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Multi Tumor Classification in MR Brain Images through deep Feature Extraction using CNN and Supervised Classifier

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ABSTRACT: Classification of brain tumor is challenging task for both radiologists and researchers. Brain tumors have different types in shapes and orientations. After tumor classification by radiologists, the treatment is planned to improving the life span of the patient. MRI is the common medical imaging modality used to acquire the brain images due to its high quality in soft tissues and less radiation. Traditional machine learning algorithms classify the brain tumors based on few handcrafted features with expert's choice, which may lead to decay in performance of Algorithms. Deep learning models became more popular in recent years in classification of Images. CNNs have proved as a master in extracting the huge number of non-handcrafted features to improve the accuracy of classification models. In this paper the MR brain images are classified by taking advantage of CNN for feature extraction and supervised classifiers for classification on publicly available two datasets. The former one is to classify LGG (Benign) and HGG (Malignant), other one is to classify glioma, meningioma and pituitary tumors. The proposed model compared with other machine learning and pre trained CNNs models, the proposed model is hybrid combination of CNN and KNN classifier attained noteworthy performance in terms of overall accuracy of 96.10% and 96.74%.

Keywords: Brain Tumor, MRI, Classification, Deep Learning, CNN, Feature extraction, Machine learning, SVM, Decision Tree, KNN.

I. INTRODUCTION

Brain is a central organ which controls the functionality of all other organ of the human body. The most dangerous and life threatening problems are tumors in brain. A brain tumor is an abnormal growth of cells in brain; there are around 120 types of brain tumors. Among them some are dangerous and some can be cured by proper treatment. MRI is the common medical imaging modality used to acquire the brain images due to its high quality in soft tissues and no ionized radiation [1, 2]. Gliomas are the most dangerous tumors in brain.

Gliomas are originates in the brain glial cells and the most predominant type of brain tumors [3]. According to WHO (World Health Organization) Gliomas are classified into four grades as type I to IV. As the grade number increases, the tumors are more severe. Meningioma is forms on the membrane of the brain and Maximum of meningioma tumors are benign [4]. However, the pituitary is a pea-sized gland that is housed within a bony structure. It can be benign, benign that expands to bones, and malignant. Vision loss is the most complications of pituitary tumors and cause permanent hormone deficiency also [5].

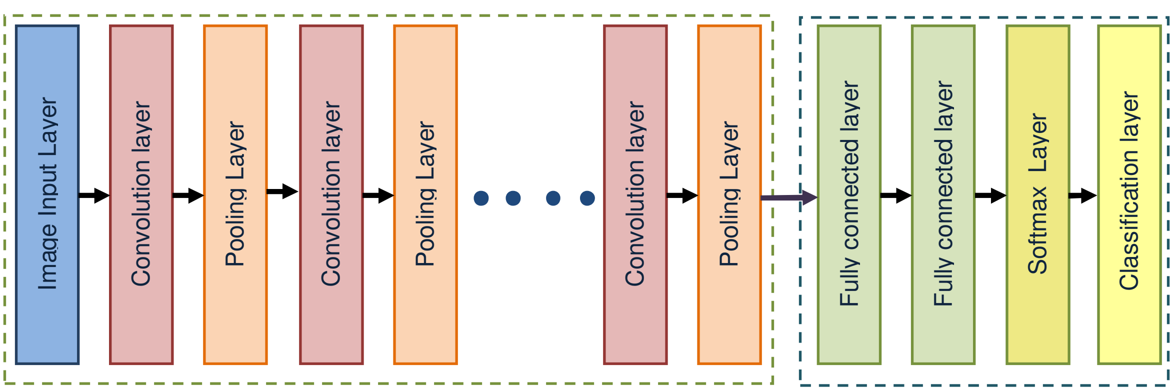


Fig. 1. Deep learning feed forward network architecture.

The challenging task for radiologists or specialists is to find the location, size and type of the tumor. But with the hectic time schedule of experts, to analyse the brain tumors is a time consuming task. Further there is mismatch between opinions of different experts in diagnosis with the same Imaging report. So in this regard, there is a need of computer aided diagnosis system which can classify the brain tumors more accurately.

