Brain Tumor Classification Using Fine-Tuned GoogLeNet Features and Machine Learning Algorithms: IoMT Enabled CAD System

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***Abstract*—In the healthcare research community, Internet of Medical Things (IoMT) is transforming the healthcare system into the world of the future internet. In IoMT enabled Computer aided diagnosis (CAD) system, the Health-related information is stored via the internet, and supportive data is provided to the patients. The development of various smart devices is interconnected via the internet, which helps the patient to communicate with a medical expert using IoMT based remote healthcare system for various life threatening diseases, e.g., brain tumors. Often, the tumors are predecessors to cancers, and the survival rates are very low. So, early detection and classification of tumors can save a lot of lives. IoMT enabled CAD system plays a vital role in solving these problems. Deep learning, a new domain in Machine Learning, has attracted a lot of attention in the last few years. The concept of Convolutional Neural Networks (CNNs) has been widely used in this field. In this paper, we have classified brain tumors into three classes, namely glioma, meningioma and pituitary, using transfer learning model. The features of the brain MRI images are extracted using a pre-trained CNN, i.e. GoogLeNet. The features are then classified using classifiers such as softmax, Support Vector Machine (SVM), and K-Nearest Neighbor (K-NN). The proposed model is trained and tested on CE-MRI Figshare and Harvard medical repository datasets. The experimental results are superior to the other existing models. Performance measures such as accuracy, specificity, and F1 score are examined to evaluate the performances of the proposed model.**

***Index Terms*—Brain tumors, pre-trained network, convolution neural network, support vector machine, K-nearest neighbor, computer aided diagnosis (CAD).**

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I. Introduction

NOWADAYS, remote healthcare systems are developing widely and mitigated the communication gap between patients, and medical experts. Off late, advanced technologies like smart and wearable devices have been an instrumental part of the Internet of Medical Things (IoMT) for providing aid to the remote healthcare systems. IoMT enabled computer-aided diagnosis (CAD) system helps the medical experts to analyze the patient data remotely. It is expected that IoMT enabled CAD systems will connect the smart healthcare devices remotely and share the supportive information with medical experts. On receiving the information, immediate treatment can be given to the affected patients, and their recovery rate can be monitored by the medical staff. For example, in case of brain tumor patients, IoMT enabled CAD system can provide useful information about the tumors and its types, i.e., Malignant or Benign. Thus, early detection of brain tumor plays a vital role in proper treatment and curative intent. Manual detection and classification of brain tumors is a challenging task and have high risk of error detection, therefore requiring an expert radiologist to classify these tumors. Off late, CAD systems have been really helpful in assisting the medical experts to detect and classify the brain tumors. Manual classification is quite challenging, requiring highly professional radiologist and time intensive for large Magnetic Resonant Imaging (MRI) data classification. To address this problem, automatic classification techniques are extensively studied to classify brain tumor from MR images. Brain tumor classification from MR images using CAD technique is highly reliable for its higher accuracy. In this work, authors focus on the brain tumor classification in order to classify three different types of tumors namely meningioma, glioma and pituitary.

The handcrafted interventions are not sufficient to detect and classify the correct tumor types. The automatic detection technique requires longer time because it needs preprocessing and extracting handcrafted features by experts. The classification accuracy depends on the extracted features which are extracted with the help of experts. In literature, authors in [1] uses few features of the proposed model in order to classify the tumor types namely shape, rotation invariant texture and intensity characteristics. The feature selection strategy increases the chances of false-positive results that leads to deterioration of the classification accuracy. In [1], proposed model uses the handcrafted features and achieves a classification accuracy in between 79% and 85%. To avoid the extracted handcrafted features, deep neural network is used to classify images [2]. Literature suggests, CAD-based tumor classification has adopted the concept of deep learning. The concepts of deep learning is widely used in various applications of medical diagnosis such as detection of lung cancer, breast cancer, skin disease, tumor and its classification, chest imaging, ultrasound, histopathology etc. Among all these applications, brain tumor classification is mostly studied in the current research direction and the qualitative results produces a valuable impact on society as well as medical field. The partitioning of brain tumor from billion cells in MR images are mostly challenging and require advanced techniques in order to identify the accurate region of the tumor. The formation of brain tumors sometimes affects the nearby cells and abrupt the normal processing of the human brain, leading to severe health issues for the affected. The IoMT enabled CAD-based identification comes up with an advanced technology to eliminate this problem. The deep learning based CAD applications are highly successful and depict remarkable results. The deep learning network architecture is known as convolution neural network (CNN) which consists of a feature extractor and a classifier. Few works are reported in literature wherein the deep CNNs are considered for brain tumor classification. A subclass of deep CNN also known as deep transfer learning is studied for categorization, classification and segmentation. Transfer learning helps IoT enabled CAD systems to solve various medical problems. The authors in [3], used a pre-trained ResNet34 for classification of brain images. The authors considered 5-cross validation method for classification of normal and abnormal MR brain images. The authors in [4], considered a pre-trained inceptionV3 network to classify benign and malignant renal tumors in computer tomography (CT) images. In [5], Khalid *et al.* used a pre-trained AlexNet architecture to classify skin cancer images. The modification of classification layer and fine-tune weights in AlexNet depicted higher accuracy results for skin lesion images. Another work reported by Douglas *et al.* in [6], considers classification of skin lesion images. The study used CNN as a feature extraction tool. The authors in [6], considered pre-trained networks such as VGG, ResNet, Inception-ResNet, MobileNet, DenseNet and NASNet. The following classifiers, namely purpose support vector machine (SVM), Random Forest (RF), K-nearest neighbor (K-NN), are also considered for classification of skin lesion images. The study claimed that the DenseNet architecture with K-NN achieved higher accuracy results for skin lesion classification. Yadav *et al.* in [7] used pre-trained networks such as VGG16 and InceptionV3 to classify pneumonia from chest X-ray dataset. It can be inferred from the work that the use of transfer learning scheme significantly improved the classification accuracy of pneumonia disease detection. Li *et al.* in [8] considered various pre-trained networks namely AlexNet, VGGNet, GoogLeNet and their variants for diabetic retinopathy fundus image classification. The work also discussed the advantages of using transfer learning techniques.

