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Tumor Classification using Block wise fine tuning and Transfer learning of Deep Neural Network and KNN classifier on MR Brain Images

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ABSTRACT

Brain tumors identification and classification is a most crucial role in medical diagnosis and treatment plan for the patients. The information acquired by medical imaging machines contains low level information which cannot be perceived my human visual system. An automatic Computer aided diagnosis system with deep convolutional networks can perform well in Medical Image classification, but requires large datasets. Generally it is difficult to obtain a large number of labelled samples in medical image classification tasks. Knowledge transfer with fine tuning of pre-trained networks can apply on small medical datasets for diagnosis. In this work transfer learning and block wise fine tuning with separate KNN classifier on pre trained deep neural network VGG net is used to classify BRATS and CE-MRI datasets. The proposed method is denoted as BT-VGGNet. The labelled BRATS Flair Images and CE-MRI T1-weighted contrast-enhanced datasets are exploited to block wise fine-tune all hidden layers in the VGG deep neural network in feature extraction and KNN for classification. Experimental results show that the proposed model exceeds the state-of - the-art classification with 97.28 percent and 98.69 percent accuracy on the BTDS-2 and CE-MRI datasets respectively.

Key words: Medical image analysis, brain tumor, CNNs, deep learning, Transfer learning, block wise fine tuning, KNN classifier.

1. INTRODUCTION

Brain tumor diagnosis and treatment planning is an important process for patient's life. Medical imaging modalities are used for diagnosis purpose. MRI is most preferable imaging modality due its high resolution of soft tissues and no side effects. There is more than World health organization defined brain tumor classifications based on the type and position of the tumor cells making this a very complicated diagnosis.

Most of the brain tumor looks like similar in structure and shape. It is a challenging task for a radiologist to identify and classify a tumor manually. In the diagnosis process, first is to investigate whether the tumor is there or not in MR images. Second, if tumor identified, then the type of the tumor to be classified. Manual classification of brain tumors is a time consuming process and there miss match between the opinions of different radiologists. Machine learning algorithms which are feature extraction based will follow steps like pre-processing, selection, reduction and classification of features [1]. The performance of these algorithms based on features extracted. Features to be extracted are two types' low level and high level that completely depends on domain expert's knowledge. Deep CNNs has been used for image processing applications for decades [2], [3]. With the advancement of CNNs changed the computer aided diagnosis with powerful GPUs in medical imaging. The automatic diagnosis is applicable for different medical imaging modalities with different dimensional images. The advantage with CNN is to transfer the knowledge from one to other target datasets. Training a deep convolutional neural network (CNN) from scratch is tough as this process needs a huge number of labelled data and an abundant skill of proficiency to guarantee proper convergence [4], [5]. For training a CNN from scratch, high computational hardware is needed and training may take more time. To make CNN learn properly, repeated setting of hyper parameters and network architecture to guarantee the training in a proper way. So at the outset training a CNN from scratch requires huge dataset, high end computational hardware memory and expertise in setting the hyper parameters. Alternatively the use of pre-trained deep CNNs with transfer of knowledge and sufficient fine-tuning can be used for medical image classification [6]. Another solution is to block wise fine tune a pre trained CNNs with transfer of knowledge.

The effectiveness of the classification knowledge transfer depends on the difference between the source dataset from which CNN is trained and the Target knowledge transfer dataset [7]. Based on the analysis of using a fine tuned pre trained CNN has performed at equality with a CNN trained from scratch in medical imaging [4]. Knowledge transfer can be two ways;

One is to use CNN for feature extraction and any classifier for classification [8]. For classifying the kidney abnormalities, Alexnet is used to derive features from US images of the kidneys and separate support vector machine (SVM) classifier. [9]. Over Feat network is trained for object detection in natural images, used for feature extraction in knowledge transfer and nodule detection in computed tomography scans with linear support vector machine [10]. For binary image reconstruction using metaheuristic optimization technique addresses issue of fine-tuning hyper parameters of Deep Boltzmann Machines [11]. It is proved from the previous work, the combination of CNN for feature extraction and KNN for classification has performed well on BRATS and CE-MRI datasets [6].

Second one is to define a new set of fully connected and classification layers in pre-trained CNNs for classification of new target datasets [12]. Use of a fine-tuned pre-trained CNN to locate standard aircraft for suggested ultrasonic images [13]. An ensemble of specific architectures of the convolutional neural network (CNN) has introduced a new method for classifying medical images [14]. Medial image classification using CAE layer transforms a set of non-redundant and relevant medical image features by extracting features from the pre-trained network [15]. With a ResNet34 model as transfer learning model brain normal and abnormal MR images are classified on 613 images acquired from the Harvard Medical School website [11]. Layer by layer fine tuning A deep learning-based training system for assisted treatment of extremity soft tissue sarcomas proposed in [16]. Five separate art-related classification tasks using comprehensive CNN fine-tuning experiments conducted on three large fine art datasets are aggregate the findings in one lacation [17]. Fine tuning and transfer learning is applied to classify tree types of brain a tumor on Resnet50 is used in [18]. To classify gastric M-NBI images into three groups, a transfer learning system is suggested: chronic gastritis (CGT), low-grade neoplasia (LGN), and early gastric cancer (EGC) by fine tuning of pre-trained CNN [19]. A transfer learning technique on Alexnet is used to classify 40 types of field crop insect images in National Bureau of Agricultural Insect Resources (NBAIR) dataset [20].

