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A Hybrid Deep CNN-SVM Approach for Brain Tumor Classification

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Abstract

Background: Feature extraction process is noteworthy in order to categorize brain tumors. Handcrafted feature extraction process consists of profound limitations. Similarly, without appropriate classifier, the promising improved results can't be obtained.
Objective: This paper proposes a hybrid model for classifying brain tumors more accurately and rapidly is a preferable choice for aggravating tasks. The main objective of this research is to classify brain tumors through Deep Convolutional Neural Network (DCNN) and Support Vector Machine (SVM)-based hybrid model.
Methods: The MRI images are firstly preprocessed to improve the feature extraction process through the following steps: resize, effective noise reduction, and contrast enhancement. Noise reduction is done by anisotropic diffusion filter, and contrast enhancement is done by adaptive histogram equalization. Secondly, the implementation of augmentation enhances the data number and data variety. Thirdly, custom deep CNN is constructed for meaningful deep feature extraction. Finally, the superior machine learning classifier SVM is integrated for classification tasks. After that, this proposed hybrid model is compared with transfer learning models: AlexNet, GoogLeNet, and VGG16.
Results: The proposed method uses the 'Figshare' dataset and obtains 96.0% accuracy, 98.0% specificity, and 95.71% sensitivity, higher than other transfer learning models. Also, the proposed model takes less time than others.
Conclusion: The effectiveness of the proposed deep CNN-SVM model divulges by the performance, which manifests that it extracts features automatically without overfitting problems and improves the classification performance for hybrid structure, and is less time-consuming.

Keywords: Adaptive histogram equalization, Anisotropic diffusion filter, Deep CNN, E-health, Machine learning, SVM, Transfer learning.

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I. INTRODUCTION

The advancement of technology creates a huge impact on medical science. For different medical diagnoses, prediction and classifications are now accomplished by the basic theme of deep learning. Brain tumor is the term used to describe abnormal growth of brain tissue [1]. It is found that 120 different forms brain tumors exist. But not all of them are cancerous types. The American Society of Clinical Oncology (ASCO) published their survey in 2020 which said 18,020 adults died of cancerous types of brain tumors and central nervous system (CNS) tumors [2] in the US. Their survey explored that brain tumor is the tenth cause of death [2]. Again, the American Cancer Society states that different types of tumors affect different ages of people in case of survival rate [3]. Early diagnosis of the brain tumor is necessary for effective therapy and patient survival [4].

The abnormal growth of cells fills up the necessary space of the brain, and it becomes more life-threatening to the patient. Cancerous cell growth produces cancerous brain tumors, and this type of tumor is more hazardous. Among all types of tumors, glioma, meningioma, and pituitary are the most frequent types [5]. Glial cells pro-duce glioma tumors, growth of meningioma tumors starts from the dura mater, and the pituitary gland is the originating place for pituitary tumors [5]. Classifying the many types of brain tumors is a difficult problem, but deep learning has already been used in many research projects. X-ray, Magnetic Resonance Imaging, CT scan or Computed Tomography are the most popular forms for medical imaging and CAD system classification processes. This type of image classification is an accelerated procedure and more flawless than manual detection.

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In the beginning, shifting of classification process from manual to machine-depended process was not easy. Preprocessing steps, post processing steps, and feature extraction steps are predetermined steps for classifying images using computer aided design (CAD) system process. For efficient classification, image preprocessing has appreciable benefaction [6,7]. Commonly used preprocessing steps like resizing, noise filtering [8], image smoothing, brightness enhancement, morphological filtering [9], and others are applied to the MRI. After that, the image post-processing technique is used for extracting the tumor region from MRI using various segmentation processes [6,8,10,11]. Following this, another highly significant part of the classification process is feature extraction. Effective feature extraction algorithms are applied to processed images. Classifier then predicts types based on those features. With the advancement of technology, Machine Learning (ML) ah resulted in a revolutionary change in image classification. This process is more accurate and straightforward. In that case, Artificial Neural network (ANN) [12-13], Support Vector Machine (SVM) [14], K Nearest Neighbor (KNN) [15], Random Forest Algorithm (RFA) [16], etc. are the most used image classifiers. The inability of complex feature extraction of handcrafted feature extraction process is counted as a CAD system limitation. In some cases, handcrafted feature extraction process fails to extract deep features, and this causes misclassification.

Deep learning (DL) is recognized as a sub-region of the ML sector. It assigns the potentiality to a computer or machine to take the decision, and has the learning capability from data. DL approach has increased the effectiveness of image classification. It is improving machine intelligence for medical image classification. It removes the complication of segmentation process selection, features extraction process selection, and classifier selection for the dataset. This process is less preprocessing dependent. The layers of the DL model pass through a learning process. Different layers use different numbers and sizes of filters for this learning. The last layer decides the output classes.

It is difficult to accurately extract features and classify brain tumors from MRI scans. In some cases, the softmax layer fails to provide a maximum accurate prediction of the test set. SVM is one of the most superior ML classifiers, which can reduce the misclassification of the multiclass dataset. With the encouragement of these facilities, this research work presents a hybrid brain tumor classification technique using a deep CNN-SVM structure which shows significant improvement. An effective DCNN is proposed to extract deep features, and SVM is employed to classify the MRI images. This research also applies resizing, anisotropic diffusion filter, and adaptive histogram equalization preprocessing techniques to ameliorate the classification performance. In addition, for more analysis, different transfer learning pre-trained models (AlexNet, GoogLeNet, VGG16) are also employed on the pre-processed data to observe the variation of the result. Handcrafted feature extraction sometimes fails to provide accurate results and thus leads to degrade the effectiveness of model. The hybrid structure avoids the conventional limitations and provides the core facilities of both models, which are the prime novelties for proposed brain tumor classification process.

The remainder of this paper's structure is as follows: analogous works, other pre-trained models, and background studies are explained in Section II, Section III provides a brief overview of the suggested model, various evaluations of outcomes are exhibited in Section IV, discussion is in Section V and the work is concluded at Section VI.

II. LITERATURE REVIEW

The classification process of brain tumors has been improved for the various artificial intelligence algorithms. This process consists of some essential steps. The two major steps are feature extraction from MR images and the other is a classification based on extracted features. Researchers have been working in this field from to improve this classification process from the conventional way. Some works are demonstrated in detail in Table 1.