The brain tumors are classified into various types and among them meningioma, glioma and pituitary tumor has higher incidence rates [9]. Cheng *et al.* in [10] reported a classification method for detection of three types of brain tumors. In this work, authors extracted various features from the tumor regions namely intensity information, gray-level co-occurrence matrix (G-LCM) and bag-of-word (BoW). Five-fold cross validation scheme was considered and the performance was validated in terms of sensitivity, specificity and accuracy. Also, the authors retrieved highest classification accuracy of 91.28%. In another work, Qader *et al.* [11] extracted some statistical features from brain MR images using discrete wavelet transform (DWT). The training was done using CNN. The authors reported an accuracy of 91.9% using 3064 number of images. In another experiment, Abiwinanda *et al.* [12], achieved an accuracy of 84.19% using CNN for Figshare dataset. Pashei *et al.* [13] designed a CNN architecture and obtained an accuracy of 81% for three types of brain tumor classification on Figshare dataset. The performance accuracy is enhanced using CNN features with a classifier model. Afshar *et al.* in [14], designed a capsule network (CapsNet) to classify brain tumors and reported an accuracy of 86.56%. Further, authors improved the capsule network and reported a classification accuracy of 90.89% [15]. Widhiarso *et al.* [16] extracted the GLCM features for brain MR images and fed this information to CNN. The study achieved an accuracy of 82% while combining the GLCM with the contrast feature.

In this paper, we propose an automated brain tumor classification method which classifies three different classes of brain tumors. The proposed system considers a deep transfer learning CNN and depicts better performance than the other state-of-the-art models reported in literature. The major contributions of our work are as follows:

1) A modified deep CNN as transfer model is designed to classify brain tumors from Brain MR images.
2) A three class classification problem is proposed to detect a specific type of brain tumor. The proposed model proves to be a powerful machine learning (ML) scheme in the classification of tumors from various medical images.
3) The proposed model also extracts the features of the input images from the deep CNN model. The features are evaluated using ML algorithms namely SVM classifier and K-NN classifier.
4) The proposed model is trained on an open source Figshare dataset and the comparisons are drawn by considering various state-of-the-art deep CNN models and ML schemes.
5) The automatic detection of brain tumor will facilitate the medical practitioners and nursing staff to identify the type of tumor in a patient, and provide them with immediate treatment.

II. Proposed CNN

A. Pre-Processing

In the proposed work, a CNN called GoogLeNet is used for brain tumor classification. It is observed that the intensity of the images varies significantly between the subjects. Therefore, it is necessary to normalize these images before applying CNN. Normalization ensures that the intensity of the images varies

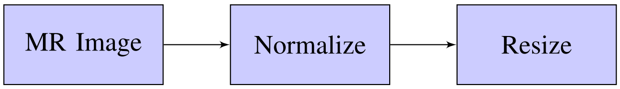


Fig. 1. Data pre-processing steps.

within a certain range. The MR images are normalized using min-max normalization. It is computed as:

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

where, y_i denotes the normalized intensity value against position x_i, $\min(x)$ the minimum intensity values and $\max(x)$ and maximum intensity values respectively.

The input layer of GoogLeNet i.e. imageInputLayer is designed to accommodate images of size $224 \times 224 \times 3$. The images in the dataset are of size 512×512. Therefore, the images are resized from 512×512 to 224×224. GoogLeNet also works exclusively on RGB images. After resizing the images, three channels are created by concatenating the values of grayscale thrice. In this manner, images are resized to $224 \times 224 \times 3$. Fig. 1 illustrates the data pre-processing steps of the proposed model using GoogLeNet.

