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MULTICLASSIFICATION OF BRAIN TUMOUR IMAGES USING A GENERALIZED ENCODER AND CONVOLUTION NEURAL NETWORK WITH AUTOENCODER

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ABSTRACT

The method involved with diagnosing brain tumors is very challenging for various reasons, one of which is the intricacy of the synaptic design, size, and state of the brain. Techniques for AI are used to help clinical experts in the location of brain tumors and to help their choices. In the new year's, approaches including profound learning have gained critical headway in the field of clinical picture handling. Profound neural networks with the capacity to classify and portion pictures are known as convolutional neural networks (CNNs). CNN designs for order and division include various unmistakable layers, every one of which fills a specific need. These layers incorporate things like a convolutional layer, a pooling layer, completely associated layers, dropout layers, and numerous others. The most common way of dividing brain tumors has been moved toward utilizing an assortment of profound learning-based approaches, and the outcomes have been empowering. We utilize this review to introduce a total assessment of as of late settled profound learning-based procedures for the division of brain tumors. This is finished considering the huge headways made conceivable by the present cutting edge innovations.

Keywords: *Brain, Tumors, Neural, Network, Convolutional, Layer.*

I. INTRODUCTION

The inherent unpredictability of cancerous growth ensures that it will continue to pose a threat to humanity [1]. Specialists in the nervous system frequently employ applications like computer-aided diagnosis (CAD) to benefit their patients. Detection, categorization, and evaluation of brain tumours are discussed in [2-5]. These programmed require brain images captured by magnetic resonance imaging (MRI), which are superior to computed tomography (CT) scans due to their superior ability to differentiate between brain's more delicate tissues. Inside CAD frameworks, AI processes are commonly employed for analyzing and organizing brain tumours. This framework's component extraction step is the foundation upon which the rest of the framework is built, and it is during this stage that the framework learns which features of MRI images are typically most important. Many different landmark extraction methods have been developed to help achieve this goal [6]. The retrieved data is then used to train a model capable of identifying and categorising brain cancers. But these frameworks typically assume that the important parts in MRI images are free, which makes the problem computationally tractable. The accuracy of their results suffers as a result of having to focus on catching the relationship associated to the concept of the highlights [7]. Many different brain-based MRI detection frameworks have undergone extensive learning to overcome these restrictions. Popular methods used to solve identification and sorting challenges include convolutional neural network (CNN) models and motion learning models. Two phases are typical for these kinds of agreements. A series of anatomically labelled MRI images are used to create a detailed model in a first, offline stage called "preparing" (preparing information). After that, we move on to an online brain MRI analysis to see if we can detect any tumours.

An abnormal and uncontrollable increase in brain size is the result of some sort of improvement in brain cells. Any abnormal event may cause injury to a human function according to the involved region of the brain, and it may also spread to other substantial organs and disrupt human activities [8]. The human skull is a solid and volume-restricted body. According to the World Health Organization's report on the state of global health, brain cancer accounts for less than 2% of all human disease but is responsible for a disproportionate share of suffering and death worldwide [9]. (WHO). About 5,250 people in the United Kingdom die every year as a direct result of brain, other Focal Sensory system (CNS), and intracranial malignancies, according to a disease research firm based in the Unified Realm [10]. Brain tumours can be categorized in a number of ways, such as essential and optional. Approximately 70% of all brain tumours are already documented, whereas the remaining 30% are represented by the third choice. Although brain tumours are the most critical because of their rapid development, the location of the cancer's genesis is not always predictable. However, cancers that form in another organ and then move to the brain are called "optional tumours," and the vast majority of these tumours are malignant [11]. Multiple imaging techniques can be used to diagnose and categories brain tumours. On the other hand, magnetic resonance imaging (MRI) is probably the most common painless method. Magnetic resonance imaging's (MRI) widespread adoption can be attributed to a number of factors, including the lack of ionizing radiation during filters, fantastic goal of delicate tissues, and the ability to obtain different pictures by changing imaging boundaries or utilizing contrast-improving specialists [12, 13].

