Comparison Review on Brain Tumor Classification and Segmentation using Convolutional Neural Network (CNN) and Capsule Network

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***Abstract*—Malignant brain glioma is considered as one of the deadliest cancer diseases that has a higher fatality rate than the survival rate. In terms of brain glioma imaging and diagnosis, the processes of detection and segmentation are manually done by the experts. However, with the advancement of artificial intelligence, the implementation of these tasks using deep learning provides an efficient solution to the management of brain glioma diagnosis and patient treatment. Deep learning networks are responsible for detecting, segmenting, and interpreting the tumors with high accuracy and repeatability so that the appropriate treatment planning can be offered to the patient. This paper presents a comparison review between two state of the art deep learning networks namely convolutional neural network and capsule network in performing brain glioma classification and segmentation tasks. The performance of each published method is discussed along with their advantages and disadvantages. Next, the related constraints in both networks are outlined and highlighted for future research.**

Keywords*—Deep learning; convolution neural network (CNN); capsule network; segmentation; classification; brain glioma

I. INTRODUCTION

Brain gliomas are the tumors that grow from the glial cells that support the brain and the spinal cord. There are three types of glial cells involved in the evolution of brain cancers: astrocytes in astrocytoma or glioblastoma tumors, oligodendrocytes in oligodendrogliomas, and ependymal cells in ependymomas tumors. Astrocytomas are mostly found in the cerebrum and cerebellum and can be in the form of slowly growing or fast-growing tumor. Slowly growing tumor is termed as low-grade glioma while fast growing tumor is called high grade glioma. The second type is oligodendroglioma. It is a rare type of brain tumor that attaches to the cerebrum. Lastly, is the ependymomas type that can occur in any section of the brain or spinal cord, most commonly near the cerebellum and lower spinal cord.

Brain gliomas are classified into two types: benign tumor and malignant tumor with cancerous cells [1,2,3]. These brain gliomas are also graded based on the staging endorsed by The World Health Organization. Low-grade gliomas (LGGs) are classified as WHO Grade II infiltrative brain tumor that typically appear solid and non-enhancing on magnetic resonance imaging (MRI) scans [3,4,5,6], in which the patient may be treated with a watch-and-wait approach. High-grade gliomas (HGG), which can resemble LGG on an MRI scan, are typically classified as WHO Grade III or Grade V tumor. The mistakenly interpreted HGG as LGG causes the patient to suffer due to the watch-and-wait strategy although HGGs are extremely aggressive and advance very quickly.

Doctors may use a variety of methods to determine the type and the staging of the primary brain tumor and metastatic brain tumor. It is common that Magnetic Resonance Imaging (MRI) is used in the early stage of brain diagnosis to capture the presence of brain tumor and the necessary biopsy or surgery to obtain tissue sample in identifying the type of the tumor. Magnetic Resonance Imaging (MRI) employs magnetic fields to create a detailed image of the body with the assistance of a special dye known as a contrast medium (gadolinium) administered via intravenous, pill, or liquid to swallow. The dye enhances the MRI image by giving a more accurate depiction of the tumor. With the aid of the diffusion weighted imaging and perfusion imaging methods used in MRIs, soft tissue, joint, and organ abnormalities can be visualized in many different areas of the body, including the brain and joints.

Treatment of a brain tumor requires a multidisciplinary approach that includes surgery, radiotherapy, and chemotherapy. A neurosurgeon will remove the tumor tissue and have it examined to determine the type. To reduce intracranial pressure and relieve symptoms, any excess cerebrospinal fluid will be drained. If the tumor cannot be removed because of its location or if there is a high risk of complications after surgery, radiotherapy and chemotherapy will be used. Radiotherapy and chemotherapy are both commonly used to kill cancer cells by using high-energy x-rays or anti-cancer drugs [7]. Every person can have a different prognosis. The likelihood of survival is influenced by the type of tumor, the severity of the disease, the size and location of the tumor, the presence or absence of metastases, the tumor's response to treatment, the patient's age and general health, and the patient's tolerance for drugs, procedures, or therapies.