CAD systems are proposed based on traditional machine learning algorithms, these classification algorithms performance is completely depends on the hand crafted features selection from the medical images. The hand crafted features are less in number and these features selection depends on the developer knowledge in that domain. These features are fed to classifier for training and the accuracy of the system is limited. The accuracy of the machine learning algorithms [20] is depends on the type and size of the feature vector. To improve the performance of the algorithms correct feature selection and training is required. In recent years deep learning models got more popularity due to its high classification capability [6, 21]. Deep learning is part of machine learning, where both come under the branch of artificial intelligence. The advantage with deep learning model is that it will take image as input instead of hand crafted features and in more in number for correct prediction with classifier. In deep learning classification can work out in three ways. First one is transfer learning in which the weights of a well proved pre trained network is used to classify the other target Images. Second one is to tune the pre trained network in each block to classify the target images and last one is to build a deep learning model from the scratch. The former two methods will take less time, but last one will take more time to build and train [7].

For classification number of features plays a major role. Deep learning models use CNNs to extract the features from the images. These features are non-handcrafted and in huge in number. The CNNs are followed by Pooling and activation layers, in each layer the feature map dimension reduction takes place. Images are passed through these layers and weights are updated in each layer. At the end all these features are fed to the dense network also called fully connected network. The output layer is fed to softmax layer followed by a classifier. Fig. 1 shows the Deep Learning plain feed forward architecture. It consists different layers like convolution, pooling, fully connected layers softmax Classifier.

Image Input layer is used to take the image as input with specified pre-defined size. Convolution is used to extract the features from the network with the help of filters. Straid and pooling concepts are used to reduce number of parameters and computations. In the feature extraction stage normalization and dropouts are used to reduce the training time and computations. The output feature map from the CNN is fed to the fully connected or dense net followed by softmax Classifier for classification.

In Section II, Discussed the related work for brain tumour classification Section III dedicated to The Proposed approaches with pre trained CNNs like Alexnet, VGG, ResNet with combination of classifiers like SVM, Decision Tree, KNN. Section IV is for the results and discussions followed by Conclusion.

II. RELATED WORK

There are much research contributions made in this area. Praveen, G. B., and Anita Agrawal are used GLCM and GLRLM for feature extraction and random forest classifier for classification, obtained classification accuracy 87.62% for the model [8]. In [9] CNNs are used to classify the CT brain images for normal and Alzheimer's disease. Cheng *et al.* has proposed a method to improve the classification performance by ring-form partition in intensity histogram, gray level co-occurrence matrix (GLCM), and bag-of-words (BoW) model with SVM and KNN classifiers. Paul *et al.*, has used a CNN to classify Axial mode images in CE-MRI dataset and got accuracy of 91.43% [10]. Abiwinanda *et al.*, proposed a CNN architecture to detect three types of brain tumors and got accuracy of 84.19% [11]. Afshar *et al.*, developed CapsNets to increase the focus by taking the tumor coarse boundaries as extra inputs within its pipeline [12]. Anaraki *et al.*, proposed method with the architecture of the CNN is evolved using GA and got an accuracy of 94.2% [13].

John *et al.*, proposed a brain tumor classification using GLCM with probabilistic neural network [14]. Javed *et al.*, proposed multiclass classification method using perceptual features, fuzzy weighting, and support vector machine (SVM) [15].

III. PROPOSED METHOD

The proposed model is shown in Fig. 2, it has four phases as dataset preparation and splitting, pre-processing, feature extraction through CNN and Classification.

A. Dataset

This work focused on two publicly available datasets former one is collected from BRATS 2018 [16, 17] and other is from CE-MRI [18].

BRATS 2018 dataset is available in .nii (NIFTI) format, it is volumetric information. This dataset is available with the ground truth; these images can be seen three modes Axial, Sagittal and coronal modes respectively as shown in Fig. 3. This volumetric dataset converted into 2D in PNG format with the ITK-SNAP Tool [19]. Each mode of Images with different sizes of $240 \times 240 \times 3$, $240 \times 155 \times 3$, $240 \times 155 \times 3$ for Axial, Coronal and Sagittal modes respectively.