Table 1 shows the foremost details of various previous works in this field. Biswas et al. [5] worked with the same dataset as this proposed method, but the major limitations were: using a lower number of data, huge MRI processing cost, and lesser accuracy. Damodharan et al. [17] worked to detect brain tumors through a neural network and employed an immense number of steps of preprocessing. Four types of features were extracted, and for the classification process, they employed a feed-forward neural net-work of 24 neurons. The authors also used two more classifiers for more evaluation: KNN and Bayesian. The observation found the highest accuracy, 83%, for the NN network. This work was trained and tested with a very small amount of data which was the major limitation of this work. In the machine learning classification technique, misclassification increases when the data number increases. Again, small data causes the overfitting problem in the neural network. In [18], Abiwinanda et al. proposed a fully CNN-based feature extraction and classification process, and the authors avoided any kind of preprocessing steps. Softmax classification layer failed to provide accuracy higher than 84.19% for the same dataset used in this method. So, the effectiveness of preprocessing steps and the CNN-SVM model of the proposed method is clearly contemplated from this. Khan et al. [19] proposed a brain tumor classification process by transfer learning. They used VGG 19 model and fine-tuned it before using it. VGG 19 is a deep CNN model where the model comprised in 16 convolutional layers and three fully connected layers. The author employed 5-fold cross-validation, and 94.82% was the best result.

Transfer learning consists of complex networks, and it takes a greater amount of time than simple CNN for complex computation.

TABLE 1
PRECEDING RESEARCH WORKS

References	Dataset	Number of classes	Preprocessing and post-processing	Feature Extraction	Classification	Major Findings or Contribution
A. Biswas el al. [5]	Figshare Dataset, utilized 563 MRI	3; Glioma, Meningioma, and Pituitary	Image resizing, sharpening filter, contrast enhancement, K-means clustering	Discrete Wavelet Transform with PCA	Feed Forward Artificial Neural Network	95.4% accuracy
Damodharan et al. [17]	20 image MRI	2; Tumor, no tumor	Skull stripping, thresholding, morphological filtering, region-based masking	Feed-Forward Neural Network	KNN and Bayesian	83% accuracy for KNN classification
N. Abiwinanda et al.[18]	Figshare Dataset, 3064 MRI	3; Glioma, Meningioma, and Pituitary	No preprocessing	Convolution Neural Network	Convolution Neural Network	Evaluate optimal CNN architecture from proposed 7 architectures, obtained 84.19% validation accuracy without any preprocessing cost.
Z. N. K. Swati et al. [19]	Figshare Dataset, 3064 MRI	3; Glioma, Meningioma, and Pituitary	Intensity normalization	Deep feature extraction using AlexNet, VGG 16 and VGG 19	AlexNet, VGG 16 and VGG 19	Adaptation of 5-fold cross validation, fine tuning transfer learning and obtained 94.82% accuracy for VGG 19.
Pashaei et al. [20]	Figshare Dataset, 3064 MRI	3; Glioma, Meningioma, and Pituitary	-	CNN	SVM, RBF, KELM	Using hybrid model and 93.68% accuracy for KELM classifier.
Jun Chen et al. [13]	Figshare Dataset, utilized 3064 MRI	3; Glioma, Meningioma, and Pituitary	Intensity normalization, ROI, augmentation	Intensity histogram, GLCM and BoW	BoW-based tissue classification and SPM scheme	Using augmented region of tumor, partitioning of ring-form, improving accuracies up to 87.54%, 89.72%, and 91.28%.
Narmatha et al. [22]	BRATs 2018, 66 cases for validation and 191 cases testing sets	-	FCM clustering	GLCM	Collaboration of fuzzy and brain-storm optimization methods	Utilizing different hybrid classifier and obtained 93.85% accuracy.
Kurmi et al. [23]	BRATs 2018, Figshare Dataset, utilized 3064 MRI	3; Glioma, Meningioma, and Pituitary	Image enhancement, tumor area initialization, masking, region refinement	Fisher vector, the autoencoder	SVM and MLP	91.76% average accuracy was obtained from MLP classification
Fatih et al. [24]	TCGA-GB	2; Benign and malignant	Fuzzy-sure entropy (NS-EMFSE)	AlexNet	SVM and KNN	Obtained 95.62% accuracy for the CNN-SVM model and 90.62 % for the CNN-KNN mode

Different classification algorithms have already been implemented to detect brain tumors. Research has also been done with various hybrid models to explore better performance. Authors have implemented various hybrid classification methods in previous. A KE-CNN-based method was proposed by Pashaei et al. [20]. In the experiment, the authors used CNN for feature extraction, and the extreme learning machine was employed for the task of categorization. The proposed CNN architecture had four convolution layers and four pooling layers. The feature vector implementation in KELM was 93.68% higher than SVM and RBF classifiers. Authors of the research work [21] utilized conventional feature extraction methods and classified the tumor types. However, authors applied various types of feature extraction methods to evaluate the best performer. On the other hand, this proposed work employed deep feature extraction scheme and obtained higher performance for this same dataset. In [22], Narmatha et al. proposed a slightly different algorithm that collaborated with fuzzy and brain-storm optimization methods. But they had to consider MRI processing cost by using FCM clustering and a typical feature extraction process by GLCM. In contrast, this proposed method used deep CNN for feature extraction, which is capable of learning in-depth features from the medical images, and this is an automated process.

The above discussion gives a comprehensible conception of past works and the new findings of this proposed method. Authors of this proposed method avoid the conventional handcrafted feature extraction. As there are more than 3000 MRIs in the dataset and augmentation is performed, deep feature extraction is more applicable in this case. Deep learning or CNN performs better when it is trained with a large amount of data and extracts satisfactory deep features. Machine learning classification with handcrafted feature extraction is not an expedient choice for this large data. As stated earlier, a variety of pre-trained deep learning models need more time to train than custom CNN models and are made up of intricate networks. Another reason for using deep CNN is to avoid this complexity. The proposed deep CNN is integrated with the Support Vector Machine for technical provision. SVM can minimize the error of classification of multiclass data. SVM is the optimal hyperplane provider. and there is minimal computational complexity. For these significant reasons, the authors use a deep CNN-SVM model and obtain better performance than those mentioned in previous works in Table 1.

