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Deep Learning-Based Methods for Brain Tumor Segmentation: A State-of-the-Art Review

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Abstract: Hospitals have lately begun using machine learning to expedite the diagnostic and analysis process. Now that they have assistance with diagnosis, doctors can expedite the start of the healing process. AI in healthcare may be used for simple to complex tasks in the future, such as phone answering, reviewing medical records, trending and analytics in primary care, computer design and therapeutic medicine, reading radiology images, creating treatment and diagnosis plans, and even having conversations with patients. Medical imaging such as CT, MRI, and X-ray pictures may be interpreted using deep learning models to establish a diagnosis. Inconsistencies and dangers can be identified by the algorithms in the medical imaging data. Cancer detection frequently makes use of deep learning. Brain tumors must be correctly segmented using MRI images in order to aid in clinical diagnosis and therapy planning. However, the lack of certain diagnostic procedures in MRI images makes medical practice more challenging. The recommended method performs better when comparing the quantitative and qualitative results of medical image analysis as it is currently performed. When it comes to the accurate identification of malignant lung nodules in the event of lung cancer detection, CT scans of the chest perform better. Early detection of lung cancer is crucial for patients' chances of survival. Using sparse chest computed tomography (CT) data from earlier research, create a multi-view knowledge-based collaborative (MV-KBC) deep model to distinguish between benign and malignant nodules. However, the MV-KBC model had more accuracy. Nevertheless, the model can only be used to supervise image data. In this research, we present a novel deep learning-based multi view model to alleviate the model's shortcoming. The accuracy of the suggested model was significantly improved, and computation and classification times were decreased, for semi-supervised medical image applications.

Keywords: Classification; MV-KBC; Inconsistencies; Computed Tomography (CT); Algorithms

1. Introduction

Over the years, interest in deep learning methods for image analysis has increased. One specific area is healthcare. Medical imaging involves the use of 3D images of the human body, usually obtained from CT or MRI [1] scanners. Doctors investigate and discover the patient's condition based on medical records. Thus, they can diagnose medical or surgical procedures. Using deep learning to analyze medical images is a revolutionary process [2]. Using deep learning for high-quality medical image analysis. Many deep learning algorithms can be used to analyze data obtained from diagnosis. Deep learning is used to learn how to process medical images using clustering, which includes detection, segmentation, and classification. In medical image analysis, three different techniques are often recognized: image reconstruction, image aggregation, and bracketing. The constant use of medical image analysis [3] for raw data can lead to errors from one task to another, especially when the data is inconsistent. The use of medical imaging in medical decision making is increasing, but using imaging as a pipeline often overlooks the level of image optimization. This is an important step because successful segmentation and other subprocesses depend on good clinical images. Digital photography is essential for everyday use. The term "image processing" refers to how a computer processes images [5]. This work includes many processes and procedures such as image capture, storage and presentation. A program that shows how to measure the nature of a scene, such as color or light. Digital images have many advantages: fast and cheap processing, easy transfer and storage, instant measurement, multiple copies without quality intervention, faster and cheaper and flexible exchange. Image processing requires high performance and data storage. Despite quality control, digital images can sometimes be violated [6]. It is important to know that research using "3D Medical Multimodal Segmentation Networks" has significant limitations. First, the diversity and accessibility of medical records are important for the effectiveness of these networks. There is not enough good information from different sources and patients hinder the network's ability to be broad. Also, the quality and consistency of human descriptions have a great impact on accurate segmentation, leading to the possibility of inconsistency and error, especially for difficult things. The diversity of deep learning models can make them computationally demanding, which can limit their applicability and accessibility in resource-limited environments. Interpretation remains a challenge, as these standards often come down to consensus, which can cause problems in important clinical applications where understanding the logic behind the decision is important. The risk of overfitting and the ability of models to generalize to new imaging or unpublished data illustrate how difficult it is to achieve robust and reliable segmentation. The use of such models is complicated by the need to resolve ethical and regulatory issues and provide good clinical data for translating scientific research into clinical practice. Finally, given the rapid pace of development of deep learning, it is important to keep up with new models and methods to make research valid and relevant. Edit photos on your computer. This method has the advantages of communication, data storage, flexibility, and adaptability. The development of image scaling technology to improve photo editing. This method requires simultaneous analysis of images on multiple systems. Both 2D and 3D images can be made in multiple dimensions [7]. This is an important task in the analysis of medical images, the identification of brain tumors, treatment planning and follow-up, because of the accuracy of the classification. Deep learning has great potential in this area because it can extract important features from data without the need for special engineering. Because clinical models vary in imaging, data acquisition, and clinical content, there are many unique issues and concerns when training cross-sectional models to evaluate different medical procedures, including X-rays, MRI, and CT scans.

