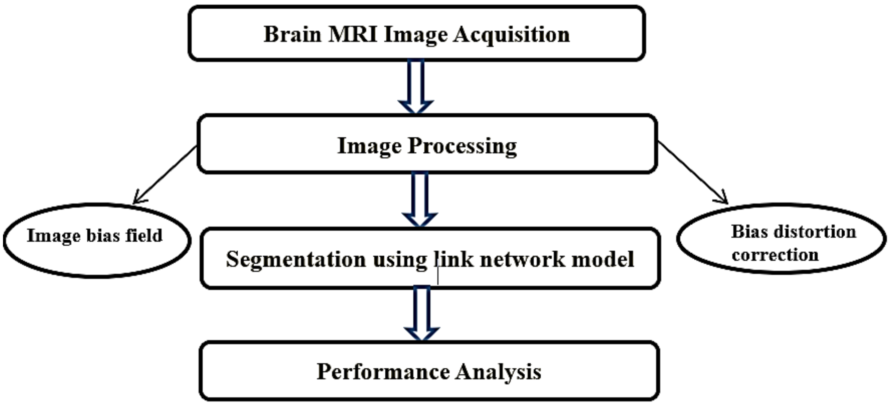


Figure 1. Flow Diagram

3.1.1. Image Acquisition

Image acquisition is the act of obtaining an image from a source. This can be accomplished using hardware systems such as cameras, encoders, sensors, and so on. It is undeniably the most important step in the machine vision workflow because an incorrect image will render the entire workflow useless. Because machine vision systems analyse the acquired digital image of the object rather than the object itself, obtaining an image with adequate clarity and contrast is critical [12]. The incoming light wave from an object is converted into an electrical signal by a combination of photosensitive sensors during the image acquisition step [13]. These small subsystems play the role of providing an accurate description of the object to the machine vision algorithms.

3.1.2. Dataset

- Using multi-institutional pre-operative MRI images, BRATS 2019 segments intrinsically diverse (in appearance, form, and histology) brain tumours, predominantly gliomas.
- The proposed brain tumors segmentation network is evaluated using the BRATS 2019 database.
- 2500 T1-weighted, contrast-enhanced magnetic resonance imaging (T1cMRI) images of brain tumours from 112 patients make up this collection. The sample images from these datasets are shown in Figure 2.

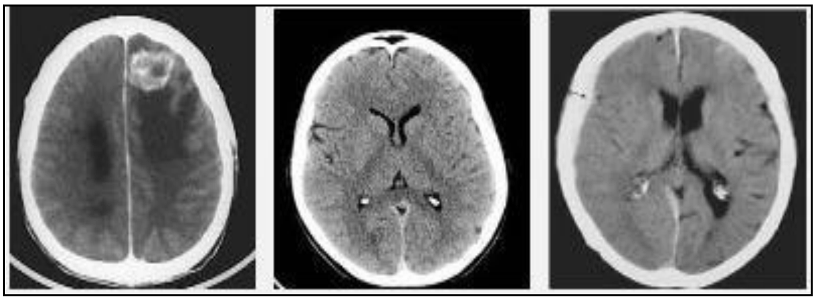


Figure 2. BRATS Dataset

3.1.3. Preprocessing

Preparing raw data for future processing through any type of processing is known as data preprocessing, which is a subset of data preparation. It has traditionally been a significant first step in the data mining process. Preprocessing involves transforming unclean data into a clean set of data. Before running the method, the dataset is preprocessed to check for missing values, noisy data, and other anomalies [14][16]. In the deep learning pipeline, preprocessing data is a typical first step to get the raw data ready for the network. To match the size of an image input layer, for instance, the image input can be resized. Additionally, preprocessing data can be used to lessen or strengthen desired features [15]. There are two different types of methods used in this preprocessing method; they are Bias field and Bias distortion method.

(i) Bias Field

Bias field in medical images is an unfavourable artefact that results primarily from an inefficient image acquisition process or the unique properties of the imaged object [18]. This item considerably impairs several medical image analysis tools and can be identified by a smooth change of intensities across the image.

(ii) Bias Distortion Correction

A single image's bias field is often seen as a smooth variation in intensity. This effect causes variations in the intensity of the same tissue in different areas of the image, rendering the piecewise constant property of medical images invalid [17][20]. Using a series of local estimations of tissue gain fluctuation, bias field correction establishes a correction field for the brain region. First, the white matter, grey matter, and cerebrospinal fluid mean values for the global tissue are calculated. This method is based on the assumption that all other tissues have been removed.