B. Training CNN

The CNNs are feed forward networks which are usually trained from the 1^{st} layer to the final classification layer. The loss or error obtained at the final classification layer is minimized by back propagation [17]–[20]. The k^{th} neuron in l^{th} layer receives an input from j^{th} neuron in $(k-1)^{th}$ layer. The weighted sum is calculated as:

$$L_k^l = \sum_{j=1}^{n} W_{kj}^l X_j + b_k \tag{2}$$

where W_{kj}^l represent weights, b_k the biases, and X_j the training samples. The weighted sum is passed through a non-linear function ReLu which gives the following output.

$$O_k^l = \max(0, L_k^l) \tag{3}$$

All the nodes or neurons present in the convolutional and fully connected layer use the above two equations (2 and 3) to calculate an input L. The non-linearly activated output is represented as O. The pooling layer reduces the spatial size of $N \times N$ feature map by using a $K \times K$ square sliding window. It either takes the average or the maximum value from the $K \times K$ window placed on $N \times N$ feature map. In this way, it reduces the size of the feature map from $N \times N$ to $\frac{N}{K} \times \frac{N}{K}$. The classification layer or the final layer of a CNN calculates the probability of each tumor type through the softmax function given below [15].

$$P\left(\frac{y_i}{X}; W\right) = \frac{e^{S_{y_i}}}{\sum e^{S_j}} \tag{4}$$

The CNNs are trained with back propagation algorithm [15]. In this algorithm, the following cost function is minimized with respect to the unknown weights W.

$$C = \frac{(-1)}{n} \sum_{i=1}^{n} ln\left(P\left(\frac{y_i}{x_i}\right)\right) \tag{5}$$

Here, n represents the total number of training samples, x_i the i^{th} training sample, y_i the label corresponding to sample x_i and $P(\frac{y_i}{x_i})$ the probability of sample x_i belonging to class y_i.

The cost function is calculated over a mini batch consisting of N samples. Taking W_l^t into consideration as the weights at t^{th} iteration for convolution layer and C as the minibatch cost, the weights in the next iteration are updated as:

$$\begin{aligned} \gamma^t &= \gamma^{[\frac{tN}{m}]} \\ V^{t+1} &= \mu V_l^t - \gamma^t a_l \frac{\partial C}{\partial W} \\ W_i^{t+1} &= W_l^t + V_l^{t+1} \end{aligned} \tag{6}$$

Here, a_l is the learning rate of layer l, γ is the scheduling rate that influences a_l and μ is the momentum that influences the previously updated weights in the current iteration.

C. Transfer Learning and Fine Tuned GoogLeNet

In this work, the CNN used for brain tumor classification is GoogLeNet [21]. The architecture of GoogLeNet is very different from previous state of architectures such as AlexNet, VGG16, VGG19, etc [22]. At its inception, the GoogLeNet architecture was designed to be a powerhouse with increased computational efficiency compared to some of its predecessors or similar networks created at the time. GoogLeNet achieves better efficiency despite the reduction in the size of the input image, while retaining important spatial information.

GoogLeNet is a deep network with 22 learnable layers. It consists of 2 convolutional layers, 2 pooling layers, 9 inception modules and a fully connected layer. The inception module is made up of 6 convolutional layers and a pooling layer. The module consists of patches or filters of sizes 1×1, 3×3 and 5×5. These filters of different sizes help to obtain different patterns of the input image. The feature maps obtained from various filters are concatenated at the output of each module. Furthermore, 1×1 convolutions are performed prior to convolutions by large filters. Using 1×1 convolution filter, decreases the number of parameters required by GoogLeNet. As a result, total computations are also reduced. Further, Fig. 2 illustrates the description of layers of a pre-trained GoogLeNet architecture [23].

GoogLeNet is trained using Imagenet dataset which consists of 1.2 million images [23]. Each image in the dataset is classified into one of 1000 defined classes. The training samples consists of both the images as well the labels associated with each image.

The training data is trained on the fine-tuned GoogLeNet. After the training of the fine- tuned network, the training features are extracted from the last Average Pool layer i.e. '$pool5 - 7X7/1$' through an activation function. The last Pool layer contains 1024 output nodes. So each and every training image has 1024 features. Each of the training images can be represented as a point in 1024 dimensional plane. For each cross

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Fig. 2. Pre-trained GoogLeNet layers and parameter details [23].