Multi-detector row CT (MDCT) is widely used to identify and confirm lung disease [9]. It is considered the gold standard for diagnosing these diseases and is particularly sensitive in diagnosing lung nodules. MRI can identify 85% to 95% of nodules measuring 5 to 11 mm [10]. Depending on the risk of lung cancer, caution is advised for lesions larger than 7 or 8 mm, even if MDCT shows only 1 or 2 mm in size. Bacteria smaller than 7 mm in diameter should be present to determine the growth pattern [11]. Koyam et al. [16] stated that non-contrast lung MRI (Figure 1) is a better method for detecting malignant tumors than thin-section MDCT. There was no significant difference between the total diagnosis and the diagnosis of malignant nodules ($p>0.05$). 97.0%, p0.05, will give lower numbers than MDCT.

The main purpose of the "MV-KBC deep model" is to determine the positive and negative aspects of chest CT images. Determining whether nodules, especially cancer, are benign (non-cancerous) or malignant (cancerous) is an important task to improve the standard nodule classification accuracy by combining a model with multiple clinical quality, anatomical data utilization and aggregation of features from multiple images.

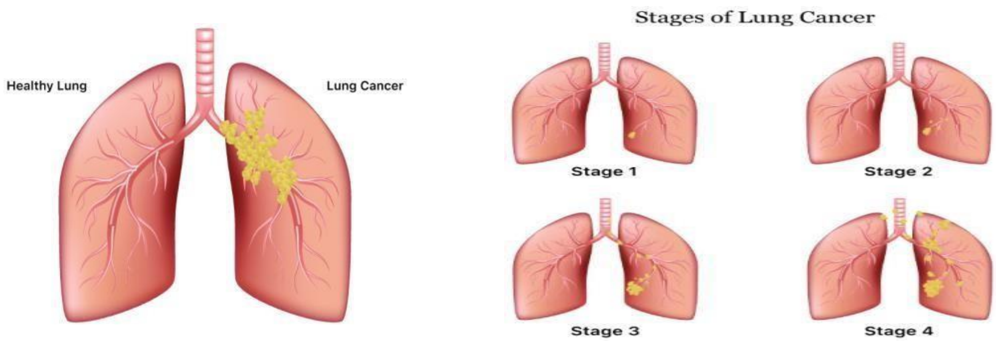

Figure 1. Normal and Affected patient's images

. The use of anonymous data may be particularly useful in cases where recorded data are difficult and expensive to obtain. Treatment decisions are not affected by the presence or absence of lymph nodes in any ipsilateral bronchial region or hilum (which may indicate N1 disease). Ipsilateral mediastinal or sub carinal lymphadenopathy is a manifestation of N2 disease and occurs when only one region is affected. Stage of classification from N1 to N3 indicating severity of disease. N3 describes the main stage of disease. In N3 disease consisting of Virchow, scalene or hilar lymph nodes, and major surgery is not recommended [12]. Printers and images combine MRI and PET [13]. However, significant advances have made it possible to make patterns and physical applications using single-detection images. The functional information provided by MRI does not imply an additional dimension compared to dynamic MDCT. Although MRI cannot measure glucose metabolism, it is considered equivalent to functional and molecular analysis (14).