II. DIFFERENCE FROM PREVIOUS SURVEYS

Several critically important studies on the classification of brain tumours have been published in recent years. Our most recent investigations, together with their nuanced and distinguishing aspects, are shown in Table 1. The overview study by Ghaffari et al. is the closest to our own. Most of the submissions for the BraTS2012–BraTS2018 competitions were covered in [14], but no analyses were performed from the perspective of the strategic class or any aspects. Late-breaking analyses focused on combining traditional approaches to sectioning brain tumours by Kapoor et al. [15] and Hameurlaine et al. [16]. [15] and [16] However, neither of them included a comprehensive specialized evaluation or a discussion of the methods of deep learning-based partitioning. As shown in [17], a survey of pre-2013 state-of-the-art algorithms for dividing brain tumours, the majority of these approaches blended regular AI models with hand-created highlights. Liu et al. [18] published the findings of a meta-analysis on the sub-division of brain tumours by MRI in 2014. Methods that require extensive study are outside the scope of this summary. In a recent study [19], Nalepa et al. investigated the nuances and effects of various information enhancement methods as they pertain to dividing brain tumours. Furthermore, we focus our inquiry on the unique study of deep learning-based brain cancer division strategies.

Throughout the years, many studies on delegate research have been published, many of which deal with topics that are surprisingly similar. Clinical image processing is an area where deep learning computations are being used now, and Litjens et al. This article provides a synopsis of previous studies on clinical picture analysis, including many cutting-edge profound learning-based brain cancer division advancements made before 2017. In [21], Bernal et al. shared the findings of a study that focused on evaluating brain images with deep convolutional neural networks. This survey will only cover the use of sophisticated convolutional neural networks. Division in an unbalanced environment and learning from only a few modalities, two other key aspects of learning, were not investigated. Akkus et al. [22] presented a work that applied significant learning to the segmentation of brain MRIs. Esteva and his collaborators did some late-breaking exploration. [23] provided research into the use of deep learning in healthcare settings. This article provided a synopsis of how deep learning can be used to improve medical applications in areas such as computer vision, natural language processing, supplementary learning, and summarization. Recent work introduced the implications on object detection and semantic separation in a review paper ([24]). A thorough understanding of object detection and semantic separation can be attained with the help of this review.

"Profound learning" refers, in particular, to the practice of employing neural network models with several stacked functional layers (the layer number is typically greater than 5). [26-27] It has been discovered that neural networks can learn complex functions at multiple levels of abstraction. Several studies, for example [29] and [28], have introduced the conceptualized systems for deep learning in light of the successes and ongoing enhancements of deep neural networks.

Table 1: A summary of the existing surveys relates to the topic ’brain tumor segmentation

Survey Title	Venue	Year	Remarks
Automated brain tumor segmentation using multimodal brain scans: a survey based on models submitted to the BraTS 2012–2018 challenges	IEEE Reviews in Biomedical Engineering	2019	A review of challenge submissions of BraTS during 2012-2018.
	2017 7th International Conference on	2017	

A survey on brain tumor detection using image processing techniques	Cloud computing, Data science & Engineering-confluence		A review of general brain tumor seg- mentation methods.
Survey of brain tumor segmentation techniques on magnetic resonance imaging	Nano Biomedicine and Engineering	2019	A general summary of classic brain tumor segmentation methods.
State of the art survey on MRI brain tumor segmentation	Magnetic Resonance Imaging	2013	Review on convolutional neural net- works used for brain MRI image analysis.
A survey of MRI-based brain tumor segmentation methods	Tsinghua Science and Technology	2014	Review on MRI based brain tumor segmentation methods.
Data augmentation for brain-tumor segmentation: a review	Frontiers in Computational Neuro- science	2019	Analyzed the technical details and impacts of different kinds of data augmentation methods with the ap- plication to brain tumor segmentation.
A survey on deep learning in medical image analysis	Medical Image Analysis	2017	A comprehensive review on deep learning based medical image analysis.
Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: a review	Artificial Intelligence in Medicine	2018	A review on use of deep convolutional neural networks for brain image analysis.
Deep learning for brain MRI seg- mentation: state of the art and future directions	Journal of Digital Imaging	2017	A survey on deep learning for brain MRI segmentation.