Table 1 shown below complete details of the brain tumor dataset BTDS-2. Three modes of 2D images are extracted of two classes, Benign and Malignant with the help of ground truth Images. This dataset consists 5940 images and are spited into training set, validation set and testing set. 10% of BTDS-2 is reserved for testing and remaining for training and validation.

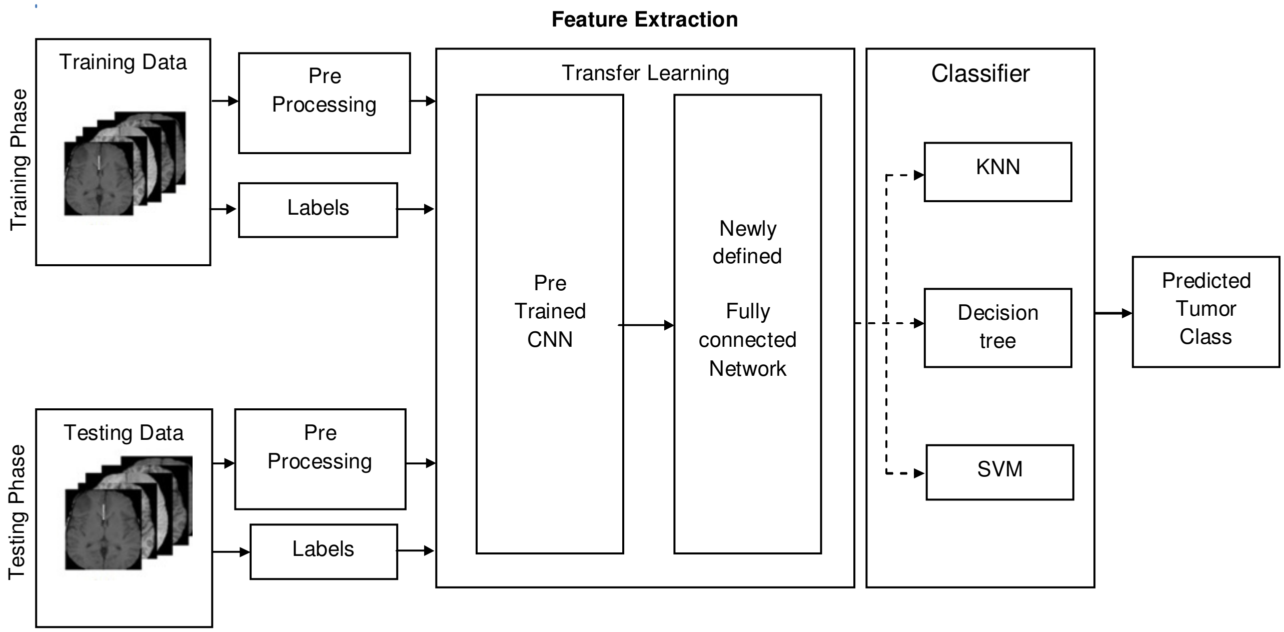
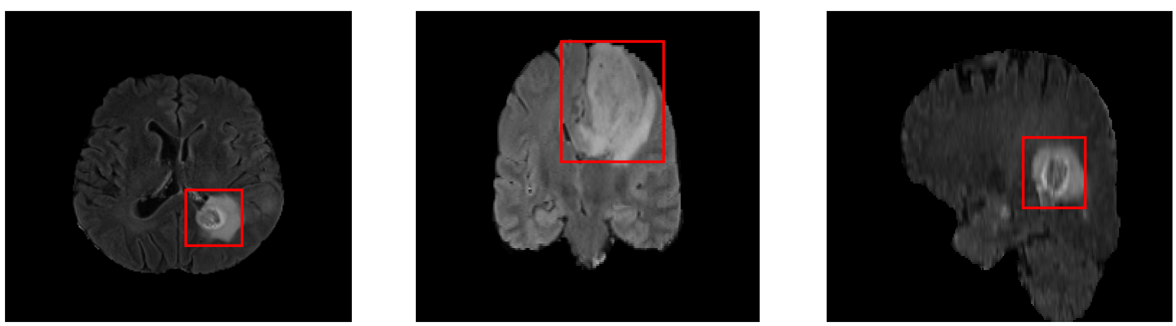


Fig. 2. CNN hybrid Classifier model.