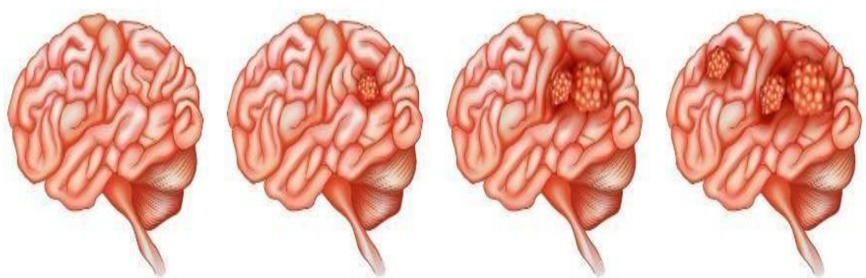

Figure 2. Different stages of Brain tumor

The evolution of cancer is shown in Figure 2. Machine learning techniques are used to detect cancer early to benefit patients. Brain tumors usually take months or years to develop. Glioblastoma is the most common and deadly form of brain cancer. It is one of our main models because its development is not detected by the immune system. It causes fatigue and weakness, a constant need for sleep and a tendency to stay in bed or rest for days. Weight loss and loss of muscle mass. Difficulty swallowing food or drinks and little or no appetite. Artificial intelligence (AI) is driving change and growth in many areas of healthcare. MRI, CT scan and X-ray. AI can share a wealth of patient information, enabling early diagnosis and treatment. AI is also using automation to develop new drugs, predict disease outbreaks, and streamline operations. AI-powered telemedicine and remote patient care are facilitating virtual consultations and information gathering. Genomic analysis helps identify genetic factors related to health issues, while natural language processing (NLP) improves communication and electronic medical records. As AI integration continues to transform healthcare, careful attention to ethics, privacy, and regulatory issues is required, suggesting collaboration between AI experts, professionals, and physicians. In order to ensure patient safety, ethical concerns, and equity in new treatments, standards and standards for responsible and equitable use of image analysis should be established. Magnetic resonance imaging (MRI) signals can identify tumors [15]. According to a recent study, lung cancer can be identified by DWI and is different from the findings detected by DWI after obstructive lobe collapse [17]. Whole-body MRI combined with DWI can be used to detect M stage in cancer patients with an accuracy comparable to PET-CT. In addition, quantitative DWI analysis can be used to distinguish infected from non-infected tumors [18].

2. Literature

In today's environment, brain tumors are more dangerous than cancer. Early detection is important for screening and treatment planning. MRI scanning is the best technique for brain tumors because it creates similar tissue without the need for radiation therapy. In terms of analysis, traditional brain tumor segmentation methods are quite effective. This study uses machine learning techniques and capabilities. However, brain segmentation is still difficult, especially when there are not many methods. There are three different groups of missing patterns. The first category refers to differences in the brain structure of the patients [19]. The second problem is that gliomas vary in size, shape and texture from patient to patient. Differentiating between different low-intensity magnetic resonance imaging techniques. H. Fu et al., "Brain segmentation with missing nodes in MRI" [20]. This approach overcomes the problem of segmentation incompleteness with the help of robust segmentation and latent representation learning. However, many segmentation methods make successful fusion difficult [21]. Anatomical landmarks and landmark identification are prerequisites for the interpretation of medical images. In this process, various methods are used to diagnose patients and plan their care. This process includes measurement analysis, segmentation method configuration, and image registration. Although seemingly simple, manual identification of anatomical locations is sometimes difficult and time-consuming. Automatic localization methods are faster and more accurate than manual identification, and are especially useful when there are a large number of image locations that need to be processed accurately. Latent feature extraction is a recently introduced segmentation method for resolving missing nodes. The problem is where to get to the core of the work and how to learn it. The HeMIS implementation [22], using Havaei's real-time framework, independently examines the appearance of each sample and then calculates the fixed features across multiple changes to estimate the final segmentation. However, analyzing the mean and variance of each representative does not help you discover the hidden representatives. The mean function is used to determine the separation. Chen et al. distilled the ideas into numerical expressions and mathematical concepts. Uncertainty operations are used in [24]. Then, through the gating operation, the content code is put into a shared representation for segmentation. Although the two coders need to match, this method is more difficult and time-consuming.