III. METHODS

This paper proposes a hybrid deep CNN-SVM-based algorithm to improve the classification process of brain tumor. Fig. 1 represents the complete workflow of the research work step by step. Firstly, some preprocessing steps are applied to MRI in the beginning to classify brain tumors. These preprocessing steps include resizing, noise reduction, and contrast enhancement. Secondly, data augmentation is performed to increase the data number and introduce data variety. Thirdly, augmented data are inputted to the proposed DCNN to extract the features. Then classification task is performed by SVM. This research work also includes transfer learning models: AlexNet, GoogLeNet, and VGG16. In [5], the authors describe how the first approach was taken with ANN for brain tumor classification. The authors aimed to bring improvement in that where a method will work effectively, like [19] but that pretraining the network is time-consuming. In [1], the authors introduce a hybrid model. The authors of this paper sought for a far-out method which can provide an improved outcome along with a new concept.

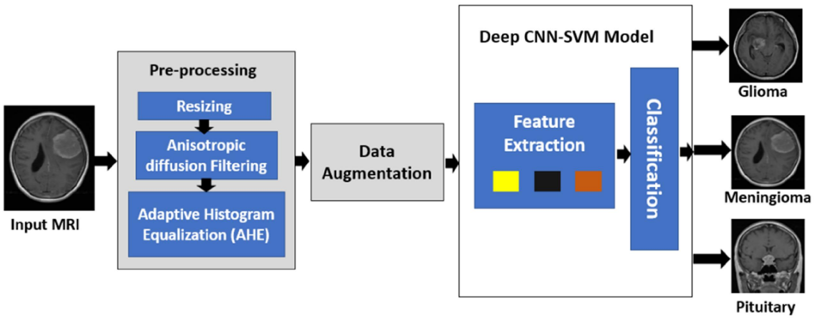


Fig. 1 Proposed methodology's Workflow

A. Dataset

For this research, a dataset of brain tumors is collected from "Figshare" [25], which is publicly available and was introduced by Cheng in 2017. This dataset contains three types of tumors where number of Glioma MRIs is 1330, the number of Meningioma MRIs is 697 and the total Pituitary MRI is 930. This paper uses a total of 2957 MRIs, and all of those are 512 × 512 pixels dimension and T1-weighted. Downloaded data are then passed for preprocessing in which 80% MRIs of the total amount of data are taken for network training, and the rest of them are utilized for validation. Three different views of MRI images can be found here: axial, coronal, and sagittal. Fig. 2 shows three different capturing views of MRI. Fig. 2(a) represents the axial view of MRI, Fig. 2(b) shows the coronal view of MRI, and Fig. 2(c) presents the sagittal view of MRI sequentially.

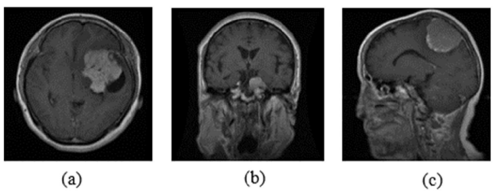


Fig. 2 MRI image from three different views (a) axial (b) coronal (c) sagittal

B. Preprocessing

1) Image Resizing

Although a dataset can be compressed using photos of various sizes, the neural network must be fed images of the same size. Again, the 512×512 pixels dimension of this MRI dataset is large enough and can take much computational time in DCNN training. There is also a memory consumption issue. Resizing the image means changing the information of the previous image to new pixel information [26]. So, it is preferable to scale down the image. and then input it to CNN. To work with AlexNet, 227× 227× 3 dimensions are required, and images are resized into this pixel size. For GoogLeNet and VGG16 models, images are converted to require dimensions 224× 224× 3 pixels [27]. Then 224× 224× 3 pixels images are used for the proposed custom deep CNN model.

2) Noise Reduction

Noise reduction is performed after resizing the image. The proposed method utilizes an 'Anisotropic diffusion filter' for noise reduction. MR images could be contaminated with noise, which hampers image classification performance [28]. An image corrupts through the noise by replacing the image pixels value with noise value, and, for that reason, noise reduction is an essential step for medical image processing [29]. Anisotropic diffusion filter works better as noise removal for MRI than other conventional filters [30]. This filter can appropriately remove the blur texture and recover the edge from noise [29]. This filter performs better than the Gaussian blur effect and denoises image preserving edge sharpness where estimated parameters are used. With the help of coefficient of constant diffusion, the filter equation solves the equation of heat. Thus, filtered images have greater signal to noise ratio, so, noise never interferes with the CNN model. Perona and Malik [30] provided the first famous anisotropic diffusion filter equation, which is given in (1) [30], and for that, they are popular as the "Perona and Malik diffusion" [29].

$$I_t = \text{div}\,(C\,(\Omega,\, t)\,\nabla\, t) = C\,(\Omega,\, t)\nabla\, t + \nabla\, C\nabla I \quad (1)$$

where, div = divergence operator, ∇ = gradient operator, t = time steps of iterations, C= conduction coefficient.

3) MRI Contrast Enhancement

Contrast enhancement of MRI has been done after performing the noise reduction using the 'AHE algorithm.' Poor image contrast degrades image classification performance. Enhancement of image contrast upgrades the visual representation of MRI [31]. In general, a histogram is the process of graphical representation, and it represents an image in various frequencies [32]. Adaptive Histogram Equalization (AHE) is one of the best contrast enhancement techniques for medical images [33]. In order to increase the brightness of low contrast MR images and make it simpler to detect the tumor further, the AHE algorithm is applied to MRI [32]. It modifies the mathematical value of image intensity and works on a small-scale region of the image [33]. This equalization technique is arranged into adaptive and non-adaptive types [34]. Pixels of non-adaptive use the exact calculation of the histogram of the real image. Pixels of adaptive are ordered by the nearest pixel. This zone is known as the contextual region [34]. Best result calculation includes moving the window of four neighbor pixel points as given in the equation following (2)

$$a = \frac{y - y_-}{y_+ - y_-},\ b = \frac{x - x_-}{x_+ - x_-} \quad (2)$$

Fig. 3 (a) represents the histogram of the original MRI and Fig. 3 (b) indicates the histogram of preprocessed MRI. The graph's X-axis represents intensity levels and the Y-axis of the graph indicates the number of pixels. The histogram is usually done to visualize the grayscale distribution of an image concerning frequency. From the histogram graph, it is clear that the second graph shows better use of the grayscale range. Better use of grayscale rage indicates high contrast and provides distinguishing visuality. Fig. 3 (a) cannot provide more detail, and it has a low histogram distribution. In the case of image analysis, high contrast image highlights the image features.

Fig. 4 displays the image preprocessing steps from the original MRI for three different types of brain tumors. Fig. 4 (a) represents the original 512 × 512 pixels dimension of MRI. After that, these images are filtered using an anisotropic diffusion filter to reduce the noise level, which is shown in Fig. 4 (b). Then image contrast is enhanced by applying Adaptive Histogram Equalization (AHE) which is displayed in Fig. 4 (c).