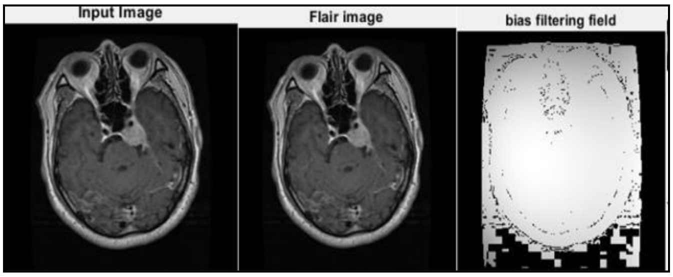


Figure 3. Preprocessed Result for Abnormal Image

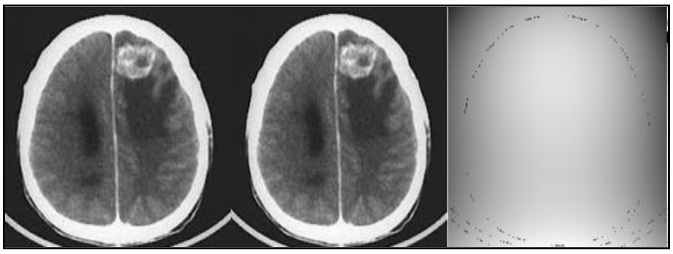


Figure 4. Preprocessed Result for Normal Image

3.1.4. Segmentation

By using a variety of local estimates of tissue gain fluctuation, a bias field correction is used to generate a correction field for the brain area. The white matter, grey matter, and cerebrospinal fluid mean values are first used to calculate the global tissue values [19]. When applied in a clinical environment, this technique assumes that all further tissues have been removed. For making diagnosis and creating treatment programmes, this information is useful. It can be used for a variety of purposes and organises pixels into groups according to how similar they are. The deep learning image segmentation technology learns how to separate an image into pieces using a neural network [21]. A collection of tagged images is utilised to train the network, and each image receives proper segmentation [23].

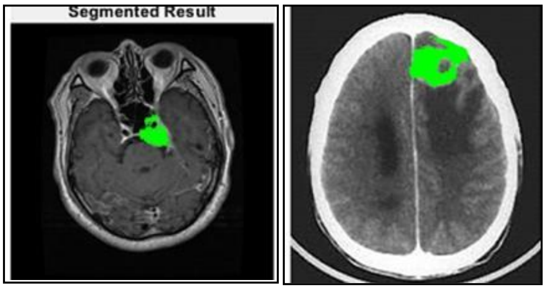


Figure 5. Segmented result for Abnormal and Normal Image

3.2. Light Deep Neural Network of Semantic Segmentation

Every pixel in an image must be labelled as part of semantic segmentation, and it's crucial to keep track of spatial information. Modern segmentation networks sometimes use Image Net Large Scale Visual Recognition Challenge (ILSCRC) winners as its discriminator, which are categorization models [22]. The decoder either uses the encoder's stored pooling indices to do up-sampling, or convolutionally learns the parameters. The discriminator employed is a pre-trained VGG. After each maximum pooling phase, pooling indices are saved, and subsequently used for up-sampling in the decoder [24][25]. Later, the idea of deep deconvolution networks, convolutional networks paired with skip architecture [21], was invented by researchers, which eliminated the requirement for pooling indices to be saved in networks for classification and prediction. Although it was very computationally expensive, it generated fairly good results as one could anticipate.

The issue was that any down-sampling or pooling layers were unable to be used, since doing so would have affected where the instances were located [26]. Numerous layers must be added to learn both low-level and high-level elements in order to retain image resolution [27]. It consequently became quite ineffective. An encoder-decoder architecture was suggested to solve this problem. The decoder is composed of deconvolutional and up-sampling layers, and the encoder is a normal convolutional network like Alex Net or Res Net [30]. Up-sampling seeks to recover spatial information, while down-sampling aims to retrieve semantic/contextual information. The suggested CNN Linknet design segmentation network is shown in Figure 6.