Deep Learning (DL), a subfield of Artificial Intelligence (AI), is one of the techniques used for analyzing raw data and extracting relationships in data sets, specifically in the

diagnosis and treatment planning of brain tumors. Deep Learning (DL) automatically learns representations and features from raw MRI image to perform the classification and segmentation of brain glioma. This approach overcomes the issue of manually computing and selecting relevant attributes from the images [8]. Since years ago, the deep learning method has showed its effectiveness to solve many issues and its application in biomedical imaging is outstandingly significant including in MRI brain glioma detection and analysis. As per current, the diagnostic, prognostic, and treatment evaluation of the brain glioma are manually handled. However, manual interpretation has its own limitations, facing the risk of ineffective patient management. Thus, deep learning approach will aid the clinical experts in making wise decisions regarding urgent clinical needs and the necessary treatments [9].

This paper discusses the previously proposed deep learning architectures utilized in classifying and segmenting the brain glioma in MRI images. We focus on CNN architecture and capsule network architecture [10], discussing their performance in terms of the advantages, and disadvantages as well as the prospective works.

II. Literature Review

A. Brain Glioma Classification

Various deep learning methods have been used in previous studies to classify brain glioma. The classification tasks can be implemented into two stages. The first stage is to classify the tumor into normal (benign) and abnormal (malignant) cases. The second stage is to further classify the malignant cases into the specific cancer type. The classification task is a difficult and challenging problem due to the inhomogeneous intensity, atypical shape of the tumors and tissue structures, and different types of noise in the MRI images. The designation of the cancer type is also equivalently difficult as the glioma tumors have similar patterns amongst each other.

Early detection and classification of brain tumors are critical in determining the most appropriate treatment for the patient. Computer aided diagnosis (CAD) based on deep learning is important in assisting the experts and clinicians with more detailed and consistent interpretation, as well as estimating the survival period of brain glioma patients [11] where the image features are extracted from the MRI image through a self-learning approach. Image processing for tumor identification begins with pre-planning, image division, extraction, and gathering. The image will then be automatically analyzed, which improves the identification of the brain structures [12].

The first deep learning algorithm used in image classification and segmentation is CNN. To improve the algorithms' accuracy, CNN has undergone several upgrades, including an adaptation of LeNet with changes to the arrangement and number of layers. Additionally, medial residual block (MidResBlock) classifier, which is based on a network of LeNet, is created by adding information about middle convolution layers to the output of each layer [13].

Another type of CNN is called Residual Neural Network (RNN) enables extremely deep training by using a shortcut connection to skip one or more layers and by utilizing data augmentation to increase the dataset size and improve the accuracy [14]. The VGG16 high performance network is used in studies that use the fuzzy c-mean algorithm for segmentation before moving on to classify the segmented images. Each image is processed through the input layer, convolution layer, max pooling layer, drop out layer, fully connected layer, soft max function, and classification layer.

To capture more specific characteristics without incurring additional computational costs when using large filters in the convolution layer, dilation is implemented in CNN [15]. Another hyper parameter that is used along with this architecture is the dilation rate, which is higher on the outer layers for learning coarse features and lower on the inner layers for focusing on finer features to achieve the best results.

Deep CNN can extract multiple levels of features from image-based data and reveals distinguishing features between classes for classification problems [16,17]. While most studies focus on MRI or Computed Tomography (CT) images, histopathological images have a high potential in the background. To get the best results from this methodology, two factors must be considered: preprocessing and CNN architecture. Patch extraction, abnormal patch detection, intensity, contrast enhancement, and background removal are all part of the preprocessing process, while CNN models are trained to extract features from images, match features with clinical data, and predict relevant brain tumor types using linear or nonlinear methods [17]. Although CNN has been widely utilized to aid human inspection in tumor classification, it has its own limitations that must be addressed.