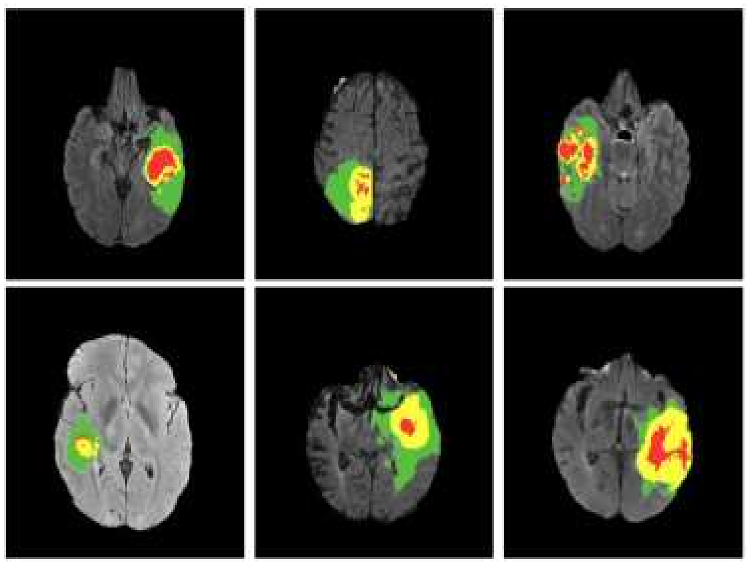
A guide to deep learning in health-care	Nature Medicine	2019	A survey health-care on deep Learning
Deep learning for generic object detection: A survey	International Journal of Computer Vision	2020	A comprehensive review on deep learning based object detection.
Deep learning	Nature	2015	An introduction review on deep learning and its application.
Recent advances in convolutional neural networks	Pattern Recognition	2018	A survey on convolutional neural networks and its application on computer vision, language processing and speech.
Deep Learning Based Brain Tumor Segmentation: A Survey	Ours	-	A comprehensive survey of deep learning-based brain tumor segmentation.

III. CHALLENGES ASSOCIATED WITH BRAIN TUMOR SEGMENTATION

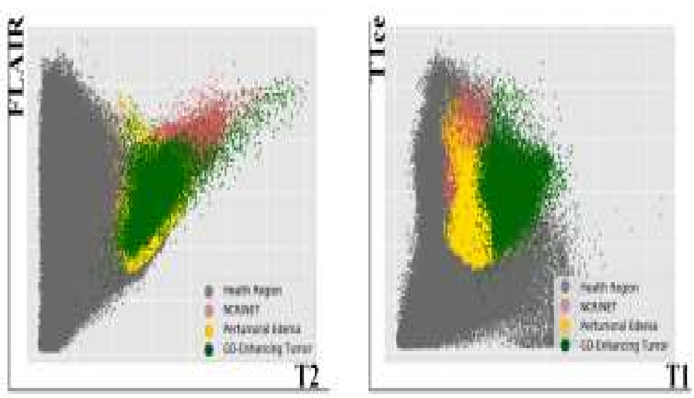
1. Uncertainty Viewing the Area Gliomas begin as transformations in the gluey cells that encompass nerve cells in the brain and spinal line. Because of the far-reaching spatial circulation of gluey cells inside the brain, either a High-Grade Glioma (HGG) or a Poor-quality Glioma (LGG) could foster in any piece of the brain.
2. A Vulnerability In regards to Morphology rather than fixed objects, the morphology of different brain tumors, like their shape and size, is profoundly factor and subject to a lot of vulnerability. Edema tissues, which make up the peripheral layer of a brain cancer, show various liquid structures, however these structures barely give any foundation data that might be utilized to portray the morphologies of the growth. The size and state of a growth's subregions can likewise shift fundamentally from each other.
3. Inadequate Difference It is guessed that photos with a high goal and a high differentiation will convey an assortment of picture data [30]. It's conceivable that the pictures delivered by a MRI will have low quality and low differentiation on account of the picture projection and tomography technique. The line that depicts one organic tissue from another is regularly indistinct and challenging to distinguish. Since it is hard

to characterize the cells that are found near the limit, precise division is made more troublesome and is more difficult to perform.

4. Annotation Predisposition Explanation utilizing manual means is very subject to the singular's degree of involvement, which could prompt inclinations in the information naming cycle. Apparently certain explanations tend to connect every one of the little districts together, while different comments can stamp individual voxels in an exact way, as found in Fig. 1 (a). Throughout learning, the comment predispositions impact the calculation that does division [31].
5. A Lopsided Battleground There is a lopsided dissemination of voxels across the different areas of the growth, as should be visible in Figure1 (b) and (c), respectively. The necrotic and non-upgrading growth center (NCR/ECT) zone, for example, is significantly more modest than the other two areas. The information driven learning approach is impacted by the unequal issue on the grounds that the recovered highlights might be significantly affected by large cancer areas [32].



