Brain Tumor Classification using Convolution Neural Network and Complex Valued-Convolution Neural Network

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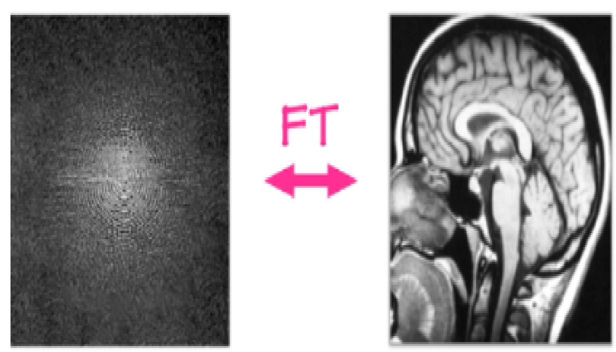
***Abstract*—One of the most popular imaging techniques for detecting brain tumors is magnetic resonance imaging (MRI). The anatomy, physiology, and metabolic activity of the lesion, as well as its hemodynamics, can all be studied using MRI. To obtain the image, MRI is acquired in frequency space (k-space) and an inverse Fourier transform is applied. The resultant image and the k-space are both complex-valued. For tumor detection, the magnitude of the resulting complex image (which is then real-valued) is typically used. In recent years, deep learning algorithms in computer vision applications, such as brain tumor segmentation and classification from MRIs, have demonstrated tremendous improvement. Convolutional Neural Networks (CNN, real-valued) are commonly used to do classification and segmentation on magnitude images. The other two complex-valued data-spaces (k-space and complex image) are, on the other hand, mostly unexplored. In those dataspaces, a complex-valued Convolutional Neural Network (CV-CNN) can be utilized to do MRI classification directly. The major goal of this study is to compare real-valued CNN performance with magnitude images to CV-CNN performance with complex images and CV-CNN performance with k-space.**

Brain Tumor Classification, BRaTs, MRI, CNN, CV-CNN

1. Introduction

A brain tumor is a collection of abnormal cells in the brain that forms a mass. The brain is protected by a highly tough skull. Any expansion in such a small location can generate complications. Brain tumors can be malignant (cancerous) or benign (noncancerous). The pressure inside the skull might rise when benign or malignant tumors get larger. This can lead to brain damage, which can be deadly. There are two types of brain tumors: primary and secondary. The origin of a primary brain tumor is in the brain. The majority of initial brain tumors are harmless. A secondary brain tumor, also known as a metastatic brain tumor, develops when cancer cells from another organ, such as the lung or breast, migrate to the brain. Some of the primary tumors include pituitary tumor , pineal gland tumor, craniopharyngiomas. Meningiomas, and schwannomas.

The Brain Tumor can be detected using physical examination such as CT Scan, MRI, Angiography, Skull X-Rays, Biopsy, etc,. Whereas MRI is widely used as it provides a detailed picture of the brain structures. Magnetic resonance imaging (MRI) is a medical imaging technology that creates detailed images of the organs and tissues using a magnetic field and computer-generated radio waves. MRI is obtained as K-Space(Frequency Space), k-space is an array of numbers that represent spatial frequencies. The typical depiction of k-space as a "galaxy" contributes. Each "star" in k-space is nothing more than a data point extracted from the MR signal. The relative contribution of each star's unique spatial frequency to the final image is represented by the brightness of that star. K-space cells are frequently represented on a rectangular grid with the major axes kx and ky. The horizontal (x-) and vertical (y-) axes of the image correspond to the kx and ky axes of k-space. However, rather than representing locations, the k-axes represent spatial frequencies in the x- and y-directions.



K-space is the Fourier transform of the MR image.

The Machine Learning and Deep Learning techniques were implemented for brain tumor detection due to substantial development in the treatment process. In this paper, we use Convolution Neural Networks(CNN) over other Neural Networks as it deals better with the image dataset by retaining the dimension of images. The CNN performs the image classification by considering the magnitude of the complex image. Thus, the K-space obtained from MRI is converted into a complex image by applying Fourier Transformation. However, the frequency space and the complex image are untouched, which motivated us to use Complex Valued-CNN(CV-CNN) which can perform classification using the complex data comprising both real and imaginary parts. In this paper, we compare the CV-CNN using K-Space and Complex image with that of the CNN using real images.