In this work, a pre trained CNN [21] is block wise fine-tuned for feature extraction and separate KNN classifier for classification of brain tumors on two different MRI datasets. The performance of block wise fine-tuned and block wise fine-tuned with KNN classifier are analyzed with performance metrics.

2. PROPOSED BT-VGG NET

The proposed BT-VGGnet model is shown in figure 1. The model has three major phases as Pre-processing, block wise fine tuning for feature extraction and classification.

In this model a pre-trained CNN (VGG19) is block wise fine-tuned for feature extraction and KNN classifier for classification of brain tumors are used.

2.1 Dataset

In this research work, the proposed model is applied on two different datasets. The former one is from the BRATS 2018 dataset available in NIFTI format [22]. This dataset is in volumetric MRI images of the brain; It is converted to 2D slices using ITK Snap Tool [23]. Axial, Coronal and sagittal mode images are extracted from Volumetric Images with different sizes 240 X 240 X 3, 240 X 155 X 3, 240 X 155 X 3 respectively, and named as a Brain Tumor database 2 (BTDS-2) consists of two types of brain tumor images, Benign and Malignant of 5940 images. Figure 2 shows the different modes of MRI Images of brain Images of BTDS-2 Dataset.

The second dataset CE-MRI consists 3064 2D slices in Axial, Coronal and sagittal mode images with 512 X 512 size [24]. The dataset was collected from General Hospital, Tian-jin Medical University and Nanfang Hospital, Guangzhou, China. The dataset has three different types of tumors as glioma, meningioma, and pituitary of 233 patients. Figure 3 shows the different modes of MRI Images of brain Images of CE-MRI Dataset.

2.2 Pre-processing

De-noising, data augmentation a intensity normalization are three pre-processing steps used to fit the dataset to the proposed BT-VGGnet model. Two datasets are used in this work, BTDS-2 and CE-MRI. The BTDS-2 dataset is available in PNG format and this dataset is passed through DnCNN and median filter used for removing the noise. Where CE-MRI data set contain gray images, it is passed through the median filter only. This de-noising process eliminates Gaussian noise and other high frequency artifacts of images which reduces computational time.

Data Augmentation is the major part of pre-processing in transfer learning and fine tuning. This involves many techniques as Resizing, Flipping, Conditions, Adding Salt and Pepper noise, Lightening Scaling, Translation, Rotation, and Perspective Transform. The BTDS-2 and CE-MRI datasets are with 240 X 240 X 3, 240 X 155 X 3, 240 X 155 X 3 and 512 X512 image sizes respectively. The BT-VGGnet image input layer size is 224 X 224 X 3. As per our proposed BT-VGGnet model only resize is required to fit the dataset into the model.

Intensity values of these datasets are not showing a static meaning. As per the observations in the datasets intensity values of MR images are varying with respect to intra and inter subjects. So Normalization is required for datasets in order to not to pull the network in ill condition. min-max normalization is used as pre-process the datasets to scale the intensity value to [0, 1] [1].

$$y_i = (x_i - \min(x)) / \max(x) - \min(x)) \tag{1}$$

Where y_i is the value of the normalized intensity in relation to x_i (where i=1 .... n) and max(x) and min(x) are the maximum and minimum levels of intensity over the entire image.