(a)



(b)

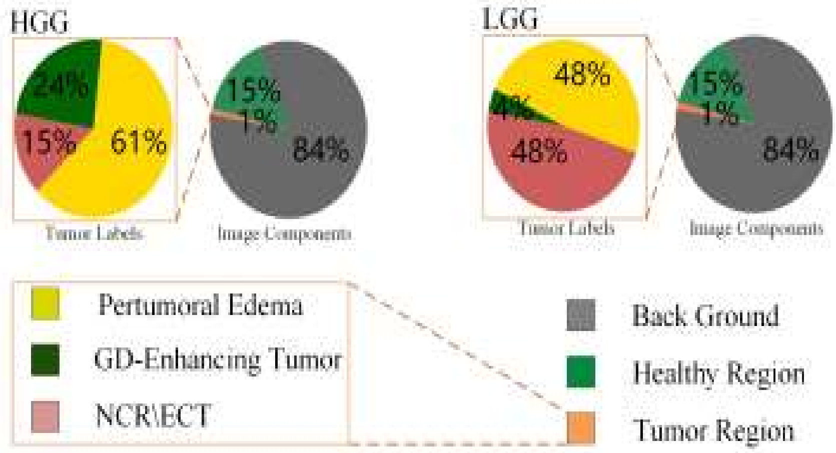


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Figure1: Challenges in segmentation of brain glioma tumors. (a) shows glioma tumor exemplars with various sizes and locations inside the brain. (b) and (c) show the statistical information of the training set in the multimodal brain tumor segmentation challenge 2017 (BraTS2017**)**

IV. CLASSIFICATION

During the process of determining a general health issue, grouping is typically the last step. As part of this process, the elements of a picture (or series of pictures) are broken down and placed in their respective categories. Frequently, the picture will be cut up to separate particular things from one another and the background, and then those things will be named. "Highlight extraction" is the process of reducing the amount of data collected by making educated guesses about the most salient features of the named items. A classifier then takes this information and uses it to determine in which category each particular object belongs based on the qualities it has been taught to search for and the benefits associated with those features. An image's overall quality is dependent on a number of factors, including the camera's intended use, its responsiveness, its data transfer capacity, and the fraction of its field of view that is dedicated to capturing motion or commotion. Pre-handling may be necessary before beginning division, which is typically a challenging process. In some cases, for instance, low-pass filtering is necessary for isolation. The intended pieces can be altered in some way or planned into a different component space before being supplied to the classifier in order to produce better highlights. Humans naturally have the ability to identify items based on their size, shape, variety, and other readily apparent cues. The goal of recognition is to become aware of something and then draw conclusions about that something based on a yes-or-no answer, such as whether or not this mammogram reveals a sore. Grouping is the process of classifying items into a set of related categories. A good example of characterization is determining whether or not a sore pose a cancer risk. Measurement-based methods and structural (or syntactic) approaches are the two primary categories into which organizing procedures fall. Even more, there's a third category that incorporates features of the first two; this concept is sometimes referred to as "mental techniques," but it's not strictly speaking any of those things. Examples of this category include neural networks and genetic equations. The primary category denoted by the letter "a" refers to concepts or instances with a primary and demonstrable cause for their evolution. Quantitative features, such as size, location, or intensity, can be used to describe such entities or instances. The second area is concerned with defining an object's inherent structural or syntactic relationships through a set of subjective attributes.

Parametric and nonparametric approaches are the two main ways that factual order can be improved. Parametric methods necessitate likelihood dispersions and the resulting gauge boundaries in order to provide a concise illustration of the classes. The average and standard deviation are used in several of these gauge limits. Differential analysis, a parametric method based on functions that distinguish between classes, and cluster analysis, a non-parametric method that looks for clusters of tests in unlabeled data, are both examples of models. An approach based on features that serve to differentiate the categories is called a discriminant analysis. Typically, parametric computations proceed slowly while being prepared, but once they're ready, they order test data quickly. But non-parametric approaches either estimate the probability distributions (in a process known as non-parametric assessment) or they skip the probabilities altogether and jump straight to the decision functions (non-parametric characterization).

V. CONVOLUTIONAL NEURAL NETWORKS

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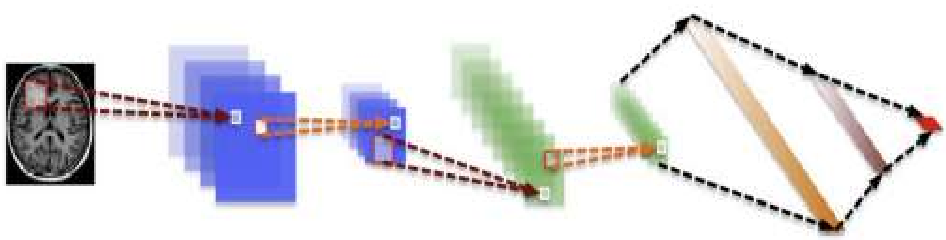