2. Related Work

Hiba Mzoughi, Ines Njeh, Ali Wali, Mohamed Ben Slima, Ahmed BenHamida, Chokri Mhiri Kharedine Ben Mahfoudhe proposed a 3D convolutional layer to provide a detailed feature map that exploits the entire volumetric spatial information to incorporate both local and global contextual information, unlike 2D-CNN architecture, which does not fully examine the volumetric information in MR images but only explores two-dimensional slices. [1]

Varied types of scanners (or sensors) show different contrast and are sensitive to different brain tissues and fluid regions, such as enhanced T1-MRI, T2-MRI, and FLAIR. The majority of present research relies on 3D brain pictures obtained from a single sensor.Chenjie Ge, Irene Yu-Hua Gu, Asgeir Store Jakola, and Jie Yange introduced a novel multistream deep Convolutional Neural Network (CNN) architecture for glioma tumor grading/subcategory grading that captures and integrates data from different sensors. [2]

Linmin Pei, Lasitha Vidyaratne, Wei-Wen Hsu, Md Monibor Rahman, Khan M. Iftekharuddin proposed that a 3D deep neural network be used to distinguish tumors from normal tissues, followed by the development of a second 3D deep neural network for tumor categorization. [3]

Chiheb Trabelsi, Olexa Bilaniuk, Dmitriy Serdyuk, Sandeep Subramanian and João Felipe Santos used complex convolutions and current techniques for complex batch-normalization, as well as complex weight initialization procedures for complex-valued neural nets, to show that complex-valued models can compete with real-valued models. [4]

A new type of complex-valued variable has been discovered. To reconstruct undersampled MRI, ResNet proposed working directly in the k-space. Preliminary tests have yielded promising results. [5]

3. Proposed Approach

In this´paper, we have used the Magnetic Resonance Image of Brain Tumour consisting of Three types of Primary Brain Tumor's. The image data is pre-processed and fed as input to the Convolution Neural Network to perform image classification. At First, we train the Real Valued CNN with the normalized PyTorch Tensors, then validate the model with Test data. Up next, we train the Complex Valued CNN to make the predictions using complex K-Space and then by the complex image. Finally, the results of real valued CNN and Complex Valued CNN is compared to make the conclusion

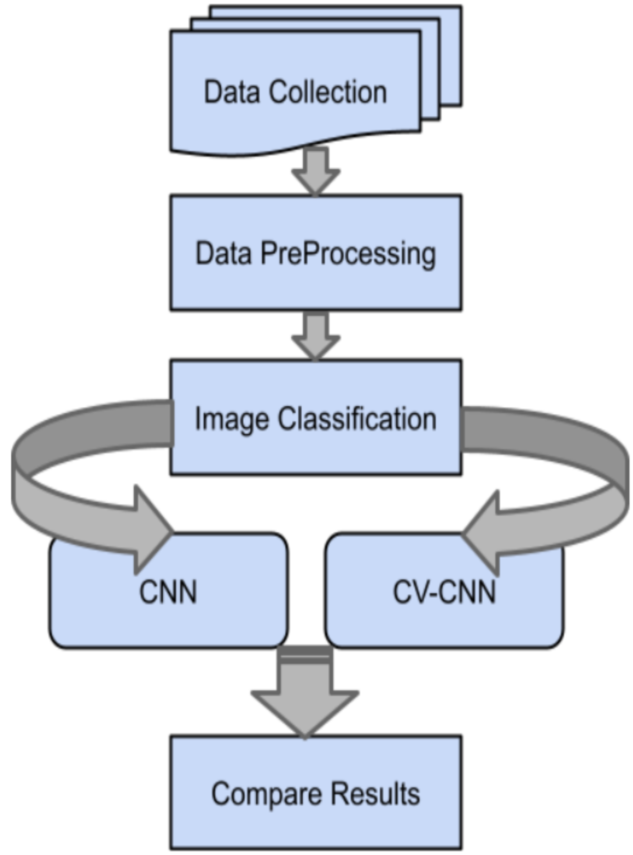


Figure 1: Flow Chart of Proposed Approach

4. Data Collection

In this paper, we have used BRaTs dataset, This brain tumor dataset includes 3064 T1-weighted contrast-enhanced images from 233 patients who had three different types of brain tumors: meningioma (708 slices), glioma (1426 slices), and pituitary tumor (930 slices). Each image has a label, PID (Patient ID), image data, tumor border and tumor mask. This MRI Data has Three channels which represents RGB respectively. Whereas, the shape of image data is 512*512*3 where 3 represents the number of channels, 512*512 represents the number of rows and columns of the image array.