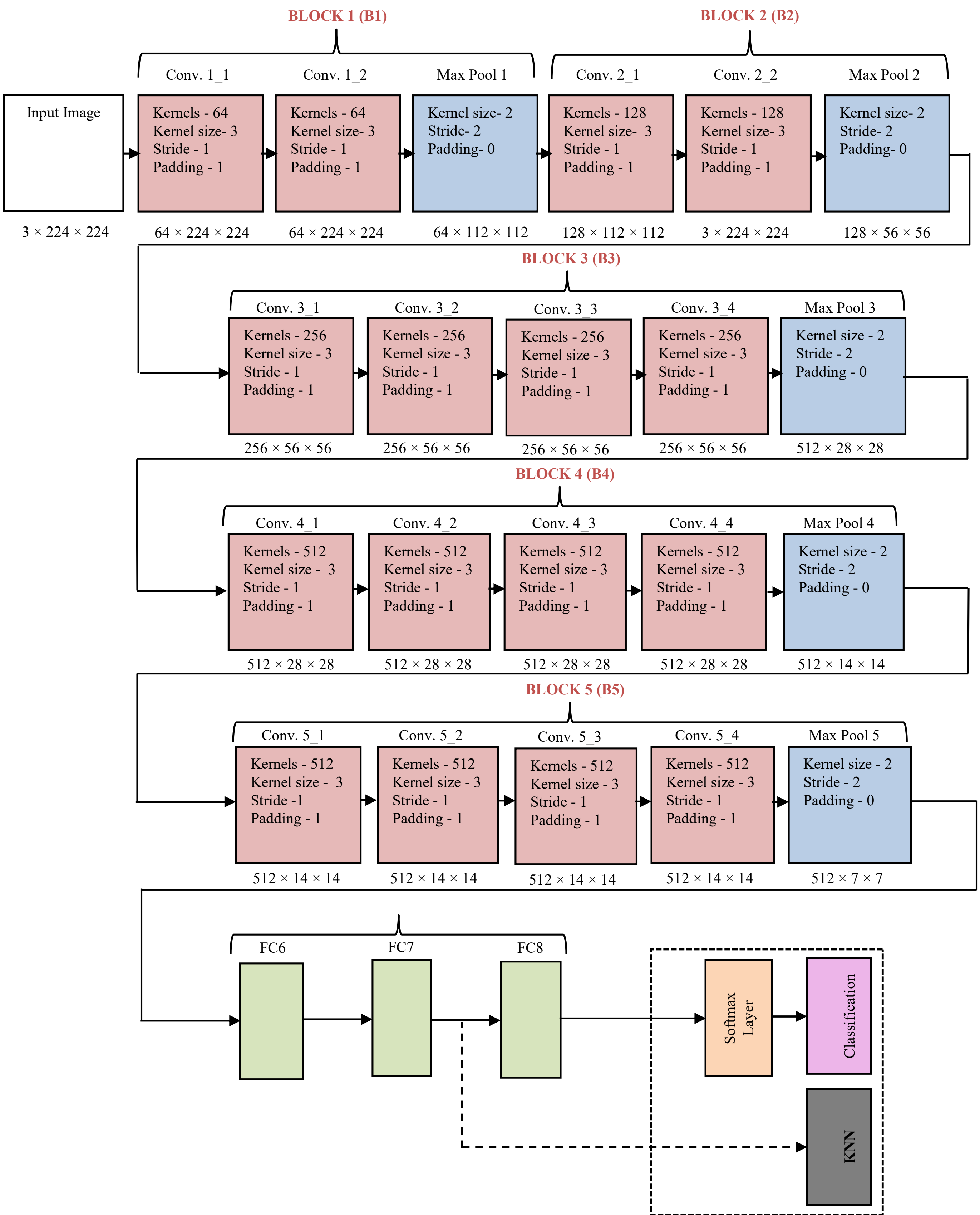


Figure 1: BT-VGGnet

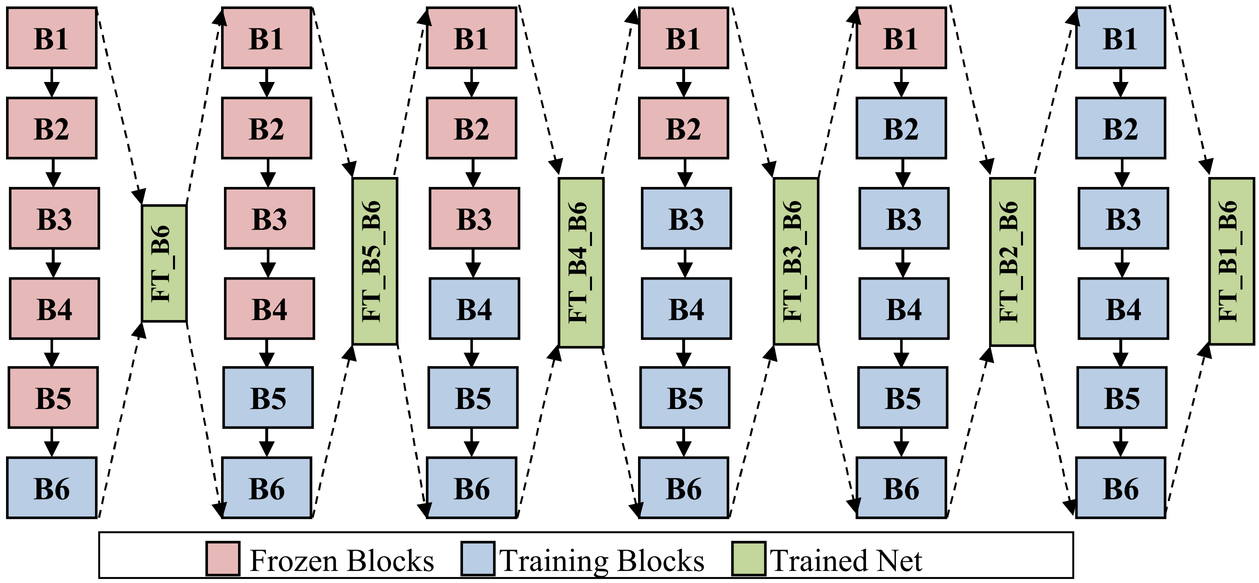


Figure 2: Block wise Fine tuning

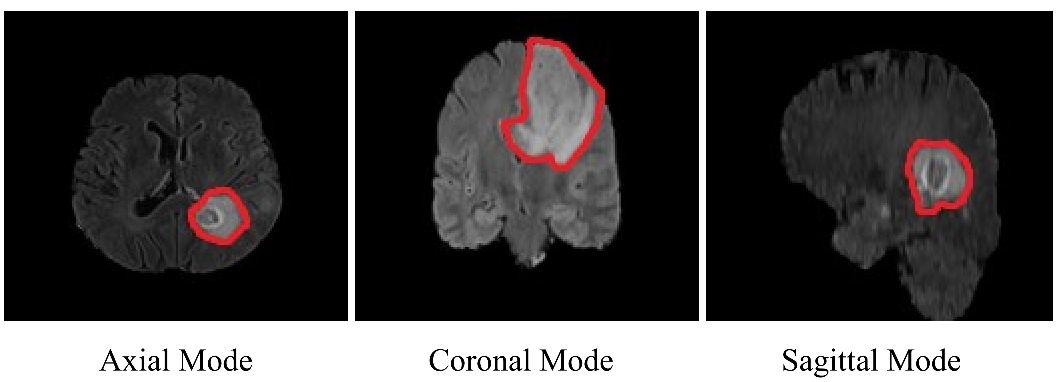


Figure 3: Modes of MRI images (BTDS-2)