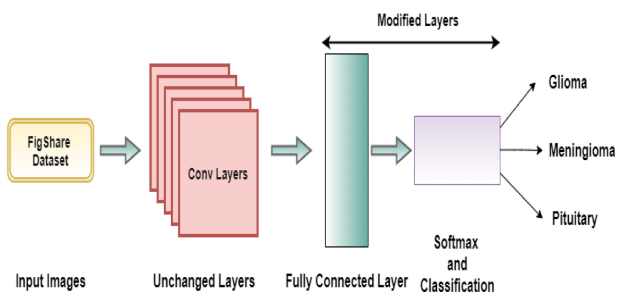


Fig. 3. Architecture of proposed model.

validation, there are around 2400 training images. In our work, tumor images from Figshare dataset are classified into 3 types. We have modified the last 3 layers of GoogLeNet to achieve our desired target. In the state-of-the-art GoogLeNet, the fully connected layer has an output size of 1000. In our work, we require a fully connected layer with an output size of 3 so that the brain tumor images can be classified into 3 different classes. In the proposed work, the fully connected layer in GoogLeNet is replaced by another fully connected layer (f_c) having an output size of 3. As the state-of-the-art fully connected layer is removed, the subsequent softmax layer and cross entropy based classification layer are also removed. They are replaced by new such layers with different names just to fit in with the new fully connected layer. The learning factors of weights and bias of f_c are set to a value of 10. After the removal and deletion of the existing layers, all the layers are connected. This modified GoogLeNet can now be used for the training of the Figshare dataset. The detailed architecture of the proposed model using GoogLeNet is shown in Fig. 3. In Fig. 3, the convolution layers are unchanged layers of GoogLeNet followed by fully connected layers. The number of neurons is set to 3 for fully connected layer in order to classify three different types of tumor. This is followed by a softmax layer used as a classifier and a classification layer. Further, SVM and K-NN classifiers are used instead of softmax layers to evaluate the performance of the proposed model. Table I depicts the parameters for transfer learning of the proposed model i.e., modified GoogLeNet.

TABLE I
PARAMETER SETTINGS FOR THE PROPOSED MODEL

Proposed Model	Parameters	Settings
GoogLeNet with Softmax	Initial learning rate	0.0003
	Mini-batch size	30
	Learning algorithm	Adam
	Loss function	Cross entropy
	Maximum epochs	20
	Learning factor at fc	10
GoogLeNet with SVM	Initial learning rate	0.0003
	Mini-batch size	30
	Learning algorithm	Adam
	Loss function	Hinge
	Maximum epochs	20
	Learning factor at fc	10
	Coding	One-vs-all
	Kernel	Linear
GoogLeNet with K-NN	Initial learning rate	0.0003
	Mini-batch size	30
	Learning algorithm	Adam
	Loss function	-
	Maximum epochs	20
	Learning factor at fc	10
	No. of Neighbors	55
	Distance	Euclidean

III. RESULT ANALYSIS

A. Experimental Setup

The experiment is performed on a computer with 64 GB RAM, Intel Xeon (R) W-2155 processor with 3.31 GHz clock frequency and having MATLAB 2020b version. The experiments consider a publicly available dataset namely Figshare dataset which is CE-MRI dataset shared by Cheng [23], available at https://figshare.com/articles/dataset/brain_tumor_dataset/1512427. This dataset is generally used for classification and retrieval algorithms. It consists of 3064 brain MRI images obtained from 233 patients admitted to Nanfang Hospital, Guangzhou, China and General Hospital, Tian-jin Medical University, China during 2005–2010. All the images in the dataset are taken across coaxial, coronal and sagittal views. The dataset comprises of 3 types of brain tumor namely glioma, meningioma and pituitary. The images in this dataset are two dimensional images stored in. mat format. The size of each

TABLE II
DETAILS OF FIGSHARE DATASET

Tumor Types	Number of Patients	MRI view and number of images			Total number of images in each type
		Axial	Coronal	Sagittal	
Meningioma	82	209	268	231	708
Glioma	89	494	437	495	1426
Pituitary	62	291	319	320	930

image is 512X512 and the pixel size is 49 mm × 49 mm. Further, Table II depicts the details of Figshare dataset. A patient-level 5-fold-cross validation evaluation procedure is designed for the Figshare data. It means that the entire dataset is divided into five subsets. These subsets have almost an equal distribution of images. When one subset is used as a test set, the rest are used as a training set. Therefore, cross validation methodology ensures that each subset is used as a test set. Splitting up of the dataset in such a manner also ensures that the datas of all the patients are present in both test and training set. The images are stored in mat files in the dataset. These mat files contain information about the tumor types of each image. Apart from these mat files, the dataset also has a separate mat file that stores exclusively index values. In this mat file, each image of the dataset is assigned an index value. The index values ranges from 1 to 5. Index 1, 2, 3, 4 and 5 consists of 541, 679, 571, 628 and 645 images respectively. It means that all the images in the dataset are divided into five folds or segments. Each segment has approximate 20 percent images of the dataset. While evaluating a neural network, images belonging to a particular index or fold are considered as test data, while the remaining are considered as training data. So, roughly 80 percent of the images fall into the training set and the remaining 20 percent under the test set. In this case, the neural network is evaluated 5 times. The values obtained after all the evaluations i.e., precision, recall, specificity, accuracy, etc are averaged over 5.