However, image data is already in the real form which signifies the fact that its an processed data which was converted from the complex form k-space to complex image by performing fourier transformation and further, the absolute values have been derived to get the real image. Thus, We must perform inverse fourier transformation to obtain the k-space of complex type which is necessary to perform the comparison between CNN and CV-CNN.

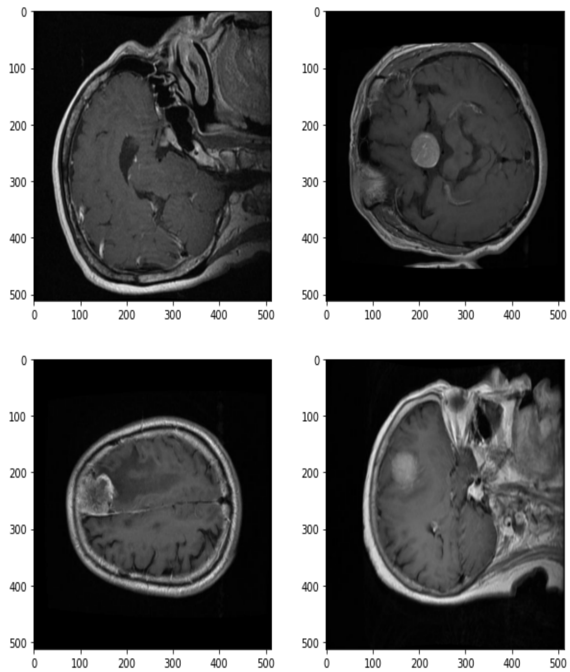


Figure 2: Image Instances from BRaTs

5. Pre-Processing

The BRaTs data was in in the matlab data format. The files were unzipped, and created a pickle file to store image data and respective labels. The data was split into 75 percent training set and the remaining 25 percent as test set. Further, a function was defined to convert the images from numpy arrays to pytorch tensors, followed by normalization.
The MRI produces k-space which is of complex type, further an Inverse Fourier Transformation is performed on the k-space to obtain the complex image which is in the form of z = a + bi, where the former is real part and latter is the imaginary part. At last, the absolute value in the form |z| is computed from the complex data, which is also known as the magnitude of the image.
Therefore, an Inverse Fourier Transformation on the image data was performed to convert it into k-space, and a second inverse fourier transformation on the above transformed data to convert it into a complex image. Then, One-Hot encoding was performed on the target variables. One-Hot encoding is a logical representation of group of bits where there is just one high value which is true and rest are false represented by zero's.
Data augmentation might be regarded an important critical aspect in computer vision that is very effective in training highly deep learning-based algorithms. Random cropping, rotation, shears, and flips are examples of data augmentation procedures. In this paper, we tried data augmentation technique 'rotation', which increased the data length and crashed the colab execution as an impact. Thus, removed the data augmentation part.
In case of real valued CNN, the normalized tensors where used, and then the k-space and complex image of type complex where used for the classification task using CV-CNN

6. Real Valued CNN

The customized Real Valued Convolution neural Network has Five layers, out of which Two are Convolution Layers and Two Fully Connected Layers with Batch Normalization. Batch normalization is a technique for making neural networks more efficient. It works by boosting the training speed by stabilizing the hidden layer input distributions. This customized Convolution Neural Network takes real valued tensors as input and provides the target label as output. As, this is a multi class classification, a Sigmoid activation function is placed in the output layer.
In this paper, we have used Stochastic gradient descent with learning rate of 3e-4 and momentum of 0.9, which is a simple optimization approach for determining model parameters that correspond to the best fit between expected and actual outputs. Then, CrossEntropyLoss is used as loss function criterion as it is a multi-class problem with unbalanced data class.
This CNN model functions just as any other Convolution Neural Network which takes Two dimensional image data as input which is in the form of tensors and performs classification.