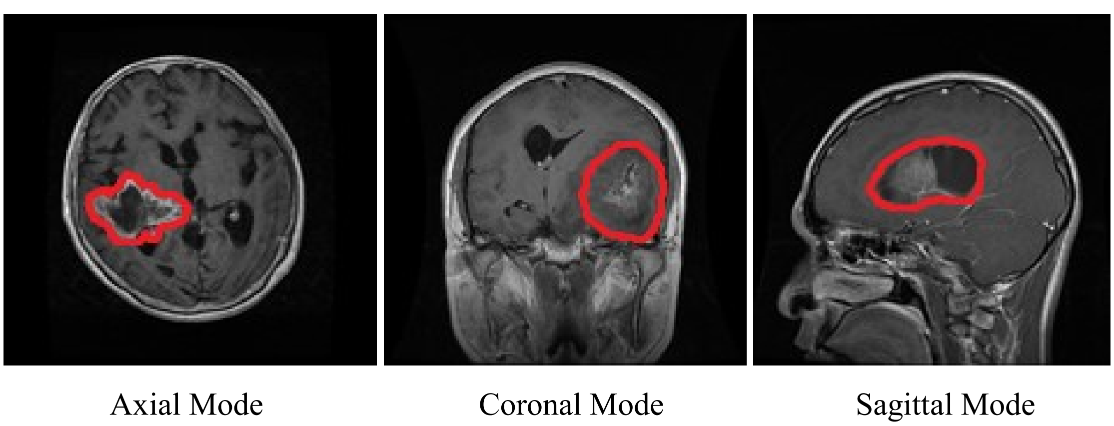


Figure 4: Modes of MRI images (CE-MRI)

2.3 Block wise fine tuning of Pre-trained network

The layers in CNN are separately considered as blocks shown in figure 1. There are six blocks from block 1 (B1) to block 6 (B6). These blocks are from image input layer to fully connected layers. This model is tuned block wise i.e. initially with B1 then B1, B2 and so on up to B1, B2, B3, B4, B5 and B6. The block wise fine tuning is done based on learning rate fixing for respective block layers. For example initially for block Bx learning rate is set to some fixed value and for remaining blocks Bx-1 to Bx-n will be frozen i.e. the learning rate is zero. Where x is number of blocks and n = x-1. In the next step the learning rate for Bx and Bx-1 is set to some fixed value and for remaining blocks Bx-2 to Bx-n, the learning rate is zero. This process will continue till all blocks are fine tuned. The block wise fine tuning CNN model is shown in figure 2.

2.4 Training the network:

The training of the CNN network starts from the input image layer to the fully connected network and classification layer. Then error estimation is done through back propagation from classification layer to first convolution layer.

Neurons of one layer get the inputs from previous layers are computed from the following equation.

$$n_j^l = \sum_{i=1}^{n} W_{ji}^l x_i + b_j \tag{2}$$

The output of the activation function

$$f(x) = \max(0, x) \tag{3}$$

The layer to layer dimensions of feature map size can be known through the equation

$$\frac{W+2p-f}{s}+1 \times \frac{H+2p-f}{s}+1 \tag{4}$$

Where W and H are width and height of input image, p is pooling, f is kernel size and s is stride value

The cost function is minimized with weights W and biases b is combination of average error and Regularization as follows

$$J(W,b) = \frac{1}{m} J(W,b;x^{(i)},y^{(i)}) + \frac{\lambda}{2}\sum_{l=1}^{L} \| W^{(l)} \|_F^2 \tag{5}$$

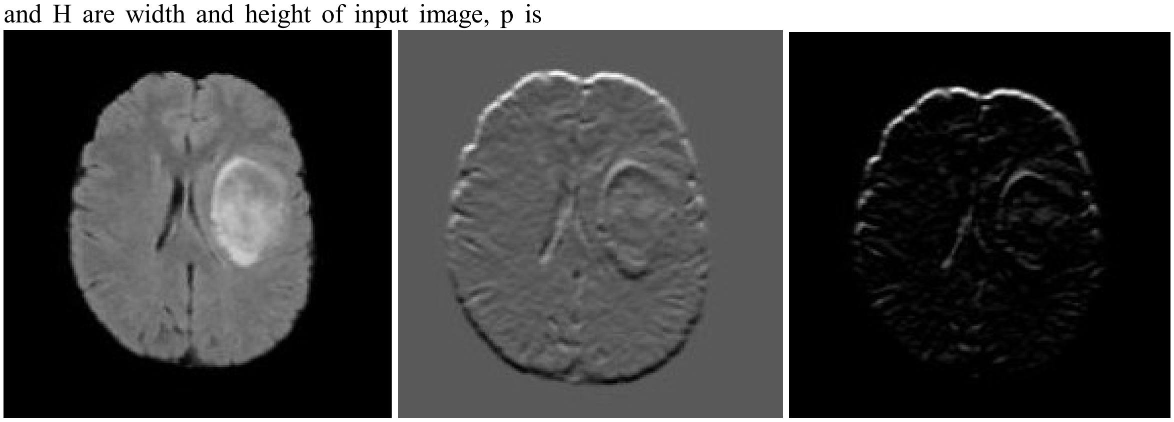
Softmax Classifier:

The classification is done through (multinomial logistic regression) softmax and KNN classifiers separately. The softmax classifier is based on following probability function

$$P(Y=k \mid X=x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}} \quad \text{Where } s = f(x_i;W) \tag{6}$$

3. RESULTS AND DISCUSSIONS

In this work two datasets are used to block wise fine tuning of CNN for feature extraction and KNN classifier for classification. The performance of these Models is evaluated to classify brain tumor as Benign or Malignant for BTDS-2 dataset and glioma, meningioma and pituitary tumors for CE-MRI dataset. The performance of the model of six different combinations of fine-tuned CNN blocks with separate KNN classifier is validated with metrics. Experimentation results state that hybrid combination of fine-tuned CNN and KNN performance is good. The performance metrics of proposed method on BTDS-2 dataset is presented in table 3. It is evident from these results, BT_FT_B1_B6 and KNN has performed well compared to all other combinations.



Input Image conv1_2 strongest activation channel relu1_2 strongest activation channel

Figure 5: Strongest Activation channel in Block 1 (B1)

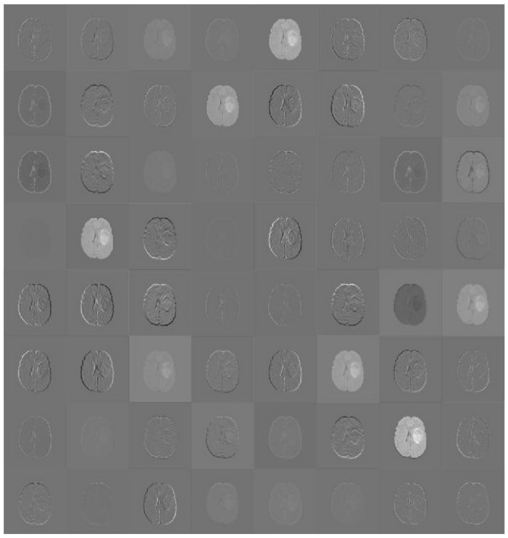


Figure 6: Block 1 (B1) Low level features of conv1_2

$$Accuracy = \frac{(T_P + T_N)}{(T_P + T_N + F_P + F_N)} \quad (7)$$

$$Sensitivity = \frac{T_P}{(T_P + F_N)} \quad (8)$$

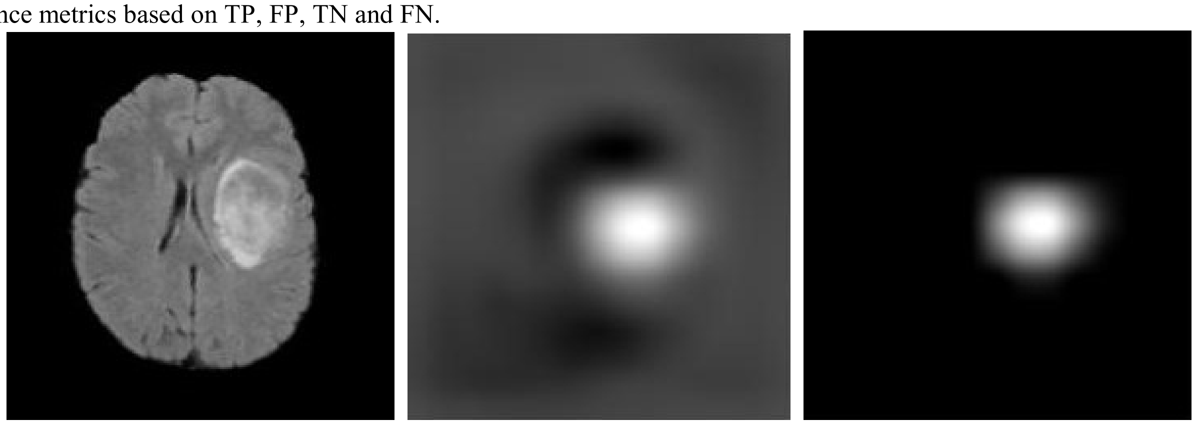
$$Specifisity = \frac{T_N}{(T_N + F_P)} \quad (9)$$

$$\Pr ecision = \frac{T_P}{(T_P + F_P)} \quad (10)$$

$$F1 - Score = \frac{2(PPV * TPR)}{(PPV + TPR)} \quad (11)$$

3.1 Validation Metrics

Some Validation metrics are considered to evaluate the proposed BT-VGGnet model. The following are the performance metrics based on TP, FP, TN and FN.