Accurate and timely identification of anatomical structures in examination and diagnosis is essential for the treatment of patients. The two biggest problems of these systems are the use of poor-quality engineering methods and the low performance of human search algorithms. J. Liu [26] proposed a system that uses artificial intelligence to detect viruses. Deep learning principles are also used in this field to help obtain images as input to estimate human anatomy. The model will be developed to characterize various image analyses. In addition, many morphological objects in scanned images are also used to distinguish target anatomical objects in our body. However, the deep learning method performs better than the state transition method [27]. However, it is important to increase the accuracy. Then, the model will calculate the relationship between them to improve the performance analysis idea. The deep network in the experiment uses features between recurrent and convolutional neural networks for classification. Tests showed that single-view mode increases efficiency and effectiveness in thinking about cancer. It shows great potential in Covid-19. It learned to use multiple views of a chest CT image. Deep learning 28 is currently the best image recognition method, but it requires multiple training models, which is not usually used in clinical settings. The authors of this study used a small amount of chest computed tomography data to distinguish breast cancer from breast cancer using multimodality integration (TMME). The technology uses the ResNet-50 model to send image data, and then uses the Image Net database to predict lung nodes. Apply weight adjustment to nodes when backpropagation errors are performed in the distribution. Image, voxel value and appearance are among the metrics produced by these three models. . The classification of lung nodules and tissues around cancer is important. Therefore, it is very difficult to use machine learning correctly. To solve this problem, the authors proposed a multilayer learning model based on 3D convolutional neural network (MMEL-3DCNN). The number of patients worldwide increased by 26% in 2017. Classification of lung nodules before diagnosis is important, especially since computerized classification can help doctors to reach an agreement. CT image classification can be done quickly and accurately using modern machine learning and computer algorithms. Low-dose chest computed tomography (LDCT) is expected to reduce the risk of death in people with early-stage disease. The accuracy and efficiency of cancer diagnosis will be increased with AI management that is equal to or better than human experts in terms of analytical ability. Technology: We developed an artificial intelligence (AI) framework for cancer diagnosis using deep neural network (DNN) [29]. First, a semi-automatic annotation method is used to map the image. Then, a DNN-based malicious classification and pulmonary nodule (LN) identification model is developed to identify cancer, especially lung cancer, using LDCT images. The LN discovery was called "deep learning" and was validated on large datasets using deep learning models. Tense core muscles differently. Negative nonlinearities exist between two models or systems. Reddy et al. [30], for example, use deep learning to determine which images have the most accuracy. In some cases, such as when generating CT images from MRI data, we use synthetic data to create libraries containing the original images. This can be useful since there is no electricity. We collected a large number of MRI images with different tumors, locations, shapes and appearances to be able to accurately represent the model. We continue to work on the SVM classifier and various optimization methods (softmax, RMSProp, sigmoid, etc.) to analyze our work. Our solution was built using TensorFlow and Keras because Python is a fast-programming language.

ANNs with multiple hidden input and output layers are called deep neural networks (DNN). Based on these techniques and methods, we can construct a hidden layer of deep neural networks (DNN). DNN architecture provides a compositional model that represents objects as hierarchical compositions of primitives. More importantly, complex data can be modeled with fewer units compared to shallow networks. Additional layers make the combination lower. Generally speaking, DNNs are feedforward networks, meaning that data flows directly from input to output or from layer to layer. Convolutional Neural Network (CNN) CNN is a neural network with a design consisting of many layers. Symptoms include hormonal changes, blood clots, weakness, unsteady gait, slurred speech, mood swings, and blurred vision. The location of the tumor determines its type, and timely diagnosis can prolong the patient's life [31]. Benign tumors are tumors that cannot invade neighboring tissues. They can be completely eliminated and are unlikely to return. Even if brain tumors do not spread to other tissues, they can cause serious, permanent brain damage and death. A malignant brain tumor is a bad place. They divide rapidly and spread throughout the brain or spinal cord, multiplying in some places. MRI scans use powerful magnets and high-frequency radio waves to provide accurate information about tissues. An X-ray beam is used to perform a tomography scan. Image preprocessing, feature extraction, segmentation, and postprocessing are the processes involved in identifying brain disease.

2.1. Technology

2.1.1. CNN

There are two parts of CNN: pooling layer and convolution layer. Both of these are considered as components of convolutional neural network. It is important to use research to develop models and implement them. The design will suggest the structure of CNN using many neurons. A useful strategy to learn how to design neural networks is to study successful implementations [33]. This is possible because CNN has been intensively researched and applied in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) from 2012 to 2016. Rapid progress in innovation. Since we deal with the small size of each brain slice, a simple and effective cascaded convolutional neural network (C-ConvNet/C-CNN) is proposed in the next step. This C-CNN model uses two different methods for local and global objects. A special remote intelligent tracking (DWA) mechanism is also proposed to improve the accuracy of tumor cells over other models. The DWA method describes the central location of the brain in the structure and effect of the tumor [35].

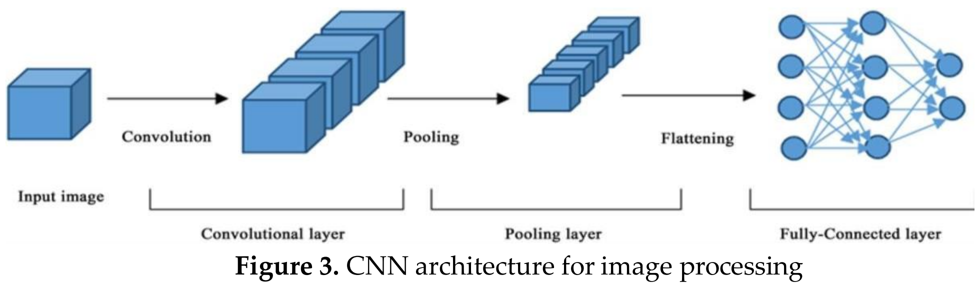

Figure 3. CNN architecture for image processing

Figure 3 explains about the CNN architecture for image processing. It contains the various layers which will segment and filter the image frames.