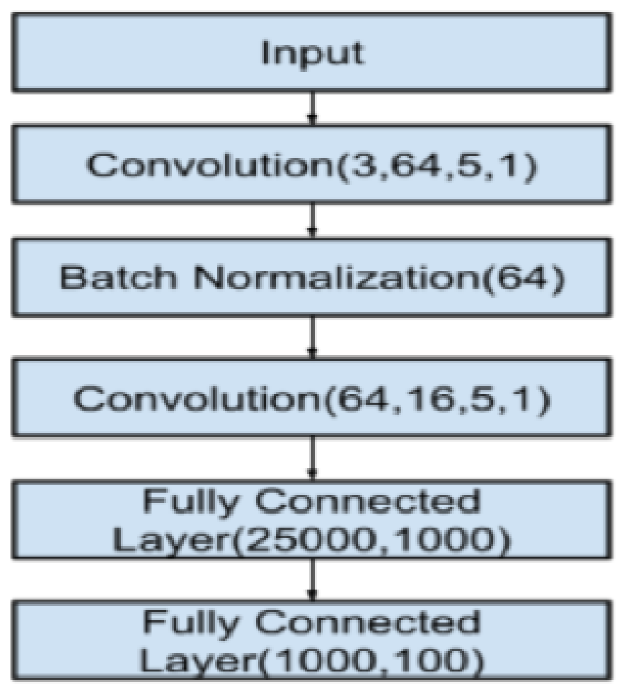


Figure 3: Architecture of Customised CNN

7. Complex Valued CNN

Convolution neural networks are most commonly employed to process data that is encoded in real values, such as digitized images or sounds. Thus, we customize a CNN which can take data encoded in complex values. There are various ways to implement complex convolution neural network. In this paper, we have used complexPyTorch package on PyTorch API which consists of ComplexBatchNorm2d, ComplexConv2d, ComplexLinear layers and complex-relu, complex-max-pool2d complex functions.

The customized Complex Valued Convolution neural Network has Seven layers, out of which Two are Real Convolution Layers, Two Imaginary Convolution layers, and Two Fully Connected Layers with Batch Normalization. It takes complex valued tensors as input and provides the target label as output. Just as the real valued convolution neural network, uses Sigmoid activation function as this is a multi class classification problem.

Eventually used the same optimization function, the stochastic gradient descent, and the CrossEntropyLoss as loss function criterion.

The structure of the complex valued convolution neural network is retained as similar to real valued convolution neural network for better comparison between both. Further, the learning rate and momentum is also retained as 3e-4 and 0.9 respectively.

This CV-CNN is used to perform classification on Brain Tumor image dataset using k-space and complex image which are in the complex form. The complex form has both real part and imaginary part. In here, the CV-CNN has Two separate convolution layers to handle the real part and imaginary part individually.

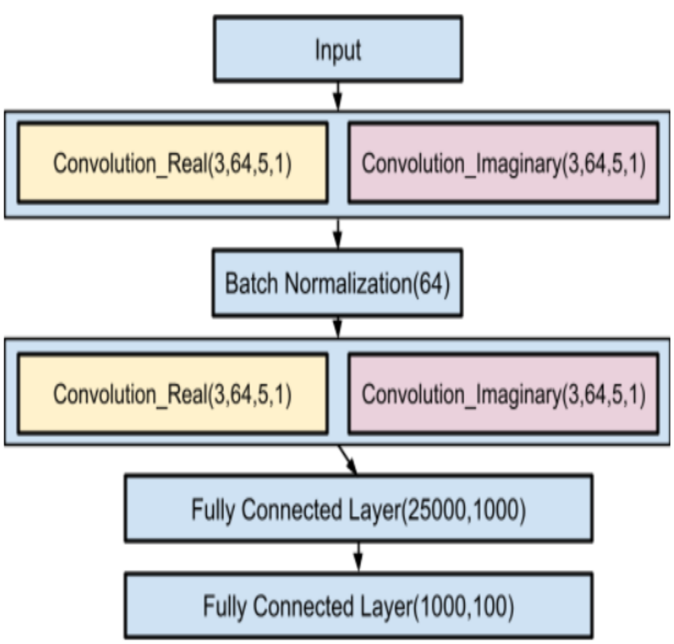


Figure 4: Architecture of Customised CV-CNN

8. Results

In this paper, we have derived results by implementing the model classification using PyTorch API on Google Colab Pro with 24GB RAM. The notebook was set to High-RAM usage and GPU accelerator. Thus, the model efficiently used CPU or GPU device CUDA based on their availability.