Capsule Network is proposed to alleviate the limitations of CNN, with the focus on maintaining image resolution and improving classification accuracy. It begins with segmented tumor regions as input and consists of a single CapsNet convolutional layer [18]. The Capsule Network demonstrates that it tends to account for everything in the input image, including the background, resulting in less detail in the image when compared to other methods [19]. The highest accuracy is achieved by reducing the number of feature maps from 256 to 64. Capsule Network sensitivity also supports the ability to access tumor surrounding tissues without distracting it from the main target [20].

Bayesian CapsNet [21] has been developed to handle uncertainty that tends to be incorrect and should be handed to a human expert for review and confirmation. Using Bayesian may result in lower accuracy and the need to filter out predictions with uncertainty over 0.15 and 0.1 to achieve more than 50% accuracy, in addition to higher computational costs. To better understand how the brain uses spiking signals and local learning rules, spiking networks on neuromorphic devices are also being conducted on CapsNet. Image-processing technology performs better because of increased use of neuromorphic computing and fresh learning algorithms [22].

DensNet201 and Inception V-3, two multiple-level feature extraction and concatenation methods, were employed for the diagnosis of brain tumors before features were sent to Softmax

for classification as in [23]. For DensNet 201 and Inception, features were taken out of DensNet blocks and the pre-trained Inception V3 model, respectively. This approach combined scratch-base models, more layers, and data augmentation techniques. A different screening and classification strategy that has been demonstrated to be effective and efficient in classifying gliomas, meningiomas, and metastatic brain tumors that is the combination of DenseNet-LSTM (CNN) and holistic 3D MRI [24]. The YOLOV2-Inception V3 is an improved version of the pre-trained Inception V3 model, which segments data based on Kaput entropy after features are extracted from the mixed layer of the Inception V3 model [25]. Table I presents recent deep learning-based classification techniques for brain tumors based on CNN and Capsule network including several other published methods [26, 27, 28, 29, 30, 31, 32, 33, 34].

TABLE I. RECENT METHODOLOGIES FOR BRAIN GLIOMA CLASSIFICATION USING CNN AND CAPSULE NETWORK

Ref.	Methods	Accuracy
19	Capsule Network	86.56%
20	Capsule Network	90.89%
21	Bayesian CapNet	73.6% (0.15) 73.9% (0.1)
23	Inception V-3 DensNet 201	99.34% 99.15%
14	Residual Network	99% (image level) 97% (patient level)
11	Fuzzy C-Means and VGG16	96.70%
22	Capsule Network	89.3%
18	Capsule Network	95.54%
24	DenseNet-LSTM	92.13%
15	Dilated CNN	97%
13	CNN- LeNet CNN-MidResBlock	90%% 95%
25	YOLOV2- Inception V3	99%
16	Deep CNN	95%
26	6 DCNN	93%
27	GAN-ResNet50	88%
28	18 DCNN	99%
29	22 DCNN	96%
30	AlexNet-LSVM	63.1%
31	FLSCBN	89%
32	G-ResNet	95%
33	MDCNN	96%
34	Deep CNN	96%

B. Brain Glioma Segmentation

Machine learning algorithms play a critical role in enabling efficient and accurate image segmentation in the field of medical imaging. Classical learning models are less accurate, require more samples for efficient classification, and have a simpler structure when compared to deep learning techniques. There is significant evidence that accurate segmentation of various tumor subregions can lay the groundwork for quantitative image analysis to predict patient overall survival. Brain tumor segmentation is important not only in the diagnosis of brain glioma, radiation therapy, and clinical surgical planning, but it also increases the chances of a brain glioma patient's survival. Several methodologies have been used to facilitate the segmentation of brain glioma, which include:

1) Cascaded neural network: Cascaded Dual-Scale LinkNet is used to improve segmentation precision. The architecture consists of two networks, the first of which learns features of specific areas of the brain tumor, while the second focuses on border areas and learns more detail about features [35]. The Deep Cascaded Neural Network system consists of two steps: (1) TLN subnet is used to localize the brain tumor and (2) ITCN subnet is used to classify the identified tumor regions into four tumor sub regions. This method can prevent pixel label imbalance where TLN merged different tumor

subregions into whole tumor and ITCN used the same number of image patches of each class to train [36].