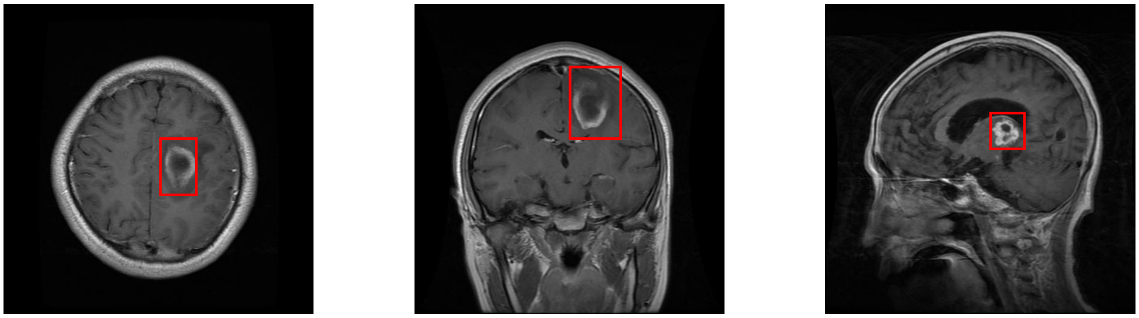
(a) Axial Mode (b) Coronal Mode (c) Sagittal Mode

Fig. 3. Modes of MRI image (BTDS-2).

CE-MRI Dataset is collected from Nanfang Hospital and General Hospital, Tianjing Medical University, China [18]. The dataset holds three types of Brain tumor MR images as glioma, meningioma and pituitary. Total 3064 images with Axial, Coronal and Sagittal modes with size of 512 × 512 × 1 are used. Unlike BRATS dataset these are not skull scripted images as shown in Fig. 4. The testing and training set split up of CE-MRI Dataset is shown in Table 2.

Table 1: BTDS-2 split up.

S. No.	Data set	Type of tumor	Mode	No. of Images	Total No. of Images
1.	BTDS-2	Benign & Malignant	Axial Coronal Sagittal	5940	5940
2.	Training set	Benign	Axial	317	921
			Coronal	334	
			Sagittal	270	
		Malignant	Axial	1547	4429
			Coronal	1223	
			Sagittal	1659	
3.	Testing set	Benign	Axial	35	102
			Coronal	37	
			Sagittal	30	
		Malignant	Axial	172	488
			Coronal	136	
			Sagittal	180	



(a) Axial Mode (b) Coronal Mode (c) Sagittal Mode

Fig. 4. Modes of MRI image (CE-MRI).

This dataset consists 3064 images and are spited into training set, validation set and testing set. 10% of CE-MRI is reserved for testing and remaining for training and validation.

B. Pre-Processing.

Preprocessing is an important step before feeding the image dataset to the model. MR brain images may effect with different noises and artifacts which are not required in the training phase of the model. Commonly de-noising is used as a pre-processing step, but in this work different pre-trained networks with different input size are used. All the pre-trained models take an RGB images as input, but CE-MRI is not in RGB format. So in order to fit the dataset into the model, it is resized to the input size of the model called data augmentation.

De-noising Convolution Neural Network (DnCNN) and median filter is used for removing the noise in both the datasets. DnCNN removes the Gaussian noise and other high frequency artifacts of images. De-noising through DnCNN can benefit computational time also at GPU.

Data Augmentation is the major part of pre-processing in transfer learning. This involves many techniques as Resizing, Flipping, Conditions, Adding Salt and Pepper noise, Lightening Scaling, Translation, Rotation, and Perspective Transform. As per our proposed hybrid model only resize is required to fit the dataset into the model.

C. Feature Extraction.

Different CNNs of pre trained networks like Alexnet, VGG16, VGG19, Resnet50, Resnet101 and Google net are used to extract the features. Out of six pre trained networks three are plain feed forward networks and remaining three are residual networks. All these networks are trained for the two datasets by newly defining the fully connected layers. After training, features can extracted from the fully connected layers or activation layers and feed to the classifier.

D. Classifier.

In the classification section each CNN model is tested with three classifiers as SVM, KNN and classification tree. Out of these classification models the CNN and KNN combination has performance is outstanding for both datasets.