Input Image Conv5_4 strongest activation channel Relu5_4 strongest activation channel

Figure 7: Strongest Activation channel in Block 5 (B5)

Table 1: Performance metrics for BT-VGGnet on BTDS-2 dataset

S.NO	Feature Extraction Fine tune Model	Classifier	Accuracy	Sensitivity	Specificity	Precision	F1-Score
1.	BT2_FT_B6	Softmax	92.71	96.92	72.54	94.41	95.65
		KNN	94.40	98.36	75.49	95.04	96.67
2.	BT2_FT_B5_B6	Softmax	94.23	98.36	74.50	94.86	96.57
		KNN	95.42	98.97	78.43	95.64	97.28
3.	BT2_FT_B4_B6	Softmax	94.91	99.18	74.50	94.90	96.99
		KNN	96.10	98.15	86.27	97.16	97.65
4.	BT2_FT_B3_B6	Softmax	95.59	98.36	82.35	96.38	97.36
		KNN	96.61	97.36	87.25	97.36	97.96
5.	BT2_FT_B2_B6	Softmax	95.93	99.38	79.41	95.84	97.58
		KNN	96.61	99.59	82.35	96.42	97.98
6.	BT2_FT_B1_B6	Softmax	96.27	99.59	80.39	96.04	97.78
		KNN	97.28	99.59	86.27	97.20	98.38

The performance metrics of BTVGGnet for BTDS-2 dataset is shown in table 1. BT2_FT_B1_B6 + KNN has outperformed compared to all other combinations

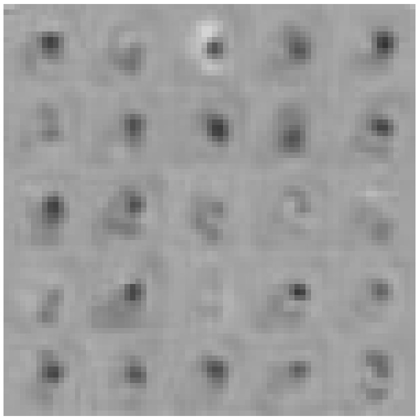


Figure 8: Block 5 (B5) High level features of conv5_4

The accuracy and F1-score plots on BTDS-2 are shown in figure 9 and figure 10. The accuracy of proposed model is compared with state of art algorithms in table 2.

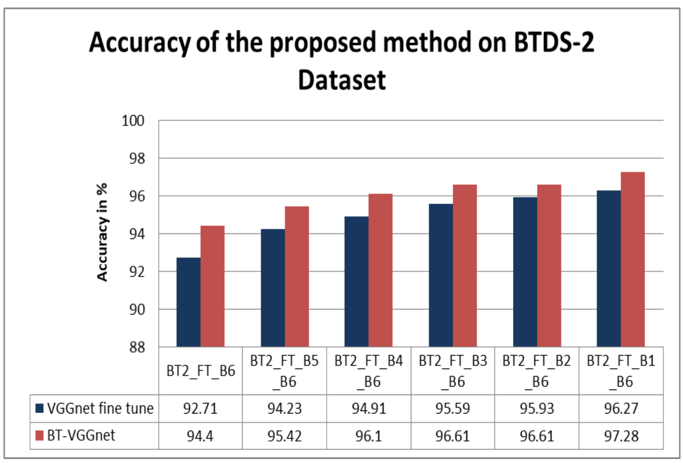


Figure 9: Accuracy plot on BTDS-2 Dataset

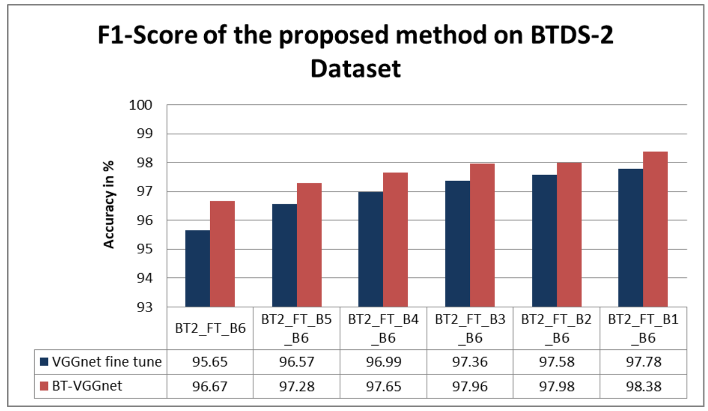


Figure 10: F1-score plot on BTDS-2 Dataset

Table 2: Comparison of Accuracy of the proposed method and state of the art methods on BTDS-2 Dataset

S.NO.	Model	Classification method	Accuracy
1	Anilkumar B et al [29]	BT2_VGG19	92.37%
2	Anilkumar B et al[6]	CNN-KNN	96.10%
3	**Proposed Method**	**BW_FT_CNN-KNN**	**97.28%**