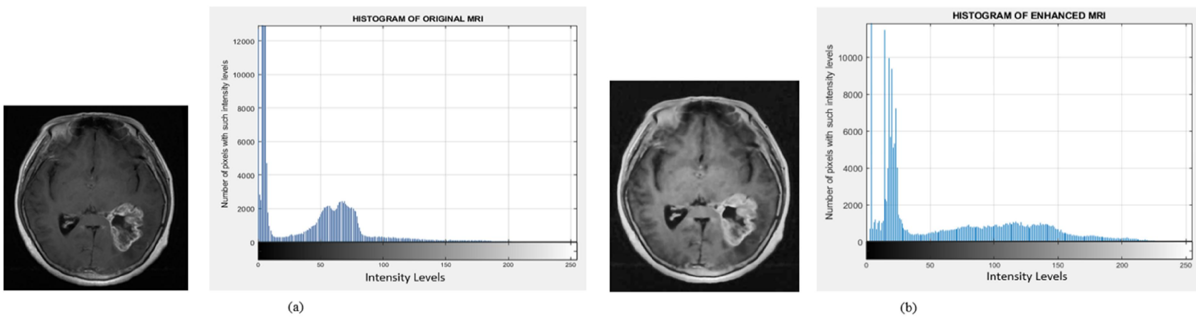


Fig 3. Histogram representation of (a) Original MRI (b) Preprocessed MRI

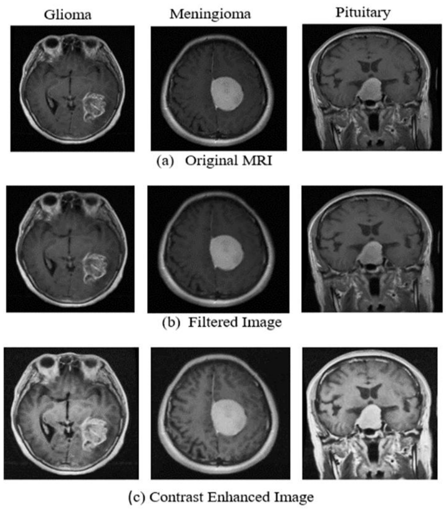


Fig. 4 Preprocessing steps for three types of brain tumor MRI (a) original MRI, (b) Filtered images for noise reduction, (c) Contrast enhanced images

The advancement of network robustness depends on data augmentation and helps in classification accuracy [36]. Image augmentation has excellent significance in MR image classification as it is difficult to generate large amounts of medical images for a network model to train with various data [37][38]. The authors also use data augmentation to enhance the network flexibility and increase the MR images. Implementation of data augmentation types is put together in Table 2. Table 2 represents the augmentation types and their corresponding values for the MRI brain tumor classification.

TABLE 2
APPLIED TYPES OF AUGMENTATION AND PARAMETERS

Augmentation	Value
Vertical Scaling	[1 2]
Horizontal Scaling	[1 2]
Horizontal Shear	[-5 5]
Vertical Shear	[-5 5]
Horizontal translation	[-10 10]
Vertical Translation	[-10 10]

C. Proposed DCNN-SVM Approach

This research presents the DCNN-SVM method for brain tumor classification. Preprocessed and augmented data are used for DCNN training, whereas DCNN is used for features extraction. After features extraction, features are passed for the classification process to classify three types of brain tumors through SVM. Then extracted features from the fully connected layer are inputted to SVM for final classification.

1) Deep Custom CNN for Feature Extraction

Fig. 1 exhibits the workflow of the proposed research work from input to the classification process. Original MRI is preprocessed before feature extraction or classification. Then, augmentation is implemented to preprocessed images, and augmented data are inputted into the proposed DCNN-SVM model. The suggested DCNN-SVM model is shown in Figure 1, with the DCNN being composed of five convolutional layers, four pooling layers, and two fully linked layers. Details of each building block are given in Table 3. MR images of 224×224×3- dimension are inputted into the network, and the first convolution neural network uses 54 filters. This convolutional layer uses a 3×3 kernel. The applied activation function is ReLU. Then down-sampling is done by max-pooling layer. The second convolutional layer uses 84 filters with a 3×3 kernel. Max-pooling is performed again, and then the third convolutional layer takes place. This layer uses the same kernel as previously with 124 filters. After that, max-pooling is performed to downscale the input image. Block 4 performs similarly with the 184 number of filters. The final block of the convolutional layer uses 224 filters with an activation layer, and then this output is sent to the fully connected layer. Then, 3-dimension values are converted into one-dimension and the first FC layer has 100 neurons. The final or output layer has three neurons for three types of tumors. To evaluate the DCNN classification result, the softmax classifier is used. Table 3 contains the detail of each block and other calculations. 387. Total learnable parameters are 9,53,387 for this proposed DCNN architecture. Table 4 indicates the hyperparameter setting of the proposed method. With this setup, the model is used for training which takes a certain amount of time and then results are observed. The softmax layer provides the classification result which is collected for record but actually extracted features are delivered to the SVM model for further evaluation.

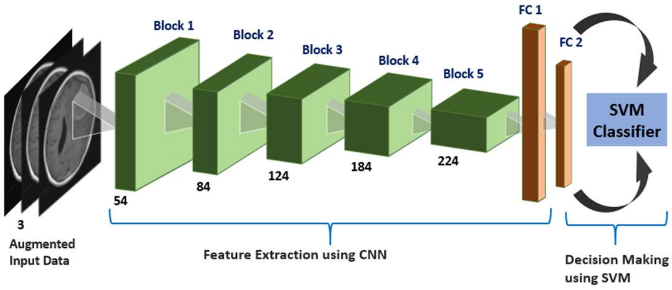


Fig. 5 Proposed DCNN-SVM structure for brain tumor classification

2) *SVM for Classification*

Support Vector Machine is a quick-learning method that requires little compute and may construct impressive accuracy. It is capable of handling a lot of data and is generally used for multiclass classification. The main goal of this proposed work is to extract the features of the image through DCNN and classify the tumor types using an SVM classifier. The SVM classifier is integrated with the DCNN by replacing the CNN softmax classifier. Obtained features from the FC layer are taken for classification. This proposed method employs multiclass SVM classifier function 'fitcecoc' in MATLAB and the amount of support vectors were K(K-1)/2. This proposed method employs multiclass SVM classifier in MATLAB. Table 5 is the record of the SVM parameter for the proposed classification. Fig. 5 indicates the block diagram of proposed DCNN-SVM approach where each layer output dimension is expressed clearly. The last layer is replaced by SVM classifier. After setting all these, training is performed with the dataset. Outcome is observed to evaluate it with respect to CNN result. Various evaluation parameters are used to estimate the outcome from various perspectives more perfectly.