2) Convolutional neural network (CNN): CNN is the most widely used technique for image analysis and computer interventions, and its success rate is quite high when compared to other techniques. It is an improved version of the Artificial Neural Network (ANN) in terms of moving from manual decision and extraction to automated feature extraction from input data [37]. As a per-pixel classifier, multiple information from a small patch around each point is labelled, only standard intensity pre-processing is applied to the input data as scanner differences, and no post-processing is applied to the CNN output [38]. To overcome the lack of image specific adaptation and lack of generalizability to previously unseen object class, image-specific fine tuning is adapted in CNN model for unsupervised or supervised to significantly improve segmentation accuracy [39].

Features on the image will be extracted by building multiple layers of convolution layers in CNN. Smaller perceptive domain is used in front shallower convolution layer to allow learning some local features of image while larger perceptive domain in use in deeper convolution layer to learn more abstract features like size, location, and direction information. The CNN-based algorithm has three layers, namely convolution layer, pooling layer, and full connection layer. The preliminary product is obtained by multiplying the input image with the weights via the convolution layer. Filter matrix is chosen, for example by letting the step length to 1 and padding on the original image to obtain an input vector x. A pooling layer is being introduced to reduce abstract dimensionality and prevent over-fitting. The output is the classification probability gained from the regression in fully connected layers [39,40].

CNN has encoder and decoder parts, which allow discriminative comparison to be done easily and provide system extensibility [41]. The encoder part is responsible for extracting spatial information, after which the semantic map is inserted into the decoder part to produce the full-resolution probability map. UNet's modified architecture [42] includes three residual blocks in both the encoding and decoding phases, and each encoding employs batch normalization and the Parametric Rectified Linear Unit (PReLU). U-five Net's residual blocks are modified in both encoding and decoding while group normalization is used to add stability. DAU-Net with normalization is used to boost domain adaptation, which are then combined to produce U-Net (DAU-Net) [43].

3) 3D dense-UNets: A triple segmentation network is created separately to predict the entire tumor, the tumor core, and the tumor enhancement. Three additional steps are included to maintain a high number of convolution layers while fitting into GPU memory. If a layer generated more feature maps than the initial number of convolution feature maps, the layer's total number of feature maps is reduced by one-fourth. A compression factor of 0.75 is applied to the total number of feature maps generated at the end of each dense block. A bottle neck block is then utilized to connect the encoder and decoder parts of the network [44].

4) Deep CNN: Deep CNN consists of an architecture component for designing a network model and a learning algorithm to optimize the calculated parameters during the training phase. DCNN's architecture is made up of convolutional, pooling, Rectified Linear Unit (ReLU), and one fully connected layer. Each layer performs a simple computational operation, and each grid is only connected to a subset of the layers. Due to limited memory space and the number of parallel GPUs, higher volume data is difficult to handle [45].

Other architectures can be adapted to segment glioma, meningioma, and pituitary tumor tissues. DCNN ResNet50 employs skip connections to avoid gradient degradation when training a deeper network [14]. A combination of HCNN and CRF-RRNN models was proposed previously, in which the HCNN generates image slices at mixed scales to better leverage location while the CRF-RRNN takes the output and produces a segmentation based on the slides input into HCNN [45,46]. The FCNN is being improved by adding a Dense Micro-Block Difference feature to help with spatial consistency and utilizing Fisher vector encoding to texture rotation and scale [47], while 3D CNN focuses on intensity inhomogeneity by using N3T-spline to reduce nose and intensity in 3D scans and a T-spline for smoothing the output [48]. The Hourglass Network is an encoder-decoder with several residual blocks that is modified with five down sampling layers to perform better and be less computationally intensive [49]. Previous research has also proposed an ensemble network based on Model Cascade (MC) Net and One-Pass Multi-Task (OM) Net. Two MC-Nets are modified, one to improve encoder-decoder feature map coverage and the other to increase the effectively extract semantic feature at different resolutions. To create a more detailed model, an additional residual block is added to the original ON-Net [50].