As was previously mentioned, the proposed study uses CNN made up of certain layers to segment brain images, as seen in fig. 5. Semantic segmentation is then applied to the data to precisely separate the cancer from MRI images. The bulk of semantic segmentation algorithms uses an encoder-decoder pair as their foundation, which draws influence from auto-encoders [3], [15]. In this case, data is first encoded into feature space by the encoder, and then decoded by the decoder into a spatial categorization. Semantic segmentation is designed for real-time applications, yet the bulk of deep networks in use today have very slow processing speeds [28].

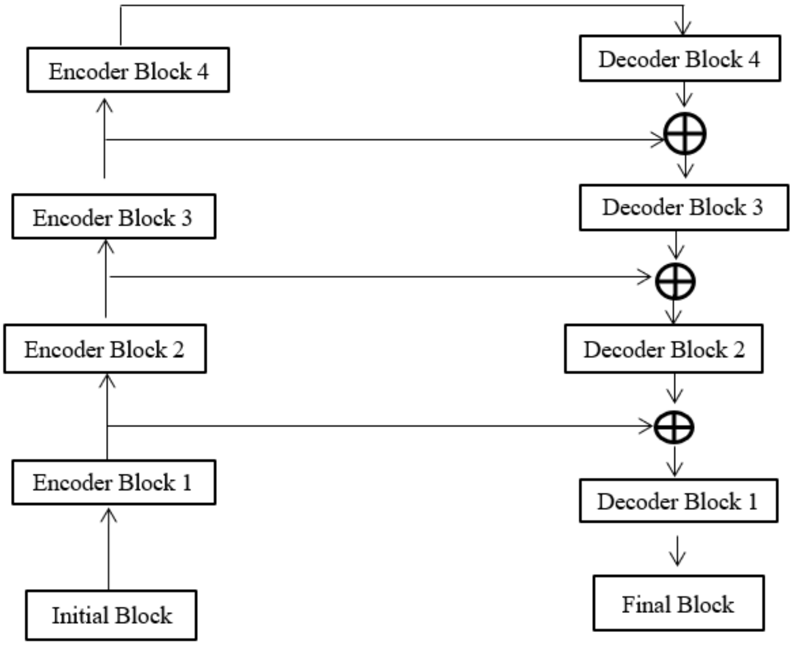


Figure 6. LinkNet Architecture

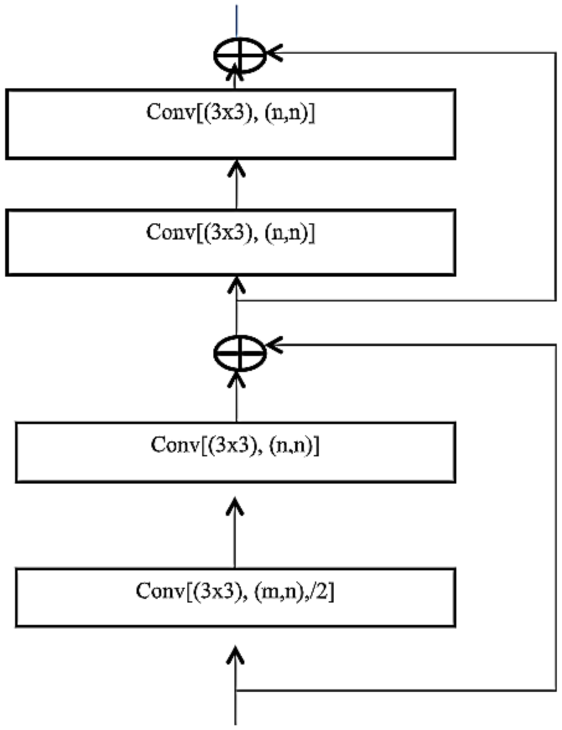


Figure 7. Convolutional Module in Encoder Blocks

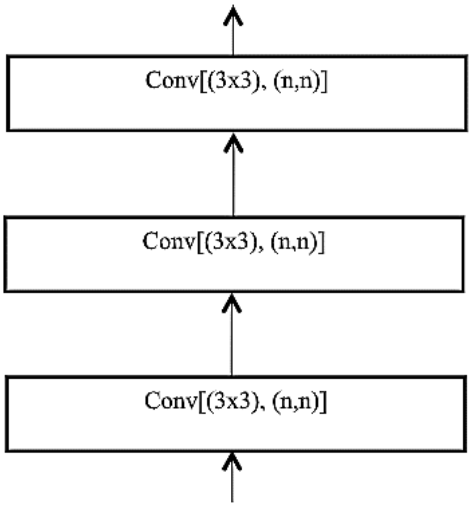


Figure 8. Convolutional module in Decoder blocks

Conv and full-conv are used here to denote different types of convolution [21]. Fig. 6 shows the Link Net architecture. Additionally, strided convolution is used to express /2, which stands for a down-sampling by a factor of two, and 2 for an upsampling by a factor of two. Between each convolutional layer, batch normalisation is applied, and then light deep neural network nonlinearity [27, 28]. The network's encoder is displayed in Fig.7 while the decoder is displayed in Fig.8. The input image is convolutioned on with a kernel size in the first block of the encoder [32].

4. Results and Discussion

Scan images are a frequent sort of medical imaging that are used to discover tumours and abnormalities in the brain [30]. The imaging technique known as Magnetic Resonance Imaging is sensitive to outside noises, and the environment outside also has an impact on its contrast and intensity. Preprocessing is therefore necessary to eliminate undesirable