TABLE 3
PROPOSED DCNN ARCHITECTURE DETAIL

Block	Layer Type	Number of filters	Kernel Size	Stride	Padding	Activation shape	Activation Size	#Parameters
	Input MRI	-	-	-	-	(224×224×3)	150528	0
Block 1	Conv layer	54	3×3	1	1	(222×222×54)	2661336	1512
	Batch Normalization layer	54	-	-	-	(222×222×54)	-	-
	ReLU layer	54	-	-	-	(222×222×54)	-	-
	Max pooling layer	54	2×2	2	0	(111×111×54)	665334	0
Block 2	Conv layer	84	3×3	1	1	(109×109×84)	998004	40908
	Batch Normalization layer	84	-	-	-	(109×109×84)	-	-
	ReLU layer	84	-	-	-	(109×109×84)	-	-
	Max pooling layer	84	2×2	2	0	(54×54×84)	244944	0
Block 3	Conv layer	124	3×3	1	1	(52×52×124)	335296	93868
	Batch Normalization layer	124	-	-	-	(52×52×124)	-	-
	ReLU layer	124	-	-	-	(52×52×124)	-	-
	Max pooling layer	124	2×2	2	0	(26×26×124)	83824	0
Block 4	Conv layer	184	3×3	1	1	(24×24×184)	105984	205528
	Batch Normalization layer	184	-	-	-	(24×24×184)	-	-
	ReLU layer	184	-	-	-	(24×24×184)	-	-
	Max pooling layer	184	2×2	2	0	(12×12×184)	12096	0
Block 5	Conv layer	224	3×3	1	1	(10×10×224)	22400	371168
	Batch Normalization layer	224	-	-	-	(10×10×224)	-	-
	ReLU layer	224	-	-	-	(10×10×224)	-	-
-	FC layer 1	-	1×1	1	0	(100×1)	100	240100
-	FC layer 2 / output layer with a softmax classifier	-	1×1	1	0	(3×1)	3	303

Network parameters are important factors for the performance of the constructed network. Table 4 contains the parameters and values which are used in this experiment. Table 5 explains more about the classifier model.

TABLE 4
NETWORK HYPERPARAMETER SETTING

Parameters	Values
Optimizer	SGDM (Stochastic Gradient Descent with momentum)
Epochs	10
Learning Rate	1e-2
Validation frequency	10

TABLE 5
SVM PARAMETER SETTING

Parameters	Values
SVM type	Multiclass SVM classifier
Solver	Linear kernel
SVM Model	1-vs-all by default designed

D. DCNN of Transfer Learning

Along with the proposed method, the authors use a few transfer-learning models (AlexNet, GoogLeNet, and VGG16) for preprocessed and augmented dataset to assess the effectiveness of the suggested approach. In Figure 6, the model is fine-tuned to use the AlexNet model. Images are resized by 227× 227× 3 dimensions for the AlexNet model. Images are resized by 224× 224× 3 dimensions for GoogLeNet, VGG-16 models. The last fully-connected layer is fine-tuned with three channels for brain tumor classification.

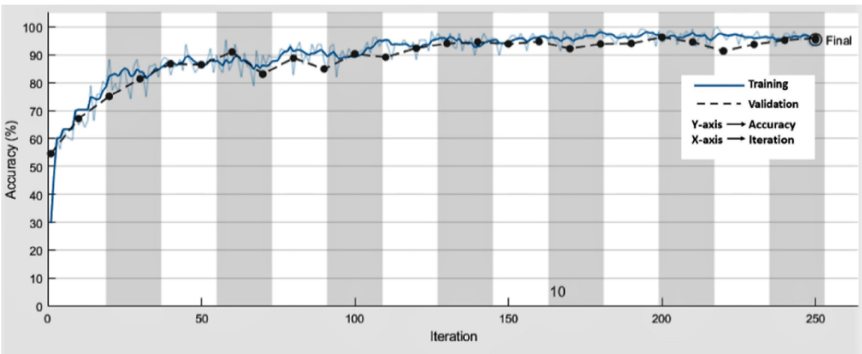
IV. RESULTS

A. Experimental Environment

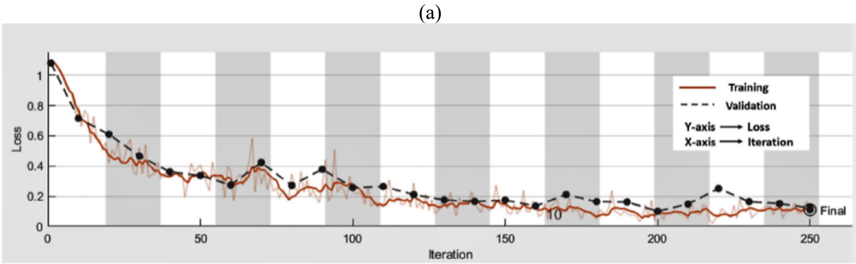
The experiment is conducted on a Core i5-7200U processor laptop. The hardware resource is a single CPU. MATLAB 2018a (Release 2018a of MATLAB and Statistics Toolbox, The MathWorks, Inc., Natick, Massachusetts, USA) version is chosen for this experiment. The proposed DCNN-SVM model and other transfer learning models are also implemented in this environment.

B. Performance of Proposed Method

The proposed method and pre-trained models are compiled using the "SGDM algorithm" for optimization. Optimization is an essential factor in optimizing the network. SDGM algorithm is the best performance provider and it is also fast. Networks are trained with preprocessed, and augmented data. The training progress of networks is shown in Fig. 6.



(a)



(b)

Fig. 6 (a) Accuracy Vs. Iteration (b) Loss Vs. Iteration training progress graphs of proposed DCNN model

Fig. 6 shows the training progress via iterations as a blue line, the red line presents the loss of data with iterations, and the black dotted line presents validation accuracy with iterations. Fig. 6 is obtained when the learning rate is 0.01, validation frequency is 10 iterations, and 18 epochs are set for training the proposed deep CNN model. Fig. 6 (a) exhibits that proposed model is overfitting free and gradually increases the classification prediction performance. Similarly, Fig. 6 (b) exhibits that misclassification or loss decreases with the iterations and is appropriately optimized. The experimental value for AlexNet, GoogLeNet, and VGG16 models is recorded in Table 6. The proposed CNN model provided higher validation accuracy among all of those models.