Table 2: CE-MRI Split up.

S. No.	Data set	Type of tumor	Mode	No. of Images	Total No. of Images
1.	CE-MRI	Glioma, Meningioma and Pituitary	Axial Coronal Sagittal	3064	3064
2.	Training set	Glioma	Axial	433	1283
			Coronal	448	
			Sagittal	314	
		Meningioma	Axial	474	637
			Coronal	211	
			Sagittal	252	
		Pituitary	Axial	256	837
			Coronal	286	
			Sagittal	295	
3.	Testing set	Glioma	Axial	61	143
			Coronal	45	
			Sagittal	37	
		Meningioma	Axial	34	71
			Coronal	21	
			Sagittal	16	
		Pituitary	Axial	433	93
			Coronal	448	
			Sagittal	402	

IV. RESULTS AND DISCUSSIONS

In this work two datasets are used to train different pre trained CNNs for feature extraction and classifiers like KNN, SVM, Tree for classification. The performance of these Models are 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 models with three combinations is tried as CNN and SVM, CNN and KNN and CNN and Tree. Experimentation results state that hybrid combination of 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, VGG19 and KNN has performed well compared to all other combinations.

A. Validation Metrics

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{F1 Score} = 2 \cdot \frac{PPV \cdot TPR}{PPV + TPR}$$

Fig. 5 shows the plot of performance metrics on BTDS-2 dataset for CNN-KNN combination.

Table 3: Performance metrics for proposed method on BTDS-2 dataset.

S. No.	Feature Extraction Transfer learning Model	Classifier	Accuracy	Sensitivity	Specificity	Precision	F1-Score
1.	BT2_ALEXNET	SVM	88.9831	78.9939	78.9880	81.2239	80.0338
		KNN	94.5763	88.9666	88.9640	91.6009	90.2107
		Tree	83.7288	69.6139	69.6048	71.3091	70.3896
2.	BT2_VGG16	SVM	92.7119	85.9008	85.8970	88.0011	86.8991
		KNN	95.2542	90.1519	90.1498	92.8663	91.4344
		Tree	89.4915	78.9135	78.9085	82.5788	80.5529
3.	BT2_VGG19	SVM	93.7288	87.6788	87.7783	90.3310	88.9343
		KNN	**96.1017**	**94.9293**	**95.0286**	**92.4511**	**93.6221**
		Tree	78.4746	61.3971	61.3842	61.8630	61.6175
4.	BT2_Resnet50	SVM	90.5085	81.4670	81.5648	84.5988	82.9115
		KNN	93.8983	87.7813	87.8810	90.7930	89.1964
		Tree	88.8136	80.0546	80.1506	80.8740	80.4566
5.	BT2_Resnet101	SVM	92.2034	85.2057	85.3042	87.3684	86.2365
		KNN	94.5763	92.0685	92.1669	90.0344	91.0011
		Tree	79.1525	64.5211	64.5076	63.9858	64.2405
6.	BT2_Googlenet	SVM	79.8305	64.5432	64.6334	64.8650	64.7020
		KNN	83.5593	72.6133	72.6024	71.4690	72.0091
		Tree	76.6102	60.2700	60.3575	59.9760	60.1115