5) Region based CNN: The region proposal network (RPN) is created by adding an extra convolutional layer that outputs the objectness score at image locations and the bounds of the region of interest (ROI). Using RCNN, it is possible to train a classifier on a smaller dataset and create bounding boxes with variable lengths. RPN will check the object's location, adjust to fit the dimension, use Region of Interest (ROI) pooling, and extract the features. The information is then used by RCNN to classify the content [51].

Before utilizing 3D volumetric CNN to fully leverage the 3D spatial contextual information of volumetric data, the RCNN model is applied to the largest area of tumor for tumor grading [52]. The 2D Mask R-CNN-based method yielded 0.935 (sensitivity), 0.972 (specificity), and 0.963 (accuracy), while the 3DConvNet method yielded 0.947 (sensitivity), 0.968 (specificity), and 0.971 (accuracy).

6) Deep convolution neural network fusion support vector machine (DCNN-F-SVM): The traditional segmentation method involves training a suitable classifier on a training set before setting it up for verification. In contrast, this model comprises of three stages: (1) preprocessing, feature

extraction, and CNN and SVM training (2) running the final segmentation result through testing (3) utilizing the CNN-SVM cascade classifier [53]. These three stages are divided by DCNN-F-SVM. To obtain the mapping from the image space to the tumor label domain, DCNN is trained in the first stage. The second stage involves feeding the integrated SVM classifier with the test images along with the labelled output of the DCNN. In the third stage, a deep classifier that has more layers is trained by iteratively connecting the DCNN and the integrated SVM classifier.

7) Capsule network (CapsNet): The concept of a capsule network was first proposed by Sabour et al. [54] to address a significant CNN shortcoming. The Capsule Network (CapsNet) extends the functionality of the conventional CNN by adding a new layer referred to as capsule layers, where each component is a capsule represented by a vector. It should represent a feature as well as the feature's characteristics, such as its location, texture, and deformation. The attitude matrix, *W* and the original input vector, *U* are processed in the capsule network to produce the final input vector, *U*. The final input vector, *U* is then multiplied by the appropriate weight, *c* and added to obtain the vector, *s*. Finally, a nonlinear function converts *s* into the final vector, *v* to enable the transition between the underlying and high-level feature. If the position of the high-level feature being pushed out by different underlying features points roughly in the same direction, the object has a high probability of existence [33].

One disadvantage of dynamic routing is that it can only be implemented in a fully connected manner. DeepCaps has been introduced to go deep into the architecture by skipping connections within a capsule cell that allow for good gradient flow in back propagation. Meanwhile, 3D convolution is used to generate votes from the capsule tensor to help route a localized group of capsules to a higher level. This combination allows architecture to go deeper while requiring less computational complexity [55]. According to the study, CapsNet performs better with a limited amount of training data and is suitable for detection or segmentation due to its high performance under class-imbalance for typical biomedical image database constraints [56].

8) Segmentation capsule network (SegCaps): SegCaps is a modification to the original dynamic routing algorithm that makes it act locally when routing children capsules to parent capsules. It also allows the capsules within the same capsule type to share transformation matrices. This reduces the memory and parameter burden and enables it to operate on large image sizes ranging from 32 x 32 pixels to 512 x 512 pixels. To compensate for information loss, the concept of deep convolutional-deconvolutional has been introduced for pixel level predictions of object labels. Finally, the masked reconstruction of the target class is extended as a regularization strategy for the segmentation problem [57,58,60]. The capsule segmentation task consists of [59]:

a) Primary capsule: Graphics inverse processes include convolution, reshape function or squash function and input image is fed into a couple of convolution layers.

b) Higher layer capsule: Due to the ability to trace the activation's path, the hierarchy of the parts can be easily sorted out. Additionally, it confirms the earlier prediction.

c) Loss calculation: Once the decision has been made, the classification takes place to determine whether the decision is correct or close to perfect.