B. Classification Methodology

In this research, the proposed GoogLeNet is trained on Figshare dataset with training images. The weighted values of different layers of the proposed model are tuned automatically to improve the classification results. This is followed by extraction of features of both training and test images from the last average pooling layer of the proposed model. Lastly, SVM and K-NN classifiers use these extracted features to classify the tumors into three different types. First, the proposed model with softmax classifier is considered for three types of brain tumor classification. Further, SVM and K-NN classifiers are used to improve the results obtained from the previous step. In each case, the results obtained from the proposed model are compared with the other state-of-the-art models.

C. Performance Evaluation

The proposed model is evaluated in terms of confusion matrix. The confusion matrix provides the value of true positive (TP), true negative (TN), false positive (FP) and false negative (FN). Further, these values are used to determine precision, recall and specificity which are calculated as follows [24], [25]:

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

$$Specificity = \frac{TN}{TN + FP} \tag{9}$$

Furthermore, F1-Score, one of the statistical parameters, is considered to evaluate the accuracy of the proposed model [24], [25]:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{10}$$

D. Results, Discussion and Comparison

In this work, pre-trained network i.e., GoogLeNet is modified in the training algorithm to improve the classification accuracy. The training steps of the proposed model are given below:

Step 1: Import the Figshare dataset and perform augmentation to resize the dataset's images.

Step 2: Divide the dataset images into testing and training data.

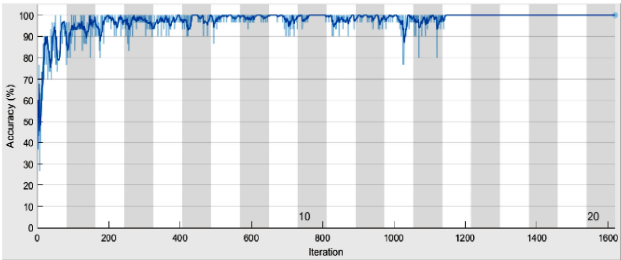
Step 3: Load the pre-trained GoogLeNet architecture and modify the f_c layer for 3-class classification problem.

Step 4: i) Extract the features and classify the tumor types using softmax classifier.

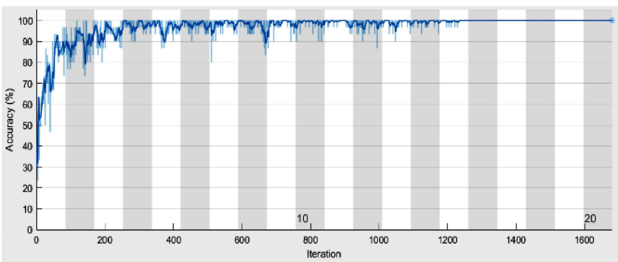
ii) Extract the features from the proposed GoogLeNet and classify the tumors using SVM classifier.

iii) Extract the features from the proposed GoogLeNet and classify the tumors using K-NN classifier.

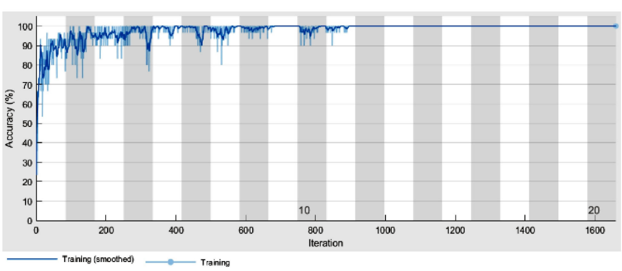
Fig. 4 shows the progress of training sets with respect to the number of iterations. In each cross validation, there are about 2400 training images and 600 test images and each mini batch is of size 30. So, the number of iterations in each epoch is $\frac{2400}{30} = 80$. The total number of iterations in 20 epochs is $20 \times 80 = 1600$. Similarly, Fig. 5 shows the sets of training loss with the number of iterations for proposed GoogLeNet, GoogLeNet with K-NN and GoogLeNet with SVM respectively. In this work, it is observed that the features extracted from f_c layer achieves better accuracy compared to the results obtained from the activation of features from the last convolution layer. Thus, the performance of the CNN is dependent on the feature set. The improvement during the training process is observed while the features are extracted from the activated f_c layer and fed to SVM and K-NN classifier. Fig. 4(a), Fig. 4(b) and Fig. 4(c) depict the training progress of the proposed CNN with softmax, SVM and K-NN classifier respectively. Similarly, Fig. 5(a), Fig. 5(b) and Fig. 5(c) depict the training loss of the proposed



(a)

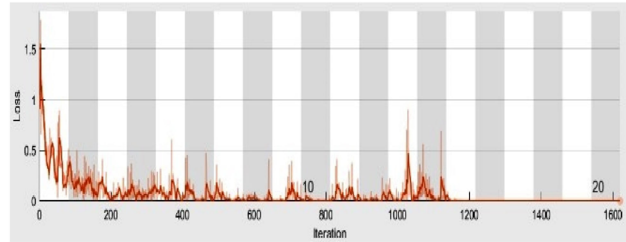


(b)