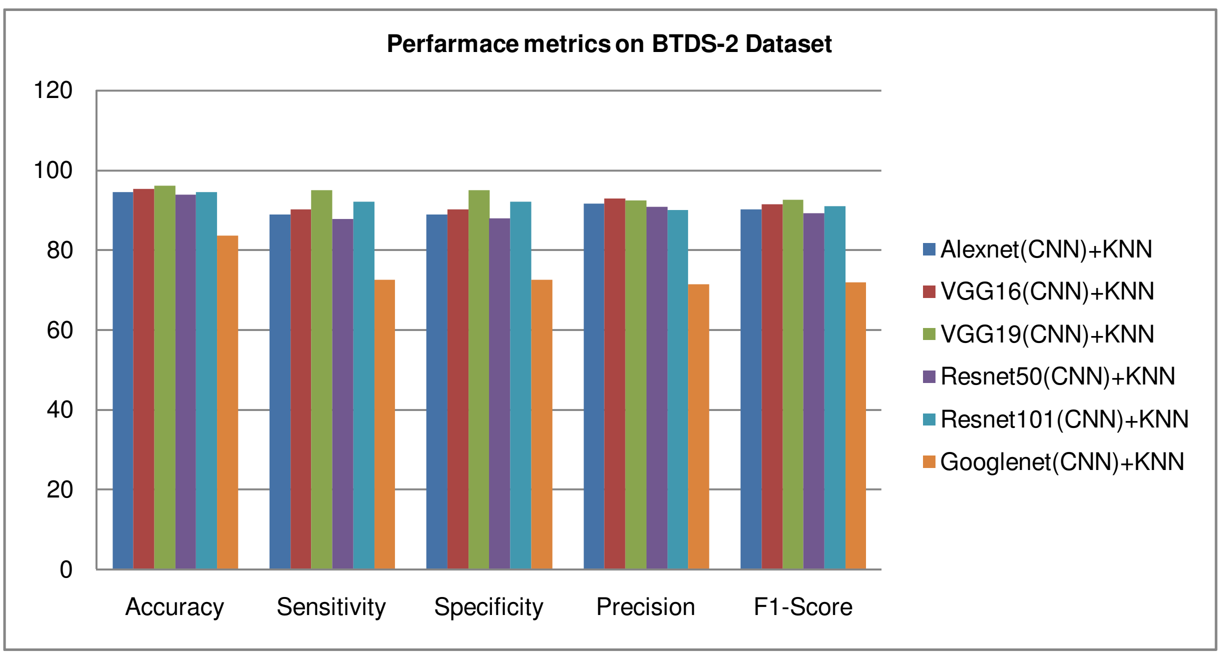


Fig. 5. Performance metrics on BTDS-2 Dataset.

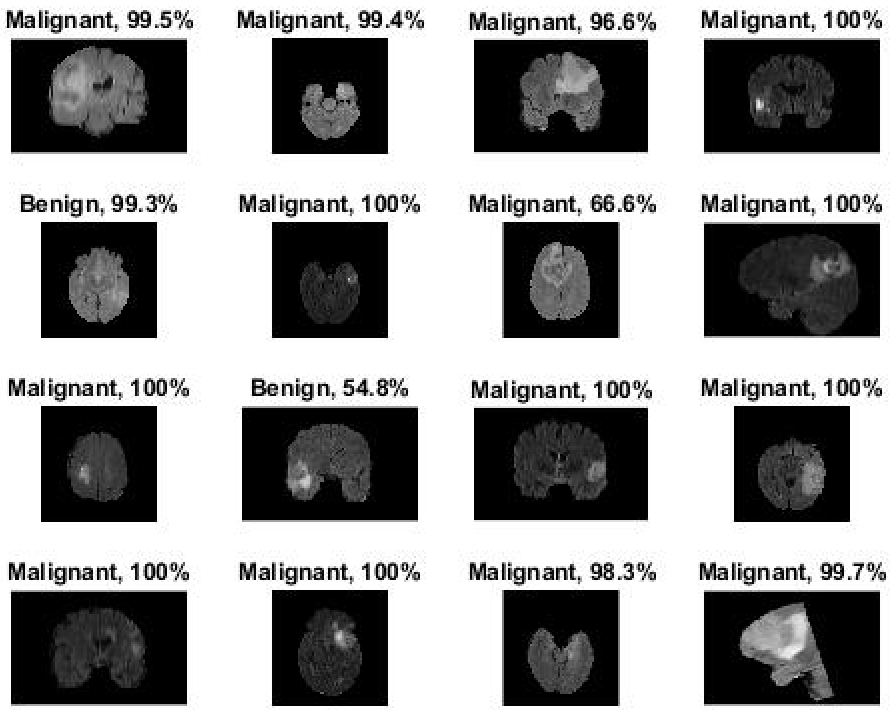


Fig. 6. Sample images from predicted classes for BTDS-2 Dataset.

Fig. 6 shows the plot of accuracy on CE-MRI dataset. The performance metrics on CE-MRI dataset is presented in table 4. The state of the art models with combinations of classifiers for three types of tumors has represented. Again the combination of (VGG19) CNN and KNN performance is outstanding.