sounds and enhance image contrast [14],[16]. Bias field correction was used in this work to uniformly distribute contrast across all images. A bias field signal is a low-frequency, extremely smooth signal that contaminates MRI scan images, particularly those produced by previous Computed Tomography machines. [17] Image processing algorithms that use grey level values of image pixels, such as segmentation and texture analysis, will not produce satisfactory results.

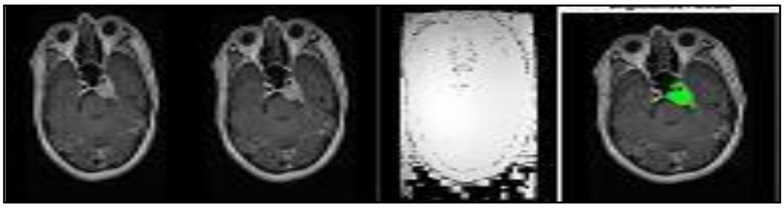


Figure 9. Result of an Abnormal Image

Figure 10. Result of a Normal Image

The preprocessing results for the sample normal and abnormal images are shown in figures 9 and 10. The input images are shown together with the bias field, and as intensity normalised images [33]. The figure clearly shows that, as compared to the original image, the normalised image has an even intensity distribution across every pixel especially with the modified intensity.

Link Net is a light deep neural network architecture that can be used for applications like self-driving cars and augmented reality, among others, for semantic segmentation. Both GPUs and embedded devices are capable of delivering real-time performance [37]. A U-shaped variation of Link Net [5] differs from LinkNet in two key aspects. It starts by swapping out the typical LinkNet convolution structure for a residual module (res-block). Second, it switches from stacking to adding the LinkNet deep and shallow feature synthesis approach [38][40]. CNN converts an image into a vector, which is commonly used in classification problems. However, in Link Net, an image is converted into a vector and then back to an image using the same mapping.

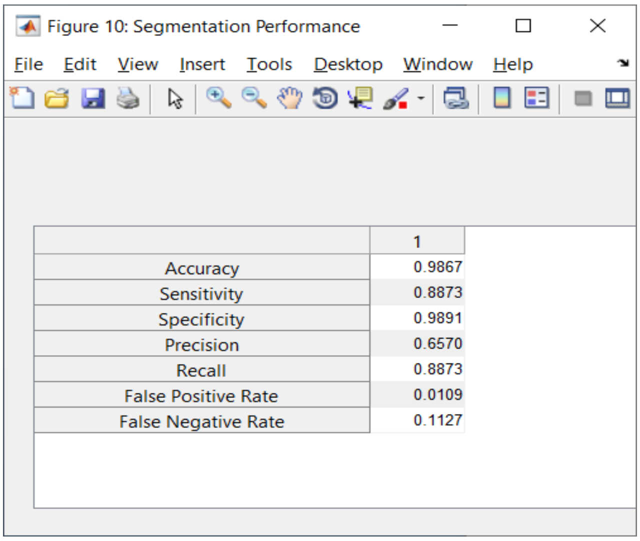
$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

Sensitivity displays how the algorithm correctly classifies data.