Automatic glioma segmentation in brain MRI images had been conducted using CapsNet [61] by training the network into two steps (80% is used for training and 20% used as the validation data). Since capsule network has the capability to generalize novel viewpoint, it learns the spatial relationship between features using dynamic routing of capsules. The two-step training method resulted in about 3% improvement in dice score on validation and uses fewer data for training and contains 95.4% less parameter. From there it can be concluded that SegCaps can overcome the problem of data limitation. Results have also shown that SegCaps has been successful in segmenting the enhancing tumor core area. SegCaps only stores feature map indices and uses them in the decoder to achieve good performance. In comparison to other architectures, it is more efficient in terms of memory and computation [62]. According to previous research, SegCaps can capture the contours of the tumor core better than the contours of the entire tumor [63]. SegCaps can segment a small tumor region of the tumor core, but it tends to ignore the inner areas of the tumor core. When it comes to whole brain tumors, SegCaps is unable to capture fine-grained details, particularly when the region is exceptionally small, and the boundaries are coarse. Despite its capabilities, the algorithm is much slower, with higher computational complexity and a longer execution time. Table II shows some of the most recent research results on brain tumor segmentation based on CNN and capsule network specifically for the complete tumor (whole tumor), the tumor core that consists of enhancing, non-enhancing and necrotic parts and on the enhanced tumor only.

TABLE II. RECENT METHODOLOGIES FOR BRAIN GLIOMA SEGMENTATION USING CNN AND CAPSULE NETWORK

Ref.	Methods	Result (Dice)			
		Complete	***Core***	***Enhance***	***Standard Mean IoU***
35	Cascade Dual-Scale LinkNet		80.03%		90.73%
36	Deep Cascaded Neural Network	89%	77%	80%	
44	3D Dense-UNet	92% (cross validation) 90% (20 held out cases) 90% (Brats 2018) 90% (Brats 2017) 85% (Clinical)	84% (cross validation) 84% (20 held out cases) 82% (Brats 2018) 80% (Brats 2017) 80% (Clinical)	80% (cross validation) 80% (20 held out cases) 80% (Brats 2018) 78% (Brats 2017) 77% (Clinical)	
45	Deep CNN	90%	85%	84%	
51	Region based CNN		91.14%		
52	3D CNN-2D Context	91.8%	88.3%	85.4%	
53	DCNN-F-SVM		90.10%		
38	2D CNN	86%	82%	81%	
14	ResNet50		99		
46	HCNN; CRF-RRNN		96.6		
47	FCNN		91		
39	PC-Net		86.29		
48	FCNN		NA		
49	Hourglass Net		92		
43	U-Net (DAU-Net)	91%			
50	MC-Net – OM-Net	90%			
42	U-Net	86.8%			
61	SegCaps			85.56%	
63	SegCaps U-Net			89.21% (whole tumor) 82.44% (Tumor core) 99.78% (whole tumor) 99.88% (Tumor core)	

C. Dataset for Brain Tumor Analysis

Deep learning tasks necessitate a large dataset for training and validation. For brain tumor analysis, various datasets are publicly offered like BraTS. The images are mostly available in NIfTI, DICOM, JPG, and PNG formats, and they are described in native (T1) and post-contrast T1-weighted (T1Gd), T2-weighted (T2), and T2 Fluid Attenuated Inversion Recovery (T2-FLAIR). Since the dataset is derived from MRI patient cases, each one contains 154 - 155 sliced human brain images, implying that for each case of subset, there are 155 images in that subset. This preview most likely using Brain Tumor Segmentation Challenge (BraTS 2013-2018). The Brain Tumor Dataset (Public and Private) and The Cancer Genome Atlas are two other common sources of datasets used for brain tumor analysis (TCGA).