2.1.2 RNN

Random neural network (RNN) is represented by a network algorithm that uses continuous data or time series [36]. Deep learning concepts are used in applications such as Siri, voice search, and Google Translate. This effective device is also used in medical treatment to protect human life [37]. In this model, researchers first create a model with the required features. The feed forward strategy in RNN is used to exit from its memory, which will affect the current input and output. A series of layers are used to process the results collected from the previous set. Therefore, the relationship and potential benefits are treated as a coefficient value. Many hidden levels are where these values can be changed. The RNN output is always based on the early stage of the network. However, due to the many layers that combine the results, the prediction of the image value is accurate.

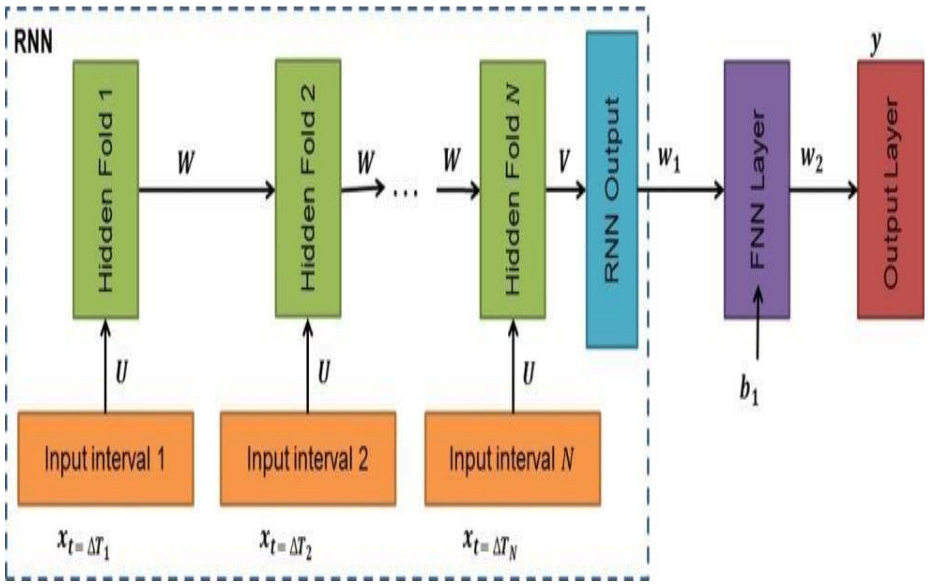

Figure 4. The RNN layer's structure

(a) BIDIRECTIONAL RECURRENT NEURAL NETWORKS (BRNN):

This alternate RNN network structure is described in Fig. 4 [38]. Bidirectional RNNs take prediction performance into account to increase the accuracy of predictions made by unidirectional RNNs, which might only use historical data. Returning to the previous example of "feeling under the weather," if the model had predicted that "weather" would be the final word in the string, it would have been more successful in predicting "under".

(b) Long short-term memory (LSTM)

This famous RNN design was developed by Sepp Hochreiter and Juergen Schmidhuber as a gradient descent solution. In other words, if the previous state influences the current prediction, the RNN model will not be able to predict the current state correctly. It is not suitable for peanuts. The specific nature of the nut allergy will determine whether nuts are present or not. However, if the data comes from many previous columns, the RNN will have difficulty integrating the input. The network's ability to predict the output depends on these gates controlling the flow. For example, if a gender of speech such as "he" occurs multiple times in the previous sentence, you can remove it from the hand state.

(c) Gated recurrent *units* (GRUs)

This RNN version is similar to LSTMs in that it makes an effort to address the problem with temporary memory that RNN models have. Instead of "cell states," it uses hidden states to control information, and it has two gates instead of three: a reset gate and an update gate. Like the gates in LSTMs, the reset and update gates control how much and what kind of information to keep.