Figure 2. An architecture of a convolutional neural network

A pooling layer is used to down-example the element guides of the preceding convolution layer after a convolution layer has been applied. Each element guide of the pooling layer is computed in light of a subset of elements in its responsive field, and each component map of the pooling layer is coupled with a component map of the convolution layer. The convolution map is convolved with the open field that finds a maximal value among a subset of the units in its responsive field, but with a step size that is proportional to the responsive field size, producing an effect that is functionally identical to a convolution layer. This ensures that open fields that are physically close together will not frequently overlap one another. The pooling layer's job is to gradually reduce the spatial size of the component maps, which in turn reduces the network's need for boundary conditions and computation. One of the most important roles of pooling layers is to ensure that the information can be interpreted consistently throughout space, even if the space in which it is located has changed slightly. Figure 2's bottom left image is an interpretation of the top left image by shifting it one pixel to the right and one pixel down, but the end results of applying convolution and pooling algorithms to both images are roughly the same, particularly for the green units.

VI. MAGNETIC RESONANCE IMAGING

X-beams, computed tomography (CT), positron emanation tomography (PET), single-photon discharge computed tomography (SPECT), ultrasound, magnetic resonance imaging (MRI), and cerebral angiography are instances of key brain imaging modalities. Imaging of the brain can be performed with a method called magnetic resonance imaging (MRI), which includes no obtrusive techniques. While distinguishing oddities in the body, magnetic resonance imaging (MRI) is used to give nitty gritty and precise photos of human organs saw from various points. The MRI is an incredible device for detecting irregularities of the brain like tumors, sores, numerous scleroses, strokes, and hemorrhages. Figure 3 shows a two-layered cut taken from a three-layered MRI of the patient's brain cancer. Exact physical three-layered (3D) models got from 2D MRI clinical picture information help in giving precise and exact analytic data. This is achieved by distinguishing the exact area of the growth, as well as giving data about the spatial connections between basic physical structures like vascular structures, articulate cortical regions, and other little interior wounds that shouldn't be visible to the unaided eye. Imaging of brain tumors is every now and again performed utilizing magnetic resonance imaging (MRI) for the accompanying reasons: I Not at all like CT, SPECT, and PET sweeps, this strategy doesn't utilize any ionizing radiation. ii)It has a more prominent difference goal than any of the methodologies examined in (I). iii) The limit of MRI machines to give three-layered space pictures assists us with pinpointing the exact area of the growth. iv) Its capacity of securing physical as well as functional data on the growth at a similar output [33].

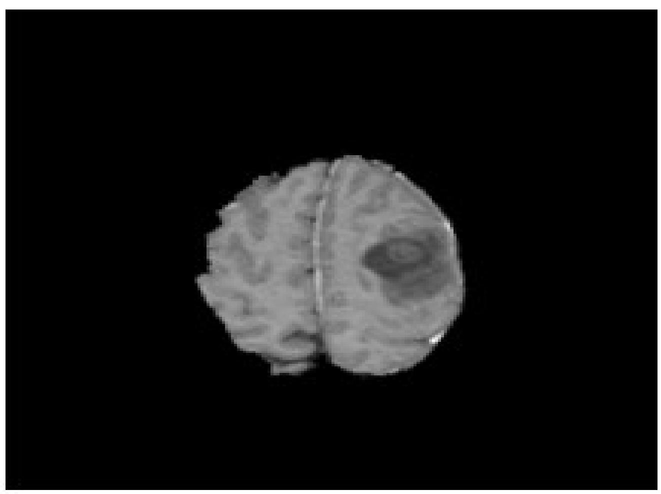

Fig. 3: An MR image of brain tumor

MRI scans can be categorized in a number of different ways, including by overall picture weighting (such as T1 or T2) and unambiguous elements (for example fat stifled or gadolinium improved). Examples of MRI classes include:

1. T1-W, also known as a T1 weighted image, is a common type of pulse sequence used in magnetic resonance imaging (MRI) that highlights differences in the T1 unwinding time of various tissues. Figure 4 shows the MR image as seen in T1-W.

2. T2-W, or a T2 weighted image, is another fundamental heartbeat grouping used in MRI to delineate differences in the T2 unwinding season of distinct tissues. Figure 5 depicts the T2-W MR image.
3. The Pizazz (Liquid reduced reversal recuperation) MRI subgroup is distinguished by a reversal recuperation modification made with the explicit aim of disguising the presence of liquids. Figure 6 depicts the expected Style MR image.