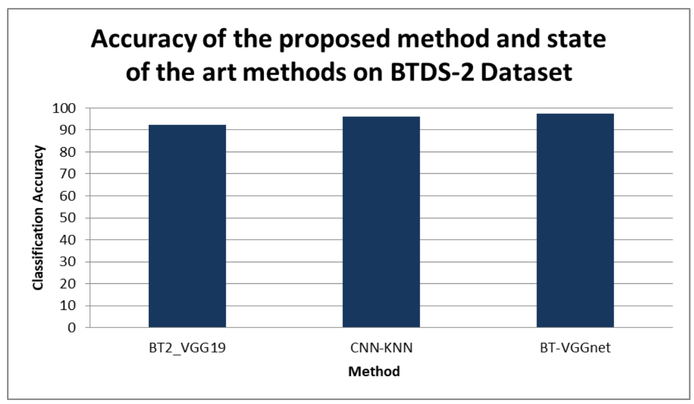


Figure 11: Accuracy comparison with state of art methods plot on BTDS-2 Dataset

Table 3: Performance metrics for BT-VGGnet on CE-MRI dataset

S.NO	Feature Extraction fine tune Model	Classifier	Accuracy	Sensitivity	Specificity	Precision	F1-Score
1.	BT3_FT_B6	Softmax	94.46	94.73	94.59	88.48	91.36
		KNN	95.43	95.66	95.54	90.34	92.83
2.	BT3_FT_B5_B6	Softmax	94.78	94.8	94.78	89.24	91.78
		KNN	96.09	95.71	95.90	92.27	93.71
3.	BT3_FT_B4_B6	Softmax	97.39	97.30	97.39	94.42	95.82
		KNN	97.71	97.53	97.68	95.18	96.33
4.	BT3_FT_B3_B6	Softmax	97.39	97.53	97.45	94.5	95.84
		KNN	97.71	97.77	97.74	95.2	96.35
5.	BT3_FT_B2_B6	Softmax	98.04	97.65	97.96	96.09	96.83
		KNN	98.37	98.36	98.39	96.44	97.37
6.	BT3_FT_B1_B6	Softmax	98.37	98.59	98.45	96.25	97.38
		KNN	**98.69**	**99.06**	**98.81**	**96.84**	**97.91**

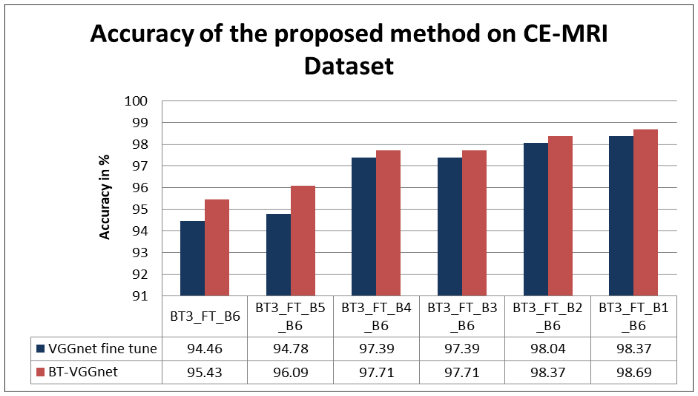


Figure 12: Accuracy plot on CE-MRI Dataset

The performance metrics of BT-VGGnet for CE-MRI dataset is shown in table 3. Again BT2_FT_B1_B6 + KNN has outperformed compared to all other combinations.

The accuracy, Sensitivity, Specificity, Precision and F1-score plots on CE-MRI dataset are shown in figure 12, figure 13, figure 14, figure 15, and figure 16. The accuracy of proposed model is compared with state of art algorithms in table 4.