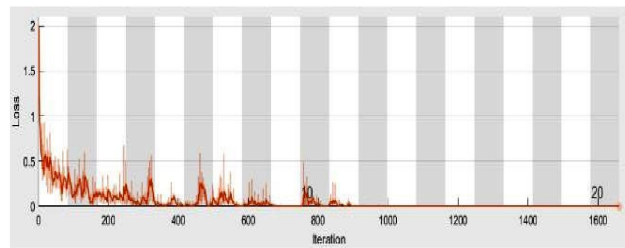


(c)

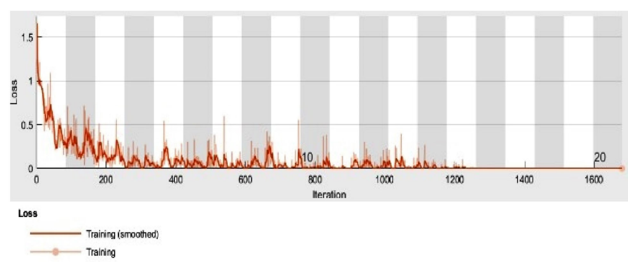
Fig. 4. Training progress of the proposed model. (a) Proposed GoogLeNet with Softmax classifier. (b) Proposed GoogLeNet with SVM classifier. (c) Proposed GoogLeNet with K-NN classifier.



(a)



(b)



(c)

Fig. 5. Training Loss of the proposed model. (a) Proposed GoogLeNet with Softmax classifier. (b) Proposed GoogLeNet with K-NN classifier. (c) Proposed GoogLeNet with SVM classifier.

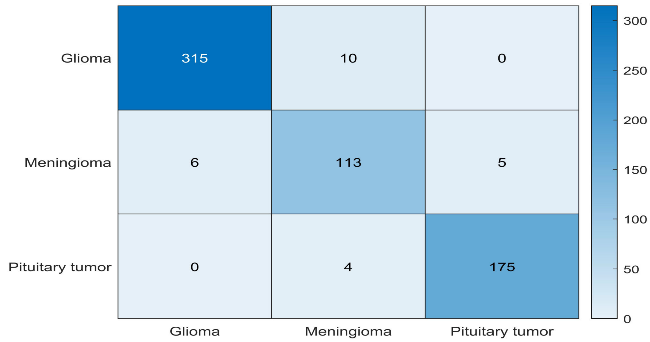
CNN with softmax, SVM and K-NN classifier respectively. It is clearly depicted from Fig. 4 that after 1150 iterations, the accuracy using proposed GoogLeNet with Softmax classifier is 94.9%. But in case of Proposed GoogLeNet with SVM and KNN classifier the accuracy shoots to 97.6% and 98.3 % after 1200 and 900 iterations, respectively.

Further, the dataset is found to be unbalanced for three different types of brain tumors and the confusion matrix helps to evaluate the performance measure of the proposed model. Fig. 6 shows the confusion matrix obtained after the testing of images from the Figshare dataset. Fig. 6(a) shows the confusion matrix for proposed GoogLeNet with Softmax classifier by considering images in index 4 as a test data whereas, other indices i.e., index 1, 2, 3 and 5 are considered as train data. Similarly, Fig. 6(b) shows the confusion matrix for proposed GoogLeNet with SVM classifier by considering images in index 1 as a test data whereas, other indices i.e., index 2, 3, 4 and 5 are considered as train data. Further, Fig. 6(c) shows the confusion matrix for proposed GoogLeNet with K-NN classifier by considering images in index 3 as a test data whereas other indices i.e., index 1, 2, 4 and 5 are considered as train data.

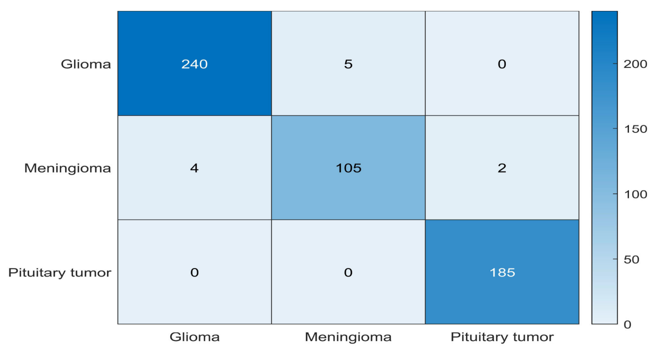
TABLE III
PERFORMANCE MEASURE OF THE PROPOSED GOOGLENET IN TERMS OF PRECISION, RECALL AND SPECIFICITY FOR THE THREE TYPES OF BRAIN TUMORS FOR FIGSHARE DATASET

Tumor Type	Precision(%)	Recall(%)	Specificity(%)
Glioma	96.02	97.00	96.00
Meningioma	93.78	86.98	98.19
Pituitary Tumor	94.48	97.10	97.47