III. DISCUSSION

Since the early stages of deep learning development, Convolution Neural Networks (CNN) have been utilized to meet current requirements and improve classification and segmentation of brain glioma. CNN is made up of several layers; the convolution layer extracts image features, the pooling layer checks whether the features are present or not regardless of their position, and the max-pooling problem. Then, the full connection layer will predict the output of the learning features from the previous two layers.

However, CNN has limitations that lead to results that are not accurate enough, such as complex calculation if a standard multi-layer perceptron (all layers are fully connected) is used because the image dimensions are too large. Other disadvantages include loss of information in the pooling layer, such as spatial resolution, and the need to over-train all possible angles to overcome it, which consumes more time

and resources. It also demonstrates the inability to identify complex field-of-view images such as overlaps, mutual masking, and different backgrounds. Many modifications to the CNN algorithm have been made, such as DCNN, U-Net, RCNN, FCNN, and others while improving the performance of CNN.

Capsule Network (CapsNet) is a new deep learning methodology for brain tumor classification and segmentation. CapsNet is made up of four layers: a convolution layer for extracting features, a primary layer for storing feature vectors using eight convolution operations, a digital layer for storing higher level features in the form of vectors, and an auxiliary layer for replacing capsules with their lengths. CapsNet reduces the number of connections by using capsule group neurons and fewer parameters. Even though fewer parameters are used, CapsNet's viewpoint invariance allows it to recognize images and objects efficiently regardless of the viewpoint from which they are observed. Due to the typical dataset constraints of medical images, this also leads to object detection and image segmentation being more helpful.

CapsNet can solve the effect of max pooling in CNN, as this unit only examines whether attributes and features are present or not regardless of their position. CapsNet can resolve this issue by capturing part-whole relationships that consider both the existence of the features and their orientation. Furthermore, max pooling causes translational invariance, which results in incorrectly sized, positioned, or ordered components of the correct image. CapsNet uses equivariance by considering the position, proportional and translational invariances to tackle invariance problem.

However, there are several things that need to be improved in CapsNet for future research, such as the uncertainty in testing on larger images and the inner loop in dynamic routing by agreement algorithm, which causes the training to slow down. CapsNet may have the weakness to accurately identify interested region in images with a more varied background and very close identical objects due to noise and crowding. Since CapsNet is still in its early stages, more changes and improvements can be made to the algorithm, particularly to the dynamic routing and convolution strides.

Furthermore, there is substantial evidence that accurate segmentation of various tumor sub-regions can provide the foundation for quantitative image analysis to predict patient overall survival. In the future, it may help to lay a more precise and accurate foundation to understand unique tumoral characteristics, as well as better insights into the quantitative and qualitative aspects of a patient's disease care. Imaging analysis may improve glioma treatment and management by determining tumor heterogeneity, more comprehensive identification of tumor genotype, cases of progression and pseudo progression, tumor grading, and survival prediction.

In general, computer-assisted diagnosis makes a significant contribution in terms of speed. Deep learning approaches benefit from adapted automatic feature acquisitions to reduce time spent on manual practice. With the introduction of GPUs, computation processes become much faster, and more data can be trained. The amount of training data increases computational performance and accuracy as well.

IV. CONCLUSION

This paper reviews the performance between two neural network architectures to classify and segment the brain glioma, namely CNN and CapsNet. It is concluded that CapsNet can overcome data loss and has a higher level of image classification and segmentation accuracy than CNN, but it involves more parameter training and requires more training time. The CNN model outperforms CapsNet in terms of less memory and training time. This review may serve as a guide in establishing future deep learning-based methods to further improve the brain glioma classification and segmentation performance.

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