The Complex Valued Convolution Neural Network and the Real Valued Convolution Neural Network are compared in terms of accuracy and loss metrics as it is a classification problem.

Further, the model was trained and tested on the train data and test data respectively for Thirty epochs. Finally, the results of training and testing was plotted using the matplotlib package. The table below depicts the results of training and testing of the CNN using magnitude, CV-CNN using k-space and CV-CNN using complex image.

Table 1: Results of CNN using Magnitude

Epochs	T-Accuracy	T-Loss	V-Accuracy	V-Loss
1	65.10	0.0590	76.24	0.7266
2	81.20	0.0590	80.55	1.1269
.	.	.	.	.
22	100	0.0000	86.81	0.0008
.	.	.	.	.
30	**100**	**0.0000**	**86.95**	**0.0006**

Table 2: Results of CV-CNN using K-Space

Epochs	T-Accuracy	T-Loss	V-Accuracy	V-Loss
1	65.36	o.2204	64.62	0.2488
2	75.81	0.1208	66.71	0.2276
.	.	.	.	.
22	100	0.0000	89.56	0.0000
.	.	.	.	.
30	**100**	**0.0000**	**90.21**	**0.0000**

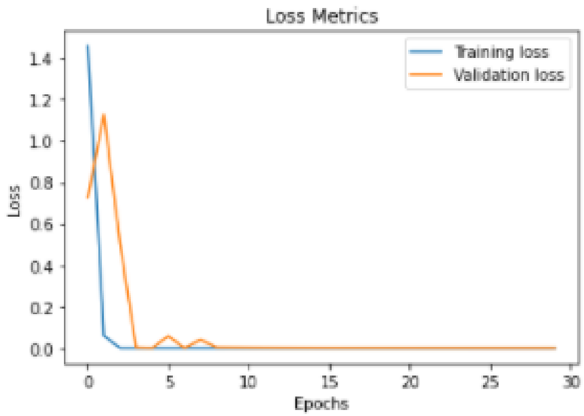
Table 3: Results of CV-CNN using Complex Image

Epochs	T-Accuracy	T-Loss	V-Accuracy	V-Loss
1	55.92	0.2119	70.76	0.0393
2	70.23	0.0658	75.53	0.0661
.	.	.	.	.
22	99.61	0.0000	90.47	0.0001
.	.	.	.	.
30	**100**	**0.0000**	**91.51**	**0.0001**

The total time used for training is 50.02 minutes, 193.95 minutes, 193.87 minutes of CNN using magnitude, CV-CNN using K-Space and Complex Image respectively.

Figure 5: Training vs Validation in Real Valued CNN using Real Valued Image

(a) Training Loss vs Validation Loss



(b) Training Accuracy vs Validation Accuracy

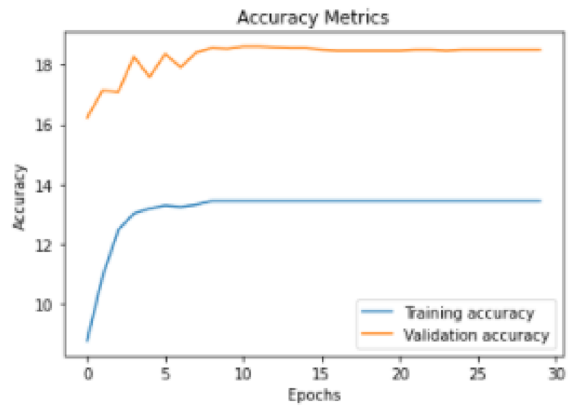
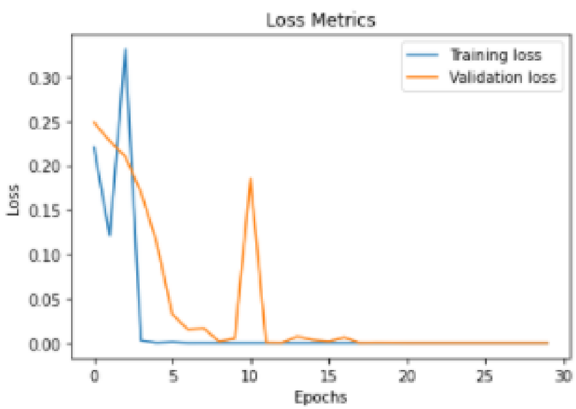