To evaluate the performance, some parameters need to be discussed. Network performance is evaluated from different parameters and those are expressed through some equations. The following mathematical equations are given below:

$$\text{Accuracy}=\frac{\text{TP + TN}}{\text{TP + TN + FP + FN}} \times 100 \tag{3}$$

$$\text{Recall or Sensitivity} =\frac{\text{TP}}{\text{TP + F N}} \times 100 \tag{4}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN + FP}} \times 100 \tag{5}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}} \times 100 \tag{6}$$

$$\text{F-measure}= 2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{7}$$

here, TN= True Negative, TP= True Positive, FN= False Negative, FP= False Positive.

Accuracy is the allover classification obtained accuracy. Acceptability of the classifier for classifying tumor types correctly is indicated by recall or sensitivity. Acceptability of the classifier for forecasting negative conditions is indicated by sensitivity. Precision is popularly known as positive predictive rate (PPR). Performance of classification concerning precision and recall value is measured from the F-measure equation.

TABLE 6
VARIOUS RELATIONS IN THE MODEL AND THEIR IMPORTANCE

Model	Validation Accuracy	Running Time	Iterations
Proposed DCNN+Softmax	95.42%	25 min 1 sec	250
Proposed DCNN-SVM	96.00%	26 min	250
AlexNet	93.05%	32 min 38 sec	250
GoogLeNet	89.39%	285 min 25 sec	288
VGG 16	85.24%	521 min 1 sec	370

Table 6 exhibits validation accuracy, running time, and iteration taken for implemented proposed DCNN-SVM model, AlexNet, GoogLeNet, and VGG16 models. The outcome show that the presented model's classification accuracy of three types of brain tumors is higher than other models with minimal running time. After the proposed model, 93.05% accuracy with 32 min 38 sec running time is exhibited by AlexNet. Again, 89.39% validation accuracy is provided by the popular transfer learning model GoogLeNet where the running time is near five hours. VGG 16 is another conventional pre-trained model deeper than GoogLeNet and takes more than eight hours for 85.24% validation accuracy. It has appeared that GoogLeNet and VGG-16 take a vast amount of time, and it is a defeatist side of using these two models providing inferior outcomes to the proposed method. The proposed DCNN classifier provides 95.42% validation accuracy, and with the utilization of the SVM classifier, the accuracy is gained up to 96%. This table represents that the proposed DCNN-SVM model provides satisfactory accuracy, and it can classify brain tumors more accurately than other models. Thus, the DCNN-SVM method is more effective. Overall, the proposed DCNN-SVM approach offers significant state-of-the-art results without a feature selection process as DCNN performs the feature extraction process automatically, and SVM improves the classification performance of tumor types.

Because of network depth, different networks take different times for the same dataset. Increment of the depth of network increase the training time. The record of time consumption of different models is also represented in Table 6, where the proposed DCNN-SVM model takes less than 26 minutes. The training and validation are finished by AlexNet within 32.63 minutes, 285.42 minutes are taken for training progress by GoogLeNet and521.01 minutes are required for the VGG 16 network, which is the most time-consuming case.

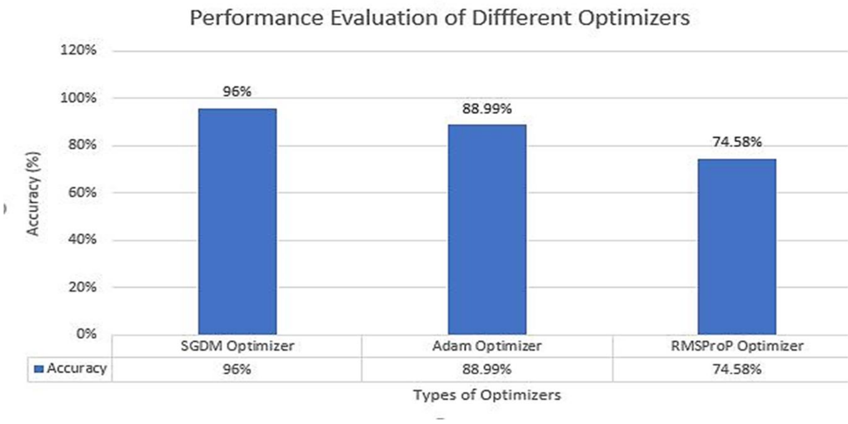


Fig. 7 Performance evaluation of the proposed method using different optimizers

The proposed DCNN-SVM model is also executed with 'Adam' and 'RMSProp' optimizers to evaluate the outcome for optimizer variations. Stochastic Gradient Descent (SGD) optimizer prevents computational redundancy [39]. Optimization acceleration is accomplished by using the "momentum" parameter with the SGD method [39]. The "Adam" optimizer, which is an enhanced version of the stochastic gradient technique, is referred to as adaptive moment estimation [39]. The Adam optimizer is effective and uses less memory [40]. It includes the feature combinations AdaGrad and RMSProp [40]. Moving average is used in Root Mean Square Propagation, or RMSProp, optimization to determine the continuously per weight of squared gradients [41]. By calibrating, the network performance may be enhanced [41]. The "SGDM" optimizer achieves classification accuracy for the proposed DCNN model. The suggested DCNN model with a 0.01 learning rate is further subjected to the use of two alternative optimizers for experimental purposes to explore the functioning. The outcome is shown in Fig. 7. Fig. 7 demonstrates that the SGDM optimizer outperforms the other two optimizers at classifying brain tumors using this dataset.

This experiment is conducted with 80% of training data. For evaluation, the number of data are reduced up to 25% in the case of training, which is shown in Table 7. It is observed that more image data in training provides more accuracy. More training data means networks contain more information and provide higher accuracy. A large number of data works for model perfection. However, a lower number of data takes less training time than 80% of training data. Classification accuracy is increased with the increment of the amount of training data. A lower amount of training provides lower accuracy as the network gets less provision to learn. For that reason, the network cannot make better predictions with poor learning.

TABLE 7
PERFORMANCE EVALUATION WITH THE TRAINING DATA REDUCTION

Training Data	Validation Data	Accuracy
25%	75%	90.33%
50%	50%	92.81%
70%	30%	94.69%
80%	20%	96.00%

To understand the impact of different learning rates, the proposed DCNN-SVM model is employed with different learning rates for all observations where other parameters remain the same.