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity demonstrates how the system disqualifies incorrect classification outcomes.

$$Specificity = \frac{TN}{TN + FP}$$



	1
Accuracy	0.9867
Sensitivity	0.8873
Specificity	0.9891
Precision	0.6570
Recall	0.8873
False Positive Rate	0.0109
False Negative Rate	0.1127

Figure 11. Segmentation Performance

The suggested segmentation method's performance metrics are shown in Figure 11 for a few sample images [37]. The accuracy of the suggested technique is found to be more than 98.98% in practically all tumors images. Additionally, all split images have less error. This table can be used to get the conclusion that the suggested LinkNet technique performs best across the board [38].

Performance Comparison of the Proposed MRI Dataset

The effectiveness of the current system is compared to that of the proposed system [36][40]. The suggested method is contrasted with the current method in table 1 based on categorization performance measures.

Table 1. Performance of Suggested Method vs Alternative Approaches

Metrics Methods	Tumor	Precision	Sensitivity	Specificity	Accuracy
Nadim Mahmud Dipu et al. [3] (2021)	Abnormal	8.592	---	---	85.95%
Ezequiel de la Rosa et al. [4] (2019)	Normal	---	0.820	0.893	89.80%
Proposed Method	Abnormal	0.5967	0.7746	0.9966	99.51%
	Normal	0.6570	0.8873	0.9891	98.67%

Table 1 compares the performance indicators for brain tumors using MRI dataset. This table unequivocally demonstrates that the suggested approach performs better than the current method in every measure of performance. The accuracy of the suggested technique is 98.67% for normal regions and 99.51% for cancer regions.

5. Conclusion and Future Scope

The suggested method successfully segments the tumours using a semantic segmentation network and classifies distinct tumour subtypes using LinkNet. The suggested model is validated using the MRI and BRATS datasets [40]. Using BRATS datasets, the quantitative findings demonstrate that the suggested tumors segmentation achieves an overall accuracy of 99.51%. Similarly, MRI datasets produce an overall accuracy of 99.63% for various tumors. The results unmistakably demonstrate that the suggested approach offers results that are more accurate in all performance areas, including the MRI dataset. In the MATLAB environment, all the provided parameters are properly set. Modified LinkNet is used to perform semantic segmentation. Because of the use of semantic segmentation, this method can segment even non-homogeneous tumours with non-homogeneity within the tumour region. The suggested segmentation's quality is on par with manual segmentation. Segmentation will be accelerated in operation imaging. This study shows that MRI tumour diagnosis provides more accurate tumour features than CT images.

References

[1] Muhammad Naqiuddin, NurNajihahSofia, IzaSazanitaIsa, SitiNorainiSulaiman, Noor Khairiah A. Karim, IbrahimLutfiShuaib, “Lesion Demarcation of CT-Scan Images using Image Processing Technique”,2018 8th IEEE International Conference on Control System, Computing and Engineering (ICCSCE),2019.

[2] Jose M. Anton-Rodriguez, Peter Julyan, Ibrahim Djoukhadar, David Russell,D. Gareth Evans, Jackson, Julian C. Matthews, “Comparison of a Standard Resolution PET-CT Scanner With an HRRT Brain Scanner for Imaging Small Tumors Within the Head”, IEEE Transactions on Radiation and Plasma Medical Sciences (Volume: 3 , Issue: 4 , July 2019), 2019.

[3] Kapil Kumar Gupta, NamrataDhanda, Upendra Kumar, “A Comparative Study of Medical Image Segmentation Techniques for Brain Tumor Detection”,2018 4th International Conference on Computing Communication and Automation (ICCCA),2019.

[4] Ezequiel de la Rosa, Diana M. Sima, ThijsVandeVyvere, Jan S. Kirschke,BjoernMenze, “A Radiomics Approach to Traumatic Brain Injury Prediction in CT Scans”,2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019),2019.

[5] Yu Wang, Changsheng Li, Ting Zhu, Chong chong Yu, “A Deep Learning Algorithm for Fully Automatic Brain Tumor Segmentation”,2019 International Joint Conference on Neural Networks (IJCNN),2019.

[6] Bin Cui, MingchaoXie, Chunxing Wang, “A Deep Convolutional Neural Network Learning Transfer to SVM-Based Segmentation Method for Brain Tumor”, 2019 IEEE 11th International Conference on Advanced Infocomm Technology (ICAIT),2019.