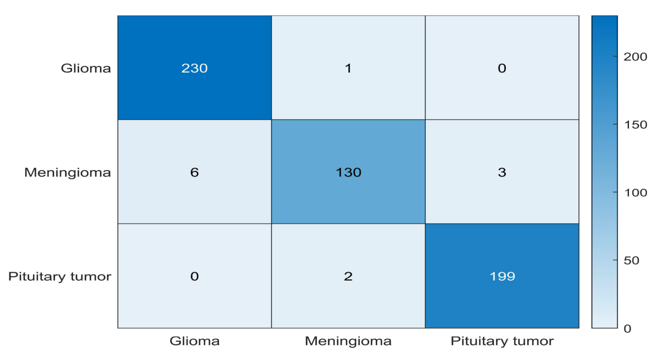
From the above confusion matrices, precision, recall and specificity can be calculated for each class of tumor. Also, the performance of the proposed model is evaluated in terms of F1-Score and classification accuracy. The F1-Score is calculated from (10) whereas, the precision and recall values are calculated using (7) and (8) respectively. These values are initially calculated from the output values of neurons in the f_c. Later on, these values are used for the performance measure using the formula mentioned above in (2). Table III depicts the performance measure of various types of tumors from Figshare dataset



(a)



(b)



(c)

Fig. 6. Confusion matrix of the proposed model. (a) proposed GoogLeNet using softmax classifier, (b) proposed GoogLeNet using SVM classifier and (c) proposed GoogLeNet using K-NN classifier.

using the proposed GoogLeNet in terms of precision, recall and specificity.

Further, the extracted features from the proposed GoogLeNet is fed to the SVM classifier in order to improve the classification accuracy for 3-class classification problem. The same process is repeated using a K-NN classifier. Table IV and Table V illustrate the performance measure of the proposed model i.e GoogLeNet with SVM and GoogLeNet with K-NN in terms of precision, recall and specificity. The F1-Score is calculated for the proposed model and the average values are shown in Table VI.

TABLE IV
PERFORMANCE MEASURE OF THE PROPOSED MODEL (GOOGLENET+SVM) FOR FIGSHARE DATASET IN TERMS OF PRECISION, RECALL AND SPECIFICITY

Tumor Type	Precision(%)	Recall(%)	Specificity(%)
Glioma	98.76	97.24	98.93
Meningioma	94.71	95.80	98.40
Pituitary Tumor	98.40	99.20	99.30

TABLE V
PERFORMANCE MEASURE OF THE PROPOSED MODEL (GOOGLENET+K-NN) FOR FIGSHARE DATASET IN TERMS OF PRECISION, RECALL AND SPECIFICITY

Tumor Type	Precision(%)	Recall(%)	Specificity(%)
Glioma	98.41	98.02	98.63
Meningioma	95.55	94.57	98.65
Pituitary Tumor	97.78	99.10	99.01

TABLE VI
AVG. F1-SCORE OF THE PROPOSED MODEL

Proposed Model		Avg. F1-Score
GoogLeNet	Softmax	94.30
	SVM	97.35
	K-NN	97.24

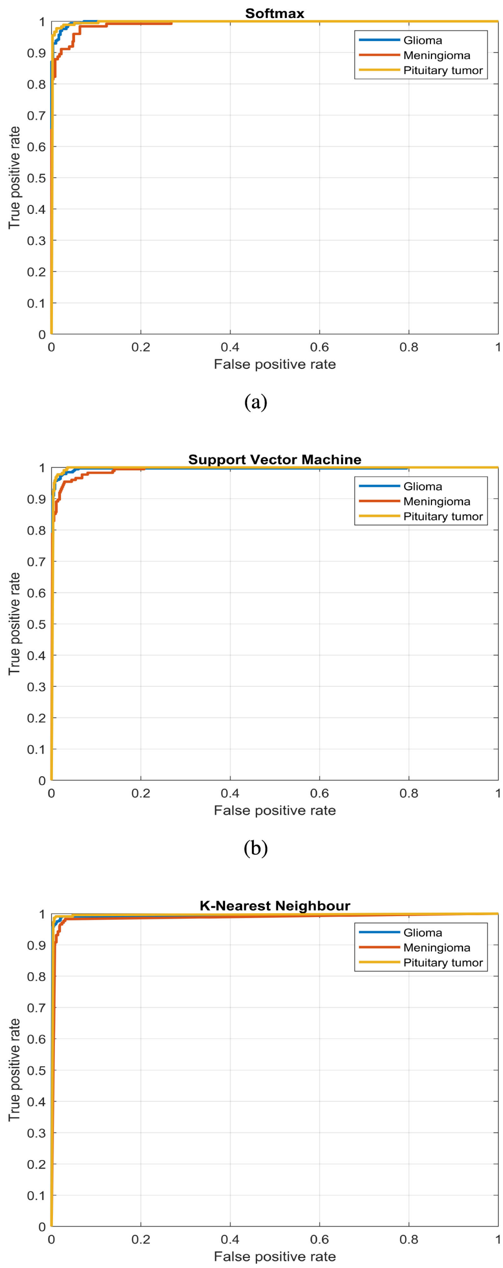
TABLE VII
COMPARATIVE STUDY OF THE PROPOSED MODEL WITH OTHER STATE-OF-THE-ART MODELS FOR FIGSHARE DATASET