TABLE 8
DIFFERENT LEARNING RATES AND OUTCOMES

Learning rate	Accuracy	Sensitivity	Specificity	Precision	F-measure
0.00001	55.9%	51.79%	93.18%	97.74%	67.70%
0.0001	68.98%	70%	91.32%	92.11%	79.80%
0.001	89.83%	92.39%	96. 49%	95.86%	94.09%
0.01	96.00%	95.71%	98.00%	99.69% ≈ 100%	96.92%
0.03	90.08%	94.74%	94.14%	92.99%	93.85%
0.04	90.5%	91.13%	97.08%	96.62%	93.79%
0.05	66.8%	76.42%	83.24%	80.45%	78.38%

The learning process is accelerated with the increase in the learning rate [27]. The loss function decreases fast with a higher learning rate, and decrement of the loss function is time-consuming if learning rate is low [27]. In Table 8, variation of accuracy is observed with the variation of learning rate. Accuracy is observed with the increment of the learning rate. Proposed DCNN-SVM model is trained with 0.00001, 0.0001, 0.001, 0.01, 0.03, 0.04, 0.05 learning rate. It is shown that accuracy rises with the learning rate increment, but accuracy starts to fall off at a certain amount. For every observation, the epoch value is kept at 10. Accuracy is increased up to 0.01 learning rate gradually. The highest accuracy is observed when the learning rate is 0.01. From the confusion matrix, other parameters are also calculated and recorded in Table 8.

In this data analysis subsection, the proposed DCNN-SVM model is employed with different epoch values, and for all observations, other parameters are kept the same.

TABLE 9
DIFFERENT EPOCH VALUES AND OUTCOMES

Epoch	Accuracy	Sensitivity	Specificity	Precision	F-measure
2	86.6%	88.93%	94.52%	93.61%	91.21%
4	89.0%	90.78%	96.75%	96.24%	93.43
6	91.2%	96.24%	96.60%	95.89%	96.06%
8	90.5%	91.525	97.72%	97.37%	94.35%
10	96%	95.71%	98.00%	99.69% ≈ 100%	96.92%

It is necessary to determine an optimum value of epoch for the experiment. In Table 9, accuracy is observed with the variation of epoch value. 2, 4, 6, 8, and 10 epoch values are taken for this experiment, and the learning rate is kept at 0.01 for all observations. It is observed that accuracy is increased with the increment of epoch value. The highest accuracy is observed at 96% when the epoch value is 10. Again, a higher epoch value takes higher iteration, and that is time-consuming. Performance is increased with the increased value of the epoch. From the confusion matrices, other parameters are calculated.

C. Utility of Preprocessing Steps of Proposed Method

To understand the effect of proposed preprocessing steps, without preprocessed MR images are inputted in the proposed CNN-SVM model. This experiment is done with the same hyperparameter setting of CNN-SVM. The outcomes are recorded in Fig. 8.

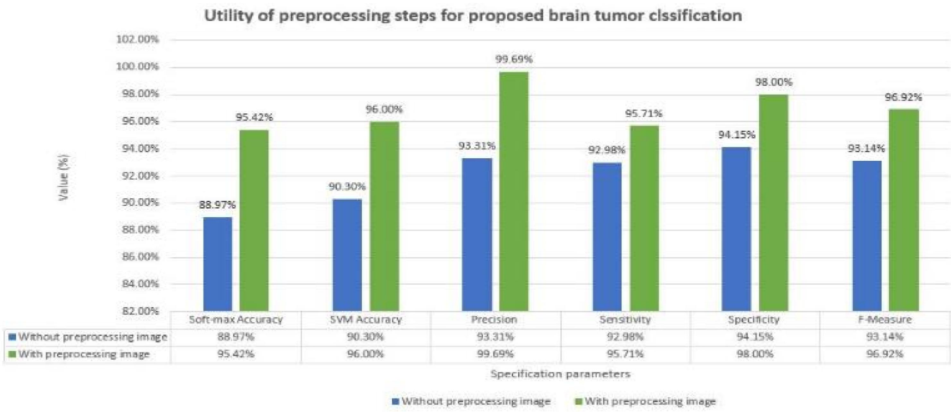


Fig. 8 The outcome of proposed CNN-SVM model with and without preprocessing images

Fig. 8 represents how the proposed deep CNN-SVM model performs without preprocessing data. Here the blue bar is an indication of without preprocessing images and green bar is the indication of preprocessed images. The result is decreased without preprocessing, and this exhibits that proposed preprocessing steps are exceedingly useful for classifying brain tumors. Accuracy is increased up to 5.7% when preprocessed MR images are utilized.

D. Comparison of performance parameters with transfer learning

Network parameters are generated and displayed in Fig. 9 to compare the proposed model's overall performance to transfer learning methods. Here, dark blue bar specifies the GoogLeNet, the orange bar discloses AlexNet, and the gray bar presents the proposed method. The confusion matrix is used to determine additional parameters through equations which are (3), (4), (5), (6), (7). Table 6 makes clear that VGG-16 provides lower accuracy than GoogLeNet and AlexNet, so others parameters are evaluated using GoogLeNet and AlexNet. After observing the values of the parameters, it can be stated that the presented DCNN-SVM model provides a better specificity of 98.00%, sensitivity of 95.71%, 99.69% precision, and 96.92% F-measure, which are better than the other two pre-trained models. The proposed DCNN-SVM is an indication of the higher value. The proposed model is exhibiting better performance.

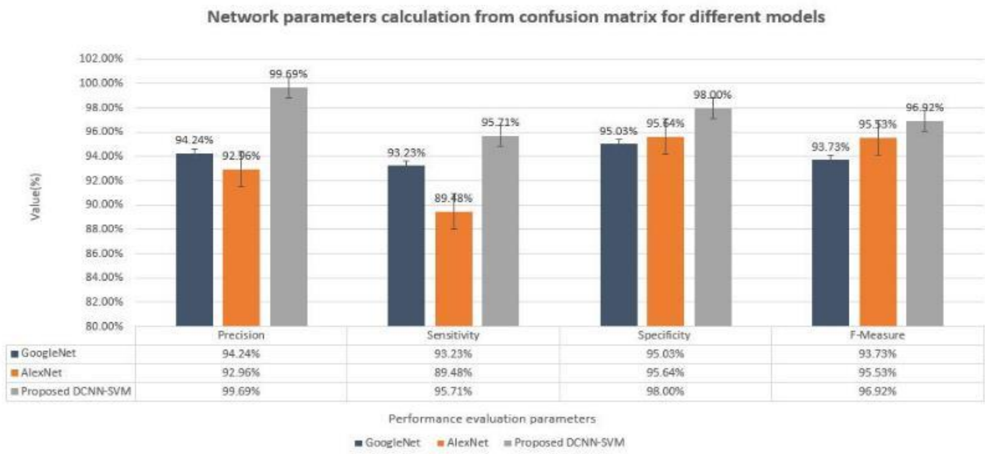


Fig. 9 Calculation of network parameters from multiclass confusion matrix for different models