The Accuracy of proposed method for CE-MRI dataset are compared with the other machine learning models shown in Table 5. The proposed research was implemented with MATLAB R2018b and GPU NIVIDA TITAN X (Pascal) with 5 GB on-board memory.

Table 4: Performance metrics for proposed method on CE-MRI.

S. No.	Feature Extraction Transfer learning Model	Classifier	Accuracy	Sensitivity	Specificity	Precision	F1-Score
1.	BT3_ALEXNET	SVM	95.4397	96.1151	95.8916	90.8587	93.3104
		KNN	95.7655	96.1051	96.1261	91.6545	93.7730
		Tree	87.2964	87.1952	87.6541	76.4477	81.3885
2.	BT3_VGG16	SVM	95.1140	95.1527	95.4041	90.5376	92.7250
		KNN	93.8111	93.9772	94.1499	87.9550	90.7504
		Tree	90.5537	89.5686	90.5857	82.2802	85.6280
3.	BT3_VGG19	SVM	96.7427	96.8044	97.0193	93.8285	95.2726
		KNN	**96.7427**	**97.1653**	**97.0978**	**93.5690**	**95.3077**
		Tree	94.1368	94.0775	94.3669	88.5796	91.2252
4.	BT3_Resnet50	SVM	95.1140	95.9998	95.6092	90.1433	92.8413
		KNN	95.7655	95.8620	96.0629	91.8008	93.7437
		Tree	76.2215	76.3498	76.5297	60.5798	67.0354
5.	BT3_Resnet101	SVM	93.1596	93.8719	93.6330	86.5422	89.8743
		KNN	93.4853	93.5011	93.7889	87.4099	90.2290
		Tree	73.9414	74.2319	74.3190	57.8571	64.3455
6.	BT3_Googlenet	SVM	89.2508	89.1300	89.5541	79.8561	83.9538
		KNN	90.2280	90.3155	90.5738	81.4854	85.4269
		Tree	71.9870	73.3044	72.5936	56.0793	62.5147

Table 5: 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.*, [18]	SVM-KNN	91.28%
2.	Paul *et al.*, [10]	CNN	91.43%
3.	Abiwinanda *et al.*, [11]	CNN	84.18%
4.	Afshar *et al.*, [12]	CNN	90.89%
5.	Anaraki *et al.*, [13]	GA-CNN	94.2%
6.	**Proposed method**	**CNN-KNN**	**96.74%**