2.1.3 GNN

Generative adversarial networks (GANs) are an interesting new advancement in machine learning [40]. GANs, or generative models, create new data instances based on your training data. For example, GANs are able to generate photographs that seem like real-world snapshots, even when the faces in those images aren't actually those of any real individuals. Generative techniques are widely used in picture synthesis. Autoregressive models, variational autoencoders, and GAN are examples of the most recent generation of models [41]. A GAN's strength is its ability to produce sharp images, but its training process is unreliable. The three most popular GAN techniques were tested in order to synthesize nodular pictures. Initially, the genuine wGAN-GP (26) and pix-to-pix (27) deep convolutional models were employed. Nevertheless, these artificially manufactured pictures were fuzzy and of poor quality. Through the use of sliced Wasserstein distance loss, international segment, and pixel normalization, we developed a growing more gradually wGAN inspired by pgGAN. It stabilized the training process and generated high-quality images

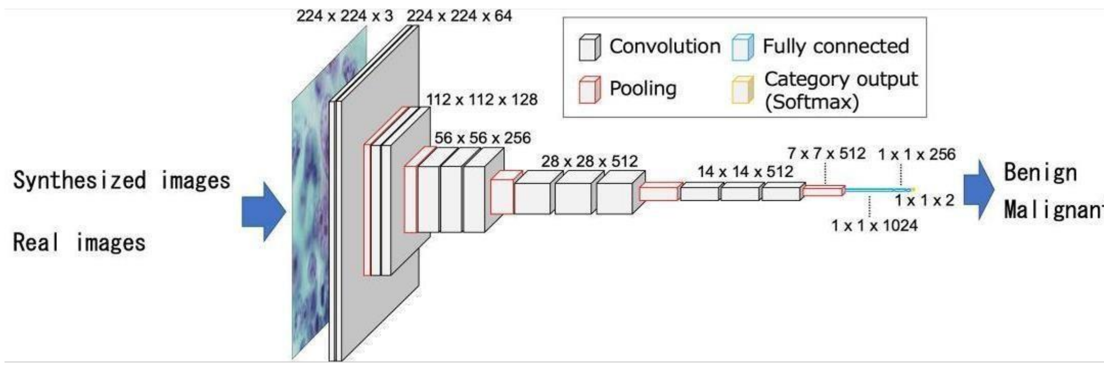

Figure 5. Image Pooling in GAN

The discriminator also had nine convolution layers. Starting with a 64-pixel image, it went through four blocks consisting of two convolution layers before producing the 44-pixel feature map [42] that is seen in Figure 5. With the generator, a mirror image of this operation was created. Mini-batch discrimination was added to the convolution network's last layer in order to improve training stability. Two compact, perfectly linked layers were applied to this feature map in order to determine the final true or false target.

3. Comparison Analysis

The multi-view model is compared with single-shot imaging and traditional imaging methods. The same data were used to ensure consistency, and the performance of each model was evaluated using the previous method. They also performed different levels of noise simulation and data augmentation to test the performance of the model. Segmentation. The network combines information from various measurement methods to improve the accuracy of segmentation tasks. It is designed to process three-dimensional medical data such as CT scans or MRI volumes. Features and models are included. Leveraging multimodal data, which can include multiple imaging viewpoints such as T1-weighted, T2-weighted, and FLAIR MRI scans, allows the network to collect additional information that increases the accuracy and reliability of the segmentation results. Such connectivity is important for identifying objects of interest, including organs, tumors, or lesions. Combining data from multiple sources makes it easier for the network to resolve issues arising from differences in image texture and appearance, resulting in more accurate and reliable segmentation.

Network models can often include encoder-decoder models with cross-connections or tracking systems. Pre- and transfer learning models can also be used to improve network performance, especially when training data is scarce. Metrics such as Hausdorff distance, Jaccard index, and dice coefficient, which measure the overlap between predicted and true segmentations, are often used to evaluate the performance of the network. They play an important role in disease assessment and treatment procedures. However, to achieve good results in certain medical tasks, good training on a large number of data and careful hyperparameter tuning are required for successful deployment.

4. Proposed System

Diagram of Latent Correlation Acquiring Knowledge for Brain Tumor Partitioning with Absent MRI Features. Magnetic resonance imaging (MRI) is a common tool used in the evaluation of brain tumors. Accurately classifying brain tumors using magnetic resonance imaging is essential for both clinical diagnosis and therapeutic planning. Further information for accurate brain tumor segmentation may also be obtained using multi-modal MR imaging [43]. It is common in clinical practice to ignore many imaging modalities. In this work, we provide a novel method for segmenting brain tumors with missing modalities. Since there is a strong correlation across several modalities, a correlation model is recommended to explicitly represent the latent multi-source correlation. If a modality is absent due to the learned correlation representation, the segmentation becomes more dependable. First, the unique representation that every encoder generates is used to estimate the modality independent parameter. Next, every single representation is transformed by the correlation model into a latent representation of a multi-source correlation.