Figure 4: T1-W

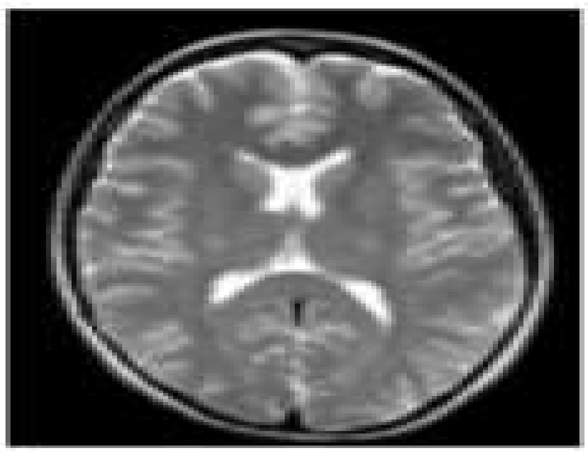

Figure 5: T2-W

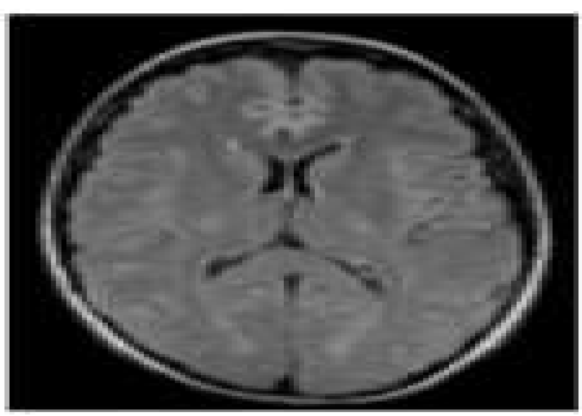

Figure 6: FLAIR

VII. BRAIN TUMOR SEGMENTATION AND CLASSIFICATION BASED SYSTEM

The ensuing section goes into detail about the sophisticated convolutional encoder-decoder architectures we developed for semantic segmentation of brain tumours. The most popular method of semantically dividing an image and assigning every pixel to the lawful objective mark using a picture of a field of view as a ground truth is referred to as [34].

7.1 Encoder

Encoders take in images having a 512x512 pixel resolution as input, and then use a channel bank to build include maps. The encoding method is a 1:1 match for the VGG16 architecture, which consists of 13 convolutional layers (7 x 7), a cluster standardization layer, component wise RELU, quitter and max pooling (2 x 2), a non-covering walk by 2, and up sampling (2 x 2). Combining max-pooling with subsampling yields interpretation invariance over often insignificant variations in the spatial region of the image. Therefore, each pixel in the final image must take increased responsibility for the information it conveys (spatial window). The spatial aim of element maps is diminished, but understanding is enhanced and characterization is enhanced by increasing the number of max-pooling layers and employing subsampling. Therefore, the limit data must be collected before subsampling. Thus, we have only managed to detect the most extreme cases of file pooling.

7.2 Decoder

For each of the 13 encoders, there is a corresponding decoder, and this decoder must up-example the component map by recalling previous max-pooling files. The encoder network's element map is sent along to it as input. Then, it recalls the max-pooling records generated by the encoder's highlight maps and uses them to up-example its matching information include maps. Since there aren't many pieces of information in the real world, the resulting component map has an ambitious purpose but an unsatisfactory visual style. Thick component guides can be generated by convolution with a teachable decoder channel bank. The resulting multilayered gloss creates a veil in the semantics.

7.3 Classifier Based on the SoftMax

The last decoder is connected to a SoftMax classifier, which sorts every individual pixel into one of a few classifications. The probabilities for the classes are dissected by the convolutional layer that is 1 x 1 and uses the SoftMax calculation. The result that is produced by the delicate max calculation incorporates the probabilities for channel k, where k is the number that addresses the complete number of classes. As an outcome of the expected division, the best likelihood of pixel-wise division has been determined. In the outcomes section, you will track down a show of the precisely fragmented pixel-by-pixel information for both the growth and non-cancer orders.

VIII. PROPOSED METHODOLOGY

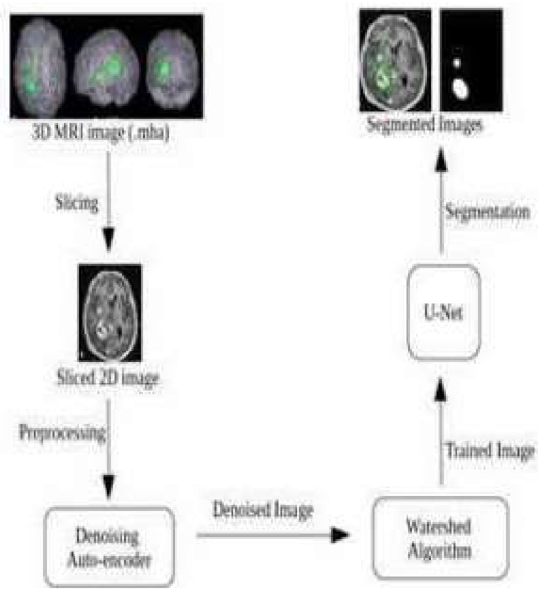

Figure 7. Proposed system architecture

Procedures from the field of picture handling and profound learning have been remembered for the model that we have proposed to find and sharing tumors. Coming up next are the means that make up our strategy:

1. **Slicing:** When using a slicer, three-layered MR images from the Imps dataset can be converted into two-layered images.