[7] Hossam.H. Sultan, Nancy M. Salem, Walid Al-Atabancy, “Multi-Classification of Brain Tumor Images Using Deep Neural Network”, IEEE Access, Volume No:7,2019.

[8] Sunanda Das, O. F. M. RiazRahmanAranya, NishatNaylaLabiba, “Brain Tumor Classification Using Convolutional Neural Network”,2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT),2019.

[9] HasanUcuzal, ŞeymaYasar,CemilÇolak, “Classification of brain tumor types by deep learning with convolutional neural network on magnetic resonance images using a developed web-based interface”,2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT),2019.

[10] Hein TunZaw,NoppadolManeerat,KhinYadanar Win, “Brain tumor detection based on Naïve Bayes Classification” ,2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST),2019.

[11] Yogita K Dubey, Milind M Mushrif, KomalPisar, “Brain Tumor Type Detection Using Texture Features in MR Images”, 2018 IEEE Region 10 Humanitarian Technology Conference (R10-HTC),2019.

[12] Moumen T. El-Melegy, Khaled M. Abo El-Magd, Ayman S. El-Baz, “Adaptive Window for Automatic Classification- Based Segmentation of Multimodal Brain Tumor”,2018 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), 2019.

[13] T. A. Jemimma, Y. Jacob Vetharaj, “Watershed Algorithm based DAPP features for Brain Tumor Segmentation and Classification”,2018 International Conference on Smart Systems and Inventive Technology (ICSSIT), IEEE Access,2019.

[14] MonikaGrewal,MuktabhMayankSrivastava, Pulkit Kumar, SrikrishnaVaradarajan, “RADnet: Radiologist level accuracy using deep learning for hemorrhage detection in CT scans”, 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018),2018.

[15] Justin Ker, LipoWangariRao, Tchoyoson Lim, “Deep Learning Applications in Medical Image Analysis”, IEEE Access, Volume No:6,2018.

[16] Guotai Wang, Wenqi Li, Maria A. Zuluaga, Rosalind Pratt, Premal A. Patel, Michael Aertsen, Tom Doel, Anna L. David, Jan Deprest, SebastienOurselin, Tom Vercauteren, "Interactive Medical Image Segmentation Using Deep Learning with Image-Specific Fine Tuning", IEEE Transactions on Medical Imaging, Volume No: 37, Issue: 7, July 2018

[17] Md. Rezwanul Islam, Md.ReezbhanImteaz, Marium-E-Jannat, "Detection and analysis of brain tumor from MRI by Integrated Thresholding and Morphological Process with Histogram based method",2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2),2018.

[18] SofianeTchoketchKebir, SlimaneMekaoui, "An Efficient Methodology of Brain Abnormalities Detection using CNN Deep Learning Network",2018 International Conference on Applied Smart Systems (ICASS),2018.

[19] Nidhi Singh, Shalini Das, A. Veeramuthu, "An efficient combined approach for medical brain tumour segmentation",2017 International Conference on Communication and Signal Processing (ICCSP), IEEE Access, 2018.

[20] SalimOuchtati, Jean Sequeira, BelmeguenaiAissa, RafikDjemili, Mohamed Lashab, "Brain tumors classification from MR images using a neural network and the central moments", 2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET),2018.

[21] M. H. O. Rashid, M. A. Mamun,M. A. Hossain, M. P. Uddin, "Brain Tumor Detection Using Anisotropic Filtering, SVM Classifier and Morphological Operation from MR Images",2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2),2018.

[22] HussnaElnoor Mohammed Abdalla,M. Y. Esmail, "Brain Tumor Detection by using Artificial Neural Network", 2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE),2018.

[23] Wei Chen, XuQiao, Boqiang Liu, Xianying Qi, Rui Wang, Xiaoya Wang, “Automatic brain tumor segmentation based on features of separated local square”, Proceeding of Institute of Electrical and Electronics Engineers (IEEE), 2018.

[24] VenkateswararaoCherukuri, Peter Ssenyonga, Benjamin C. Warf,Abhaya V. Kulkarni, Vishal Monga, Steven J. Schiff, “Learning Based Segmentation of CT Brain Images: Application to Postoperative Hydrocephalic Scans”,IEEE Transactions on Biomedical Engineering (Volume: 65, Issue: 8, Aug. 2018),2017.