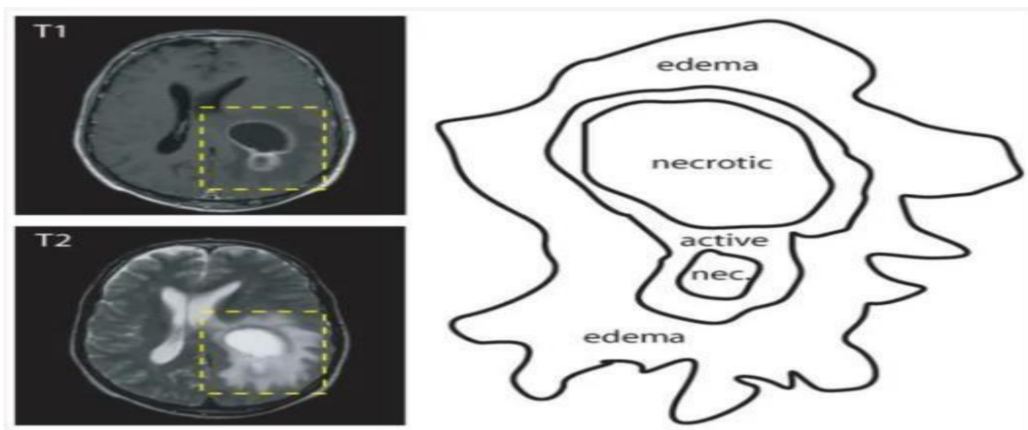

Figure 6. Brain segmentation

Figure 6 illustrates how brain tumors may be statistically analyzed to better understand their characteristics and develop treatment plans. Accurate lesion segmentation necessitates the use of multiple imaging modalities with different contrast levels. Therefore, for bigger studies, manual segmentation—unquestionably the most accurate segmentation technique—would be unfeasible.

Deep learning's unprecedented efficacy has made it a feasible alternative for quantitative analysis in recent times. Nonetheless, there are unique challenges with medical image analysis.

(a)Fusion Strategy

In this paper, we examine a set of deep multimodal fusion methods in the context of point guidance. In other words, given more video inputs (such as thickness and color information), our goal is to process information from multiple streams when describing motions. We specifically focus on the construction of shared representations across layers, which has been neglected in previous studies. In the past, late fusion was used to combine joint fusions for each model. We investigated the late fusion technique and used the C3D [44] backbone, which has shown good results in investigating various aspects. In addition, we evaluate the convergence of the middle levels of the network and provide a simple way to join the early execution by analyzing 111 convolutions of different processes. Finally, we present a new model called C3Dstitch that can learn to combine the signals of two neurons at any level using parallel lines. Dynamic methods use late fusion (a method often used in action recognition) to combine the results of two or more networks at the end of the connection process.

Three different training models were investigated: 1) final integration of multiple networks, calculating the loss after summing the average; - the method combining progress and fine-tuning. The models used for the backbone were trained separately with the same training as the network for each change, except for the positive stage, which was trained in several stages [46]. The main goal of this research is the technology of exchanging information on special maps of the middle layer of the network. Our first impulse is to separate the flow at the lowest level and then combine it into a later model. Simple convolutions combined with multiple output extraction features form a simple fusion concept. Each input of two combined modules must be the same as the input of the shared module in the lower layer (post-fusion). Therefore, we cut half of the output filter in each of the 111 convolutional layers (i.e., subtract the number of flows of the filter). Convolution can be used to reduce the dimensionality of the filter space. As a result, the final architecture consists of three parts: 1) a general network that uses the combined representation in the final stage, 2) two early networks for each variable.

i. Fusion on multiple Levels via Cross-stitch Units

The model phase where the streams would be combined up until this point had to be explicitly chosen. Our objective in this paragraph is to develop a paradigm that permits simultaneous knowledge exchange on several levels without limiting the locations of individual or group learning. We provide a novel multi-stream methodology where each modality has its own unique C3D network that interacts with the others at the fully connected and pooling layers. In this design, the output of every layer is combined using a learned weighted average called cross-stitch units [47]. Put differently, all networks interact pairwise at every level, and the degree of interaction between foreign modalities is found all along the way.