2. **Pre-Processing:** The picture should be properly denoised and preprocessed before the actual division of the picture can happen. The Stacked denoising autoencoder is utilized to perform both the denoising and the pre-handling.

3. **Segmentation:** After the image has been denoised, it will be sent to the Marker-Controlled watershed group.
4. The development of the marker-controlled watershed was motivated by the problem of excessive division within the watershed division.
5. Once the watershed division is complete, the morphological work can be completed, and the cancer's location can be estimated using the supplementary equation. By multiplying the even picture component by the upward picture component by the

absolute number of pixels in the cancer region, expressed as square inches, we may calculate the growth region.

IX. **Advanced Classification Techniques** Using Fully Convolutional Neural Networks: The watershed generates a large number of images. Highlights from this image will be put to neural networks so that they may be extracted. The output of these neural networks will define the expansion as benign or dangerous.

X. CONCLUSION AND FUTURE WORK

In this presentation, we discussed several methods for detecting cancer using advanced machine learning and image processing. However, when used independently, each of these tactics has its own set of drawbacks and constraints. Pre-processing and component extraction seem to help deep learning work effectively, and it appears that picture handling can produce exceptionally precise results with the right pre-handling [35]. Thus, when these two approaches are combined, miraculous results can be achieved. Here are some directions the future guide might go in

1. One example of this is the pre-handling technique known as "Profound Picking Up" (Stack Auto encoder).
2. Using image processing for tumour segmentation and confirmation of affected areas (Watershed Division).
3. Profound Learning (Completely Convolutional Neural Networks) is being used to extract cutting-edge highlights, such as classifying tumours as benign or malignant, gliomas or glioblastomas, and so on.

Use of these methods in tandem with transfer learning will aid in the development of a system that is highly automated, accurate, and reliable for cancer ID. This framework will be able to correctly conduct tasks such as growth detection, division, region computation, and further grouping of the cancer, reducing the need for human error and facilitating early diagnosis. It can also perform these tasks simultaneously. Our proposed model will yield accurate answers regardless of the amount of time spent on calculations. It will also be possible to predict the patient's chance of surviving the illness in the future.

REFERENCES

[1] Pottumarthi V Prasad. Magnetic resonance imaging: methods and biologic applications, volume 124. Springer Science & Business Media, 2006.

[2] Yuehao Pan, Weimin Huang, Zhiping Lin, Wanzheng Zhu, Jiayin Zhou, Jocelyn Wong, and Zhongxiang Ding. Brain tumor grading based on neural networks and convolutional neural networks. In 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pages 699–702. IEEE, 2015.

[3] S Deepak and PM Ameer. Brain tumor classification using deep CNN features via transfer learning. Computers in biology and medicine, 111:103345, 2019.