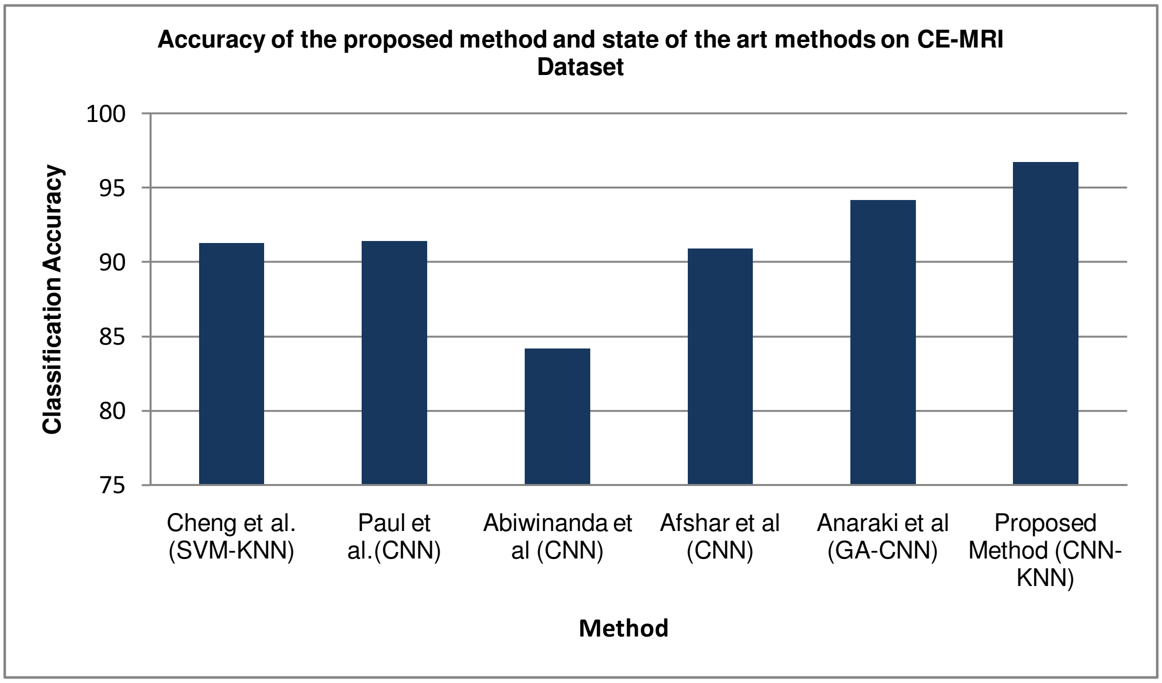


Fig. 7. Accuracy plot on CE-MRI Dataset.

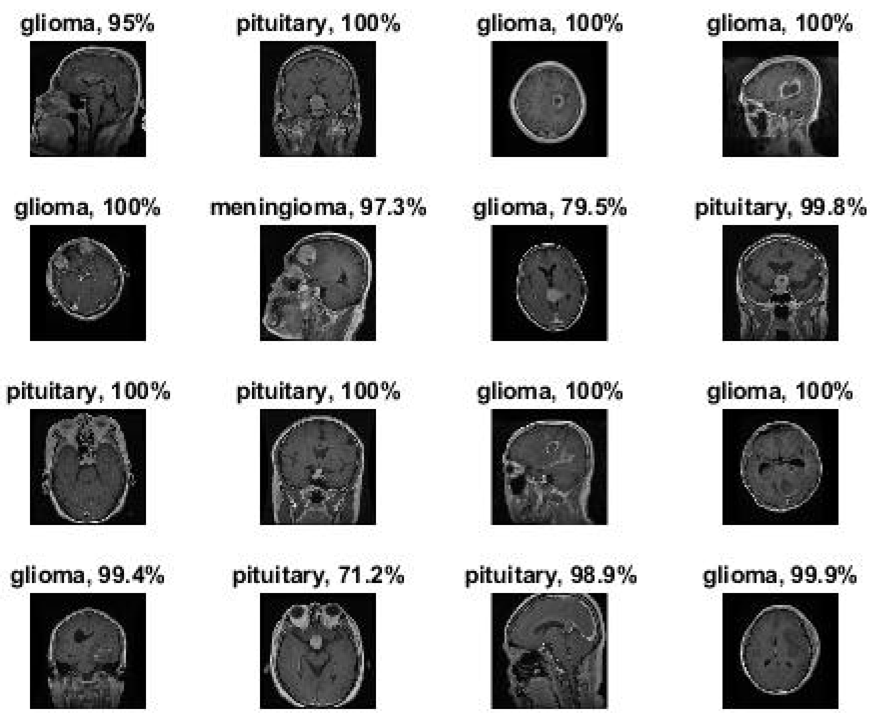


Fig. 8. Sample images from predicted classed for CE-MRI Dataset.

V. CONCLUSSION AND FUTURE SCOPE

In this work, a CAD system is proposed for the classification of gliomas MR images into two types (Benign and Malignant) in one study, and further classifying into three different types (meningioma, glioma, and pituitary) using a transfer learning and hybrid supervised classifiers. Both datasets are pre-processed with de-noising and data augmentation to fit into the CNN input layer. The proposed model is constructed from 19 layers pre-trained CNN as an off-the-shelf feature extractor starting from the input layer to fully connected layer and finally a supervised classifier to predict the class. The model also explains the conversion of natural scene image classification learning to medical image classification. The future scope of this method can be applicable to other body organs with different medical imaging modality like X-Ray, CT and PET etc. This model can be implemented on hardware for instant classification of MRI scans in hospitals. The proposed model has achieved the highest accuracy of 96.10% and 96.74% concerning the two datasets used in this paper.

Conflict of Interest. The authors confirm that this article contents has no conflict of interest.

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