Figure 6: Training vs Validation in Complex Valued CNN using K-Space

(a) Training Loss vs Validation Loss



(b) Training Accuracy vs Validation Accuracy

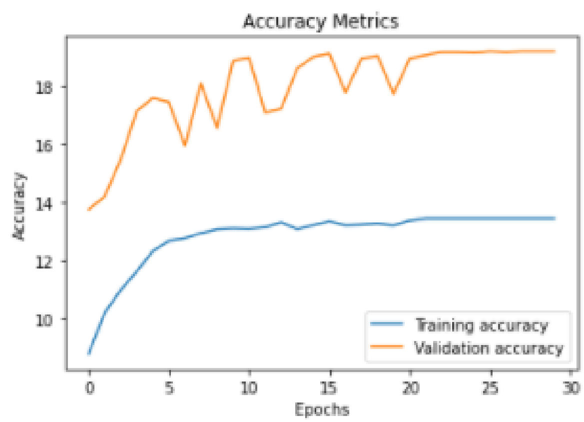
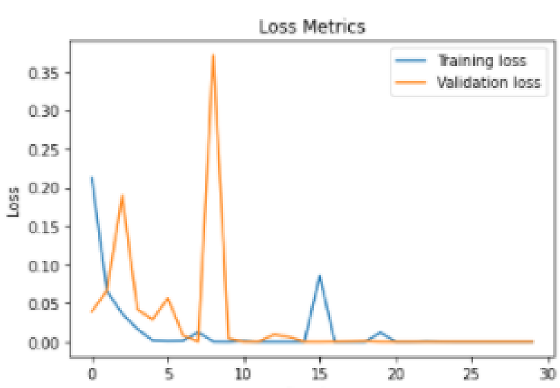
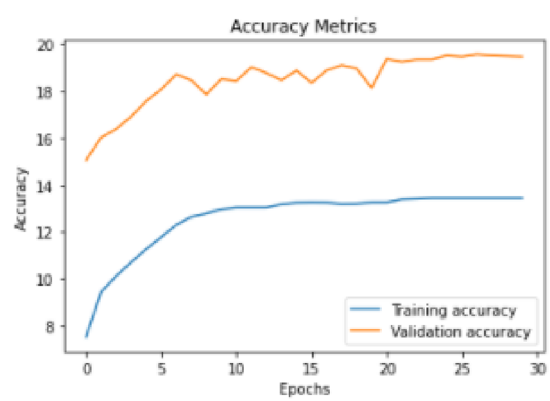


Figure 7: Training vs Validation in Complex Valued CNN using Complex Image

(a) Training Loss vs Validation Loss



(b) Training Accuracy vs Validation Accuracy



9. Conclusion and Summary

The CNN consumes less training time and reduced memory due to its simple architecture.As, the training time for real valued CNN is Four times smaller than the CV-CNN. However, The Complex Valued CNN performs better than Real Valued CNN in terms of accuracy and loss metrics. As shown in the results, the validation accuracy at the last epoch is around 90 with loss of 0.0001 for both the CV-CNN. Whereas, the CNN has an accuracy of 86.95 with loss of 0.0006 at the last epoch. This proves that the CV-CNN outperforms CNN in terms of accuracy and loss metrics.

10. Future Work

In future, we can perform this comparison task using various architectures for better results. In order to make fair comparison, we can double the features in the real valued CNN which is equivalent to CV-CNN.
We can implement the real valued CNN with existing pre-trained CNN's, and then build the same for CV-CNN.

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