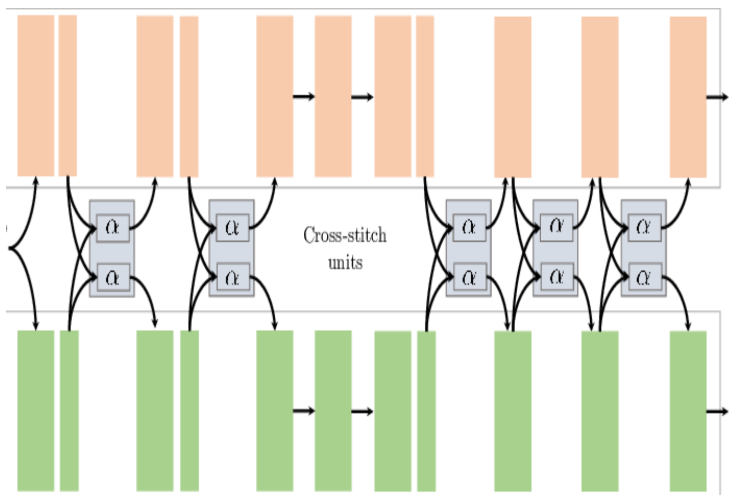

Figure 7. Cross stitch unit in network layers

ii. 3D Medical Multi-modal Segmentation Network Guided by Multi-source Correlation Constraint:

To improve the segmentation results, the relationship between several modalities may be taken into account in the field of multifunctional segmentation [48]. In this work, we propose a sub classification scheme with a correlation constraint. Our network contains N model-independent encoding paths with N image inputs, feature fusion, decoding, and correlation constraint. The model independent encoding approach may be used to record the modality-specific properties of the N modalities. Since there is a strong correlation between the various modalities, we first insist on using a linear correlation block to determine the correlation between them. Next, we use a loss function to aid the network in learning the related features, using the linear correlation block as a guide.

This block instructs the network to identify the latent associated properties that are more valuable for segmentation. Since not all of the features collected from the encoders are suitable for segmentation, we propose to change the features along the modalities and geographical routes utilizing a dual concentration suggested fusion block. This can assist in highlighting relevant information and hiding less helpful information. In the end, the segmentation result is generated by projecting the fused feature representation through the decoder [49].

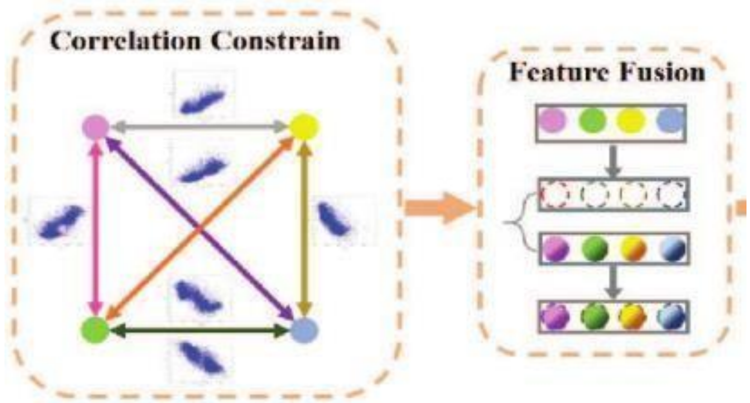

Figure 8. Correlation constraints

5. Conclusion

Early detection of brain tumors is important for cancer diagnosis, because accurate diagnosis can ensure survival. Three-dimensional (3D) magnetic resonance imaging (MRI) is frequently used in deep learning-based brain cancer research due to the problems associated with tumor formation. The model-free coding method can be used to record the modality-specific behavior of N modalities. Since there is a relationship between variables, we first report the relationship between variables to examine their relationship. Then, it instructs the network and uses the loss function to primarily understand the characteristics of the connection. The network is guided by the relevant blocks to determine the most useful features for segmentation. Since not everything received by the encoder can be used to identify the separation, we recommend using two face-based fusion blocks to restore features relative to the path and body. This can help highlight important information and hide less useful information. The following are research gaps that need to be filled in the future. A special deep learning-based brain segmentation technique is used on MRI images of brain tumors to diagnose the disease. We are developing deep learning to reduce computational and time allocation in semi-supervised medical images and improve detection accuracy. The process of integrating all MRI systems simultaneously has the greatest potential, is beneficial for future medical research and can help doctors diagnose Cancer.

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