Model	Features	Classifier	Accuracy(%)
Afser et al. [14]	CapsNet	Softmax	86.56
Afser et al. [15]	CapsNet	Softmax	90.89
Deepak et al. [27]	GoogLeNet	SVM	97.1
Nyoman et al. [12]	CNN	Softmax	84.19
Proposed model	GoogLeNet	Softmax	94.9
		SVM	97.6
		K-NN	98.3

The proposed model is compared with the other-state-of-the-art models for this specific 3-class classification problem. The classification accuracy signifies the performance of the proposed model. All the state-of-the-art models considered in this work are tested on the Figshare dataset. Table VII depicts the comparative study of the proposed model with other state-of-the-art models by Afsher *et al.* [14], [15], Deepak *et al.* [27] and Nyoman *et al.* [12]. It is evident from the table that the experimental results obtained using the proposed model is significantly better compared to the other state of art models. The extracted features obtained from the final f_c layer in the form of activation is fed to different classifiers namely softmax, SVM and K-NN. In literature, Deepak *et al.* [30] used the SVM classifier on extracted features from GoogLeNet and achieved a classification accuracy of 97.1% whereas,the proposed model integrated with SVM classifier produces a classification accuracy of 97.6%. It is further observed that the proposed model using K-NN classifier achieves the highest classification accuracy of 98%, compared to the other state-of-the art models.

E. Misclassification Analysis

The misclassifications by these classifiers are analysed through receiver operating curve (ROC). It is a graph in which



(a)

(b)

(c)

Fig. 7. ROC of proposed CNN. (a) Softmax, (b) SVM, and (c) K-NN.

true positive rate is plotted with respect to false positive rate. Fig. 7 illustrates the ROC of the proposed model. The calculation of area under curve (AUC) from ROC provides the information regarding the ability of the proposed model to distinguish various types of tumor. Higher values of AUC indicate better performance of the classifier. The AUC vlaues using softmax classifier are 0.9979, 0.9916 and 0.9973 for three types of tumors i.e., glioma, maningioma and pituitary respectively. Similarly, the AUC values using SVM classifier are 0.9949, 0.9926 and 0.9970 whereas, the values obtained using K-NN classifier are 0.9937, 0.9865 and 0.9954.

TABLE VIII
COMPARISON OF VARIOUS STATE-OF-THE-ART MODELS FOR HARVARD DATASET (4-CLASS BRAIN TUMOR CLASSIFICATION)

Model	Features	Classifier	Accuracy (%)
Mohsen et al. [29]	DWT	CNN	96.97
Deepak et al. [30]	CNN	Softmax	94.5
		SVM	98.7
Proposed model	GoogLeNet	CNN-Softmax	95
		CNN-SVM	100
		CNN-K-NN	100

F. Evaluation on Harvard Dataset

The experiment is further extended by considering a different dataset from Harvard medical repository [27], available at http://med.harvard.edu/AANLIB. The arrangement of the class considered here is a 4-class classification problem i.e., four different types of tumors, namely normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma. The Harvard dataset consists of a total 96 number of MRI images, of which 24 images belong to each class, i.e. normal category and the other three are malignant tumors. In this experiment, 80 % images are considered as training set and 20 % images are considered as test set. For this 4-class classification problem, the f_c layer of the proposed GoogLeNet is considered as four neurons. The proposed GoogLeNet features are classified using softmax, SVM and K-NN classifier. The classification accuracy obtained using softmax classifier is 95% whereas, SVM and K-NN classifier depict 100% classification accuracy. Table VIII illustrates the comparative study of the proposed model with the other state-of-the-art models by Mohsen *et al.* [29] and Deepak *et al.* [30] on Harvard medical repository dataset images. In our experiment, more number of training images is considered compared to the other two state-of-the-art models. It is inferred that the proposed model produces accurate classification results for the 4-class classification problem.

IV. CONCLUSION

The early detection of brain tumors using IoMT enabled CAD system is essential, which reduces the death rate. The classification of tumors ensure that the risk factor of the patient is reduced and early treatment can be provided by enabling IoMT based remote healthcare system. In this paper, we have successfully implemented a transfer learning based classification model for brain tumor classification from brain MRI images of Figshare dataset. The proposed model requires minimum data pre-processing. In comparison to the other state of art models, proposed model showcases the highest classification accuracy for 3-class tumor classification problem. Further, the proposed model also achieves better results in terms of precision, recall, specificity and F1 score. The experimental results obtained from the proposed method outperform the state-of-the-art traditional ML methods as well as the other state-of-the-art CNNs for the Figshare datatset. Furthermore, the proposed model produces better classification results for 4-class tumor classification problem for Harvard medical repository dataset images. In future, our work can be extended by increasing the number of classes for various brain related diseases such as secondary tumors, Alzheimer's disease, etc.

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