[4] Sanjeev Kumar, Chetna Dabas, and Sunila Godara. Classification of brain MRI tumor images: A hybrid approach. Procedia computer science, 122:510–517, 2017.
[5] Geethu Mohan and M Monica Subashini. Mri based medical image analysis: Survey on brain tumor grade classification. Biomedical Signal Processing and Control, 39:139–161, 2018.
[6] Muhammad Sajjad, Salman Khan, Khan Muhammad, Wanqing Wu, Amin Ullah, and Sung Wook Baik. Multi-grade brain tumor classification using deep CNN with extensive data augmentation. Journal of computational science, 30:174–182, 2019.
[7] Ahmed Shokry, Marwan Torki, and Moustafa Youssef. Deeploc: a ubiquitous accurate and low overhead outdoor cellular localization system. In Proceedings of the 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pages 339–348. ACM, 2018.
[8] L. M. De Angelis, ‘‘Brain tumors,’’ New England J. Med., vol. 344, no. 2, pp. 114–123, Jan. 2001.
[9] B. W. Stewart and C. P. Wild, World Cancer Report 2014. Lyon, France: IARC, 2014.
[10] Brain, Other CNS and Intracranial Tumors Statistics. Accessed: May 2019. [Online]. Available: https://www.cancerresearchuk.org/
[11] A Behin, K. Hoang-Xuan, A. F. Carpentier, and J.-Y. Delattre, ‘‘Primary brain tumors in adults,’’ Lancet, vol. 361, no. 9354, pp. 323–331, 2003.
[12] A Drevelegas, Imaging of Brain Tumors with Histological Correlations. Berlin, Germany: Springer, 2002.
[13] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sánchez, ‘‘A survey on deep learning in medical image analysis,’’ Med. Image Anal., vol. 42, pp. 60–88, Dec. 2017.
[14] M. Ghaffari, A. Sowmya, R. Oliver, Automated brain tumor segmentation using multimodal brain scans: a survey based on models submitted to the brats 2012–2018 challenges, IEEE reviews in biomedical engineering 13 (2019) 156–168.
[15] L. Kapoor, S. Thakur, A survey on brain tumor detection using image processing techniques, in: 2017 7th international conference on cloud computing, data science & engineering confluence, IEEE, 2017, pp. 582–585.
[16] M. Hameurlaine, A. Moussaoui, Survey of brain tumor segmentation techniques on magnetic resonance imaging, Nano Biomedicine and Engineering 11 (2) (2019) 178–191.
[17] N. Gordillo, E. Montseny, P. Sobrevilla, State of the art survey on mri brain tumor segmentation, Magnetic resonance imaging 31 (8) (2013) 1426–1438.
[18] J. Liu, M. Li, J. Wang, F. Wu, T. Liu, Y. Pan, A survey of mri based brain tumor segmentation methods, Tsinghua Science and Technology 19 (6) (2014) 578–595.
[19] J. Nalepa, M. Marcinkiewicz, M. Kawulok, Data augmentation for brain-tumor segmentation: a review, Frontiers in computational neuroscience 13 (2019) 83.
[20] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. van der Laak, B. Van Ginneken, C. I. S´anchez, A survey on deep learning in medical image analysis, medical image analysis 42 (2017) 60–88.

[21] J. Bernal, K. Kushibar, D. S. Asfaw, S. Valverde, A. Oliver, R. Mart´ı, X. Llad´o, Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: a review, Artificial intelligence in medicine.

[22] Z. Akkus, A. Galimzianova, A. Hoogi, D. L. Rubin, B. J. Erickson, Deep learning for brain MRI segmentation: state of the art and future directions, Journal of digital imaging 30 (4) (2017) 449–459.

[23] A Esteva, A. Robicquet, B. Ramsundar, V. Kuleshov, M. DePristo, K. Chou, C. Cui, G. Corrado, S. Thrun, J. Dean, A guide to deep learning in healthcare, Nature Medicine 25 (1) (2019) 24–29.

[24] L. Liu, W. Ouyang, X. Wang, P. Fieguth, J. Chen, X. Liu, M. Pietik¨ainen, Deep learning for generic object detection: A survey, International journal of computer vision 128 (2) (2020) 261–318.

[25] I Goodfellow, Y. Bengio, A. Courville, Deep learning, 2016.

[26] H. Lin, S. Jegelka, Resnet with one-neuron hidden layers is a universal approximator, Advances in Neural Information Processing Systems 31 (2018) 6169–6178.

[27] D. Yarotsky, Error bounds for approximations with deep relu networks, Neural Networks 94 (2017) 103–114.

[28] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, nature 521 (7553) (2015) 436.

[29] I Gu, Z. Wang, J. Kuen, L. Ma, A. Shahroudy, B. Shuai, T. Liu, X. Wang, G. Wang, J. Cai, et al., Recent advances in convolutional neural networks, Pattern Recognition 77 (2018) 354–377.

[30] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, A. C. Berg, Ssd: Single shot multibox detector, in: European conference on computer vision, Springer, 2016, pp. 21–37.

[31] Y. Chen, J. Joo, Understanding and mitigating annotation bias in facial expression recognition, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 14980–14991.

[32] S. R. Bulo, G. Neuhold, P. Kontschieder, Loss max-pooling for semantic image segmentation, in: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, 2017, pp. 7082–7091.

[33] Rajesh C Patil, Dr. A. S. Balachandran, 2017. “Brain Tumor Extraction from MRI Images Using MATLAB”, International Journal of Electronics, Communication & Soft Computing Science and Engineering Vol. 2, Issue 1.

[34] Badri Narayanan, V., Kendall, A., Cipolla, R.: Segnet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE transactions on pattern analysis and machine intelligence 39(12), 2481–2495 (2017)

[35] Long, J., Shelhamer, E., Darrell, T.: Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 3431–3440 (2015)