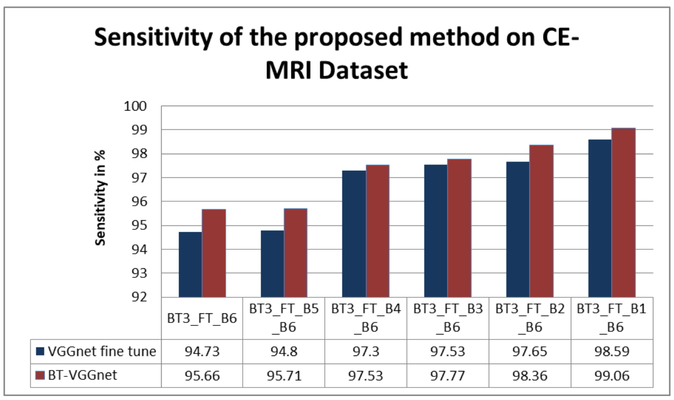


Figure 13: Sensitivity plot on CE-MRI Dataset

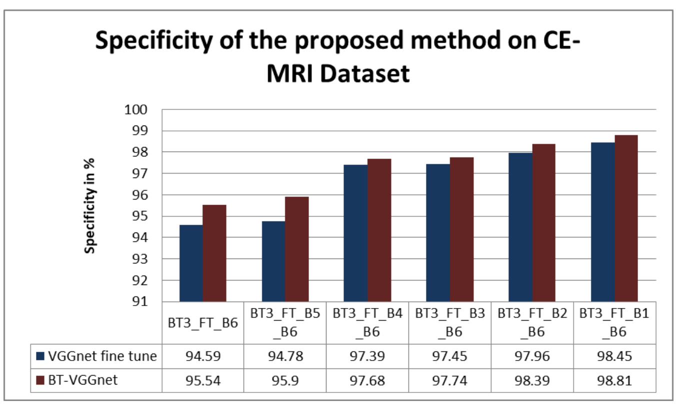


Figure 14: Specificity plot on CE-MRI Dataset

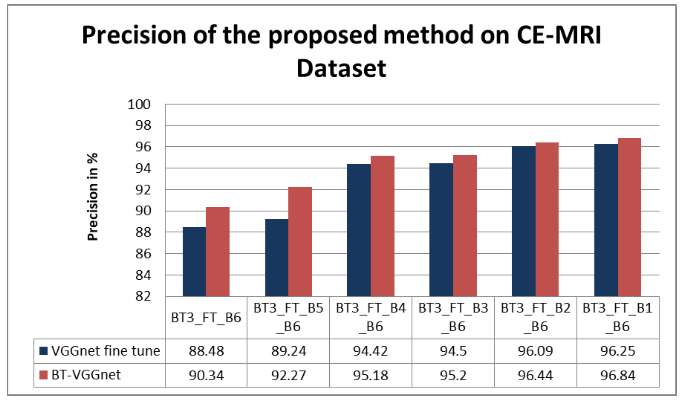


Figure 15: Precision plot on CE-MRI Dataset

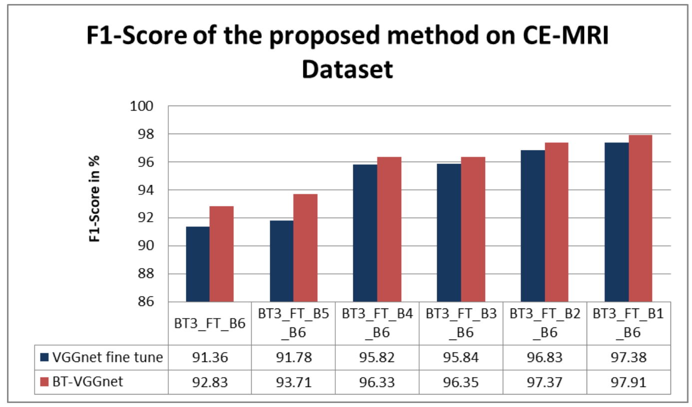


Figure 16: F1-Score plot on CE-MRI Dataset

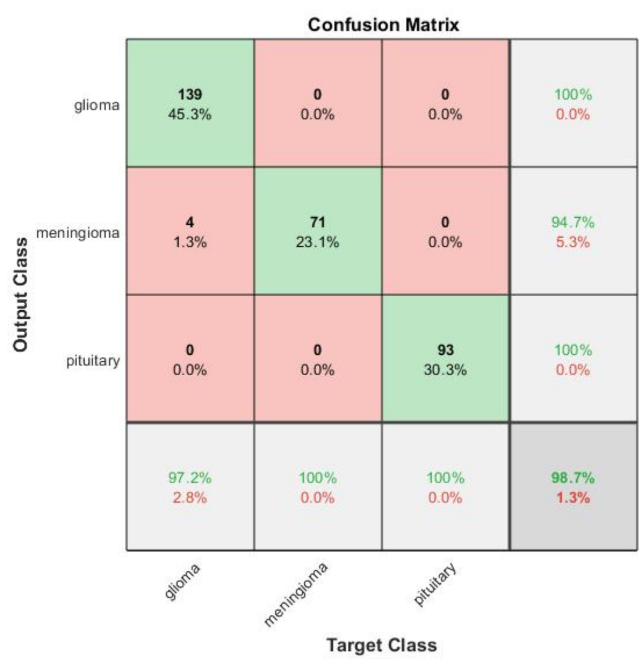


Figure 17: Confusion Matrix for CE-MRI Dataset

Table 4: Comparison of Accuracy of the proposed method and state of the art methods on CE-MRI Dataset

S.NO.	Model	Classification method	Accuracy
1	Cheng et al.[24]	SVM-KNN	91.28%
2	Paul et al.[25]	CNN	91.43%
3	Abiwinanda et al.[26]	CNN	84.18%
4	Afshar et al.[27]	CNN	90.89%
5	Anaraki et al[28]	GA-CNN	94.2%
6	Anilkumar B et al [29]	BT3_VGG19	95.43%
7	Anilkumar B et al [6]	CNN-KNN	96.74%
8	**Proposed Method**	**BW_FT_CNN-KNN**	**98.69%**

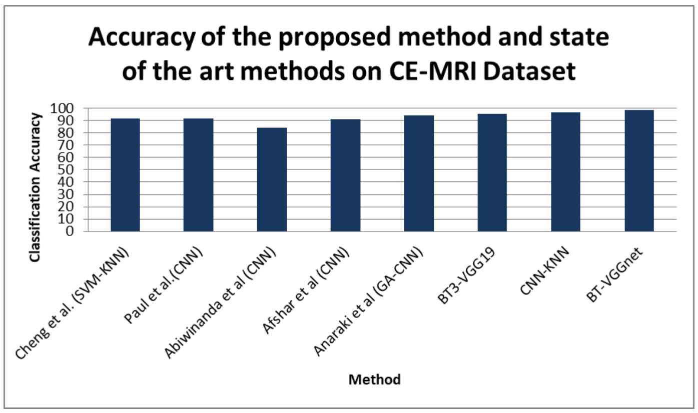


Figure 18: Accuracy comparison with state of art methods plot on CE-MRI Dataset

5. CONCLUSION

Brain tumor identification and classification is a crucial task to radiologists for further treatment plan. Computer aided diagnosis of brain tumor is an accurate and quick resulting process. In this work, BT-VGGnet is proposed to classify and validate against BTDS-2 and CE-MRI datasets. A block wise fine tuning is applied on VGG19 model, this pre trained model is divided into six blocks from B1 to B6. BT-VGGnet is trained block by block by setting the learning rate for each block individually. Softmax and KNN classifiers are used to classify the tumors. The proposed model outperforms compared to state-of-the-art classification with accuracies 97.28% and 98.69% respectively.

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