[25] Rizal RomadhoniHidayatullah,RiyantoSigit,SigitWasista, “Segmentation of head CT-scan to calculate percentage of brain hemorrhage volume”,2017 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC),2017.

[26] Chuen Rue Ng,NorlizaMohd Noor, Omar MohdRijal, “Level set segmentation for brain region using CT scan images”, 2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES),2017.

[27] C. HemasundaraRao, P.V. Naganjaneyulu, K. Satya Prasad, “Brain Tumor Detection and Segmentation Using Conditional Random Field”,2017 IEEE 7th International Advance Computing Conference (IACC),2017.

[28] Wang Mengqiao, Yang Jie, Chen Yilei, Wang Hao, “The Multimodal Brain Tumor Image Segmentation Based on Convolutional Neural Networks”, 2nd IEEE International Conference on Computational Intelligence and Applications (ICCIA),2017.

[29] EmreDandil, “Implementation and comparison of image segmentation methods for detection of brain tumors on MR images”,2017 International Conference on Computer Science and Engineering (UBMK),2017.

[30] Najeebullah Shah, Sheikh Ziauddin, Ahmad R. Shahid, “Brain tumor segmentation and classification using cascaded random decision forests”, 2017 14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2017.

[31] AmiyaHalder, OyendrilaDobe, “Rough K-means and support vector machine based brain tumor detection”,2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2017.

[32] S. K. Shil,F. P. Polly, M. A. Hossain,M. S. Ifthekhar,M. N. Uddin ,Y. M. Jang, “An improved brain tumor detection and classification mechanism”, 2017 International Conference on Information and Communication Technology Convergence (ICTC,2017.

[33] SomayehMolaei, Frederick K. Korley, S.M. Reza Soroushmehr, Hayley Falk,HarisSair, Kevin Ward, KayvanNajarían, “A machine learning based approach for identifying traumatic brain injury patients for whom a head CT scan can be avoided”,2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC),2016.

[34] Pham N. H. Tra, Nguyen T. Hai, Tran T Mai, “Image Segmentation for Detection of Benign and Malignant Tumors”, 2016 International Conference on Biomedical Engineering (BME-HUST),2016.

[35] AasthaSehgal, ShashwatGoel, ParthasarathiMangipudi, AnuMehra, DevyaniTyagi, “Automatic brain tumor segmentation and extraction in MR images”, Conference on Advances in Signal Processing (CASP),2016.

[36] C. C. Benson, V. Deepa, V. L. Lajish, Kumar Rajamani, “Brain tumor segmentation from MR brain images using improved fuzzy c-means clustering and watershed algorithm”, International Conference on Advances in Computing, Communications and Informatics (ICACCI),2016.

[37] BoucifBeddad, KaddourHachemi, “Brain tumor detection by using a modified FCM and Level set algorithms”, 4th International Conference on Control Engineering & Information Technology (CEIT), 2016.

[38] M. Kadkhodaei, S. Samavi, N. Karimi, H. Mohaghegh, S. M. R. Soroushmehr, K. Ward, A. All, K. Najarían, “Automatic segmentation of multimodal brain tumor images

based on classification of super-voxels",2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC),2016.

[39] AbdelkhalekBakkari, Anna Fabijańska, "Segmentation of cerebrospinal fluid from 3D CT brain scans using modified Fuzzy C-Means based on super-voxels", 2015 Federated Conference on Computer Science and Information Systems (FedCSIS),2015

[40] YehualashetMegersa, GetachewAlemu, "Brain tumor detection and segmentation using hybrid intelligent algorithms",AFRICON 2015, IEEE Access, 2015.

[41] Liya Zhao, KebinJia, "Deep Feature Learning with Discrimination Mechanism for Brain Tumor Segmentation and Diagnosis",2015 International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP),2015.Computer Applications. Volume 8– No.12, October 2010.

[42] S. Tekinary and B. Jabbari, "Handover and Channel Assignment in Mobile Cellular Networks", IEEE Commun. Mag. Vol. 29, pp. 42-46, Nov.1991.

[43] Liton Chandra Paul," Handoff / Handover Mechanism for Mobility Improvement in Wireless Communication",Global Journal of Researches in Engineering Electrical and Electronics Engineering. Volume 13 Issue 16, Year 2012