E. A Comparison of Proposed Work with Existing Work

TABLE 10
COMPARISON OF PROPOSED WORK WITH PREVIOUSLY COMPLETED WORK

Reference	Publication year	Method	Accuracy
[17]	2015	Skull stripping+ Thresholding + Morphological filtering+ Region-based Masking+ Feed Forward Neural Network	83%
[24]	2019	NS-EMFSE + AlexNet-KNN	90.62 %
[21]	2015	Augmentation+ Intensity histogram+ BoW+ SVM	91.14%
[23]	2020	Image enhancement+ area initialization+ masking+ region refinement+ fisher vector-auto encoder + MLP	91.76%
[22]	2020	FCM + GLCM + FBSO	93.85%
[1]	2019	CNN-GA	94.20%
[19]	2019	VGG-19	94.82%
Proposed Method	-	Resizing + Anisotropic Diffusion Filter + Adaptive Histogram Equalization + DCNN-SVM	96%

Table 10 represents different methodologies for brain tumor classification. A variety of works were done in the past by different researchers [1], [17], [20], [21], [22], [24]. The author's proposed method is able to provide better results than others, which are shown in Table 10. Comparison of different methodologies and accuracy are recorded in Table 10.

All analysis and result evaluation make clear that the proposed method is effective enough for brain tumor classification. This hybrid model combines the efficacious properties of CNN and SVM algorithms. This hybrid model achieves 96% classification accuracy within minimal time, which is competitively superior to other previous methods and transfer learning networks.

V. DISCUSSION

For classifying brain tumor, the Deep CNN-based deep learning model is proposed, which is integrated with SVM. Brain tumor classification from MRI depends on some specific logic. MR image can be corrupted by noise, which can decrease the prediction rate [28]. Enhanced contrast MRI can provide more detail about that image rather than a poorly enhanced image [31]. Before initiating training and classification, preprocessing is done to ensure noise diminishing and contrast enhancement. Data augmentation is employed to increase the data number to train the model and increase the data variation for robustness [37]. Deep learning or machine learning-based classification technique has main motivation known as feature extraction. Better feature extraction is masterful in providing a better prediction. With this motivation, the deep CNN model is employed to extract features from MRI more precisely than handcrafted feature extraction. Mainly the network is trained through feature value, so it has significant importance. The proposed deep CNN model is capable of extracting features precisely for further prediction. This proposed model provides 95.42% classification accuracy. This model is integrated with an ML model SVM, and SVM classification accuracy is 96.00% which is slightly higher than normal CNN accuracy. This result verifies that SVM is capable of predicting brain tumor classes more accurately in this case. These are the basic strategies that are followed for better outcomes. To verify this outcome, the same preprocessing steps and augmented MRI are employed in three different transfer learning models (AlexNet, GoogLeNet, and VGG 16). Classification accuracy of these models are 93.05%, 89.39%, 85.24% subsequently. That means the proposed DCNN-SVM model presents better accuracy than the transfer learning model. Experimental time is also evaluated, and it is observed that the presented model requires less training and classification time. Evaluation matrices: sensitivity, precision, specificity, and F-measure of the proposed model are 95.71, 98.00%, 99.69, and 96.92%, consecutively, which is better than the other transfer learning models and recorded in Fig. 9. Performance variation of model with the variation of learning rate and epoch values are also experimented, and shown in Table 9, and Table 10. These previous works and our proposed methodology have various diversity. In, [42], the authors show a considerable improved accuracy from their research where they use GoogLeNet for brain tumor classification. The authors propose two approaches where f first they use only GoogLeNet for brain tumor classification and GoogLeNet-SVM for the second approach. Behind this notable accuracy, a few things are unsettled. These kind of pretrained networks take a huge amount of time, which is already explicated in this research and [42] does not make clear the time consumption. Again, for research work, [42] uses the dataset of three classes but in the description section four classes were explained. The proposed research clarifies the matter of accuracy, time consumption and network complexity. Similar research is done by [43] where malignant and benign type tumors are categorized by transfer learning model. This model is not used for feature extraction but used for classification. The authors utilize handcrafted feature extraction process and then those are used for Res Net 152 model to classify the tumor type. The authors obtained better accuracy but network complexity and time consumption are intensified to a large degree. In contrast to this method, the proposed method is a simplified form of tumor type classifier. Appropriate preprocessing of MRI, performing of augmentation, and proposed hybrid DCNN-SVM model work behind for providing more exact classification than others. Overall, this proposed method is sufficiently efficient but this will be more superior if another brain tumor MRI dataset is used to prove the model stability and performance. Again, this model can be developed as more predominant by getting the outcome of tumor size.

VI. CONCLUSIONS

In this study, a hybrid DCNN-SVM classification model for differentiating brain tumor kinds is presented. The deep CNN structure for deep feature extraction and the SVM for tumor class prediction make up the proposed DCNN-SVM structure. The deep CNN model includes 23 layers in all. Five convolutional layers, four max-pooling layers, and two fully linked layers make up the proposed DCNN model. Adaptive histogram equalization, resizing, and anisotropic diffusion filtering are used in the preprocessing of MR images before feature extraction. Then augmentation takes place, and SVM classification provides 96.00% accuracy. For more evaluation and comparative analysis, VGG-16, AlexNet, and GoogLeNet – three transfer learning models - are implemented. These pre-trained models are fine-tuned and then implemented. After evaluation of performance using accuracy, sensitivity, specification, precision, and F-measure, it is noted that the DCNN-SVM model offers the best outcome in comparison to others. The proposed method obtains 96.0% accuracy, where AlexNet, GoogLeNet, and VGG16 classification accuracies are 93.05%, 89.39%, and 85.24%, respectively. Again, this proposed model provides higher performance within less required time, where VGG-16 and GoogLeNet take huge execution time for training. Though this result is satisfactory, and this model provides better performance than some previous works, the authors are highly interested in improving this classification performance. In the future, the authors are interested in working with modified transfer learning and other hybrid models to classify brain tumors.

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