Brain MRI Classification using Deep Learning Algorithm

Sunita M. Kulkarni, G. Sundari

Abstract*: The brain tumor is one of the most dangerous, common and aggressive diseases which leads to a very short life expectancy at the highest grade. Thus, to prevent life from such disease, early recognition, and fast treatment is an essential step. In this approach, MRI images are used to analyze brain abnormalities. The manual investigation of brain tumor classification is a time-consuming task and there might have possibilities of human errors. Hence accurate analysis in a tiny span of time is an essential requirement. In this approach, the automatic brain tumor classification algorithm using a highly accurate Convolutional Neural Network (CNN) algorithm is presented. Initially, the brain part is segmented by thresholding approach followed by a morphological operation. The AlexNet transfer learning network of CNN is used because of the limitation of the brain MRI dataset. The classification layer of Alexnet is replaced by the softmax layer with benign and malignant training images and trained using small weights. The experimental analysis demonstrates that the proposed system achieves the F-measure of 98.44% with low complexity than the state-of-arts method.

Keywords*: AlexNet, Brain Tumor classification, MRI, Convolutional neural Network, Deep Learning.

I. INTRODUCTION

In the twentieth century, it observed that the rate of diseases is increasing rapidly. The brain is the vital and most multifaceted organ of the human being which is functional with billions of cells. The brain tumor is one of the cause which affects the proper functioning of the brain. It is solitary uncontrolled grows neurological tissue inside or around the brain [1,2]. The brain tumor is named according to the type of cell from which the cell/tissue grows. Tumors are classified as primary and secondary tumors. The tumor which is initiate and grown within the organ is called primary tumors while the cell from a different part that spreads in the other part of the body is called a secondary tumor. The tumor may be cancerous and noncancerous. The tumor also classified as benign (noncancerous) and malignant (cancerous) tumors. Benign tumors are noncancerous and non-progressive. They are originated at the brain and grown slowly with less aggression. Also, they cannot spread in a different part of the body. However, malignant tumors are cancerous and progressive. They spread quickly with indeterminate boundaries. They can be primary as well as secondary tumors [3-5].

The diagnosis of the brain tumor at the early stage is more important. Brain MRI plays a vital role in the analysis of the diagnosis of patients having brain tumors. MRIs have a big impact on medical image processing and analysis due to its capacity to provide high-resolution information about brain structure and deformity [6-8]. Radiologist analyzes the brain abnormalities based on the visual clarification of the presence of a brain tumor in brain MRI. But, there might be the possibility of misclassification when a huge volume of MRI data to be analyzed. Another possibility of the wrong diagnosis is because of the sensitivity of the human vision decreases with the number of cases, mostly when the little number of slices are affected. Also, it is a time-consuming technique. Hence there is a need for an efficient system for analysis and categorization of brain abnormalities. The early diagnosis will help to fix the damage and to provide the right treatment to the patient at earliest. MRI broadly used nowadays in hospitals and clinics for medical diagnosis, especially in brain imaging. MRI has the advantage of soft-tissue contrast and its noninvasiveness. MRI doesn't use any ionizing radiation. MRI is used in brain imaging because it is a non-radioactive, non-aggressive and pain-free method.

In this decade, the researcher proposed automated approaches for brain tumor segmentation, detection, and classification using brain MRI. Support Vector Machine (SVM) and Neural Network(NN) are mostly used approaches for the classification of different abnormalities in brain MRI because of their good performance [9]. Recently, deep learning algorithms set the trends in the classification of objects because of its efficient architecture, complex relationships without requiring an enormous number of nodes [9-10].

The main contribution of this paper is to the classification of brain MRI into malignant and benign using deep learning algorithm especially Convolutional Neural Network (CNN). Due to data limitations, this proposed methodology uses AlexNet as a transfer learning model.

The paper is organized as Section II gives an overview of the recent development in the brain MRI classification using the machine and deep learning algorithms with its pros and cons. Section III presents the architecture of the proposed methodology for brain MRI classification using a deep learning algorithm. Section IV describes the experimental results in a qualitative and quantitative manner. Conclusion and Future work is presented in section V.

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Sunita M. Kulkarni, Research Scholar, Sathayabama Institute of Science and Technolgy, Chennai, India. Assistant Professor, MITWorld Peace University, Pune, India. Email:sunitak105@gmail.com
Dr. G. Sundari, ECE Department, Sathayabama Institute of Science and Technolgy, Chennai, India. Email:sundariece16@gmail.com

II. LITERATURE SURVEY

In recent years, artificial intelligence algorithms such as Machine Learning (ML) and deep learning (DL) were mostly used for classification.

Saleck et al. [11] presented a Fuzzy C-Mean (FCM) algorithm to extract the brain tumor mass. This approach aim was to avoid the dilemma of estimation of the number of clusters in the using FCM by selecting the pixel intensities and mostly clustered into two. In this approach, Gray Level Co-Occurance Matrix (GLCM) a texture feature extraction algorithm is used to extract the features for estimation of the threshold value. The performance of the system is evaluated by using sensitivity, specificity and accuracy metrics.

Vijay Wasuleet. al [12] proposed the methodology for brain MRI classification into malignant Vs. benign and low-grade Vs. high-grade glioma. In this paper, features were extracted using the GLCM algorithm and extracted features were classified using supervised SVM and K-Nearest Neighbor (KNN) algorithm. The system was tested on clinical as well as standard brats 2012 dataset. The accuracy of the system is 96% and 86% for SVM and KNN respectively for the clinical database while 85% and 72.50% for SVM and KNN for the standard database respectively.

Ravindra Sonavane et al. [13] presented the classification of brain MRI using the AdaBoost algorithm. Firstly the brain skull skipping technique is used to remove the unwanted part of the brain MRI by using anisotropic diffusion filtering and edge detection algorithm. Secondly, the features were extracted from the DWT decomposed filter image. Finally, features were classified using the AdaBoost algorithm.

K. Sudharani et al. [14] proposed KNN based identification and classification of brain tumors. The experiments were performed for different values of k. Manhattan distance metric is used to estimate the distance between the testing sample and the training sample. This algorithm is implemented using LabView software.

Parveen et al. [15] proposed the hybrid approach of SVM and FCM for the classification of brain MRI. In the early stage of the algorithm, the MRI is enhance using image enhancement algorithms such as contrast enhancement and mid-range stretch. Thresholding with morphological operation used for skull skipping. The brain tumor part and background are segmented using the FCM clustering algorithm. Grey Level Run Length Matrix (GLRLM) is used for feature extraction from the brain MRI, followed by classification using SVM. The proposed algorithm achieved an accuracy of 91.66%, 83.33% and 87.50% for linear, quadratic and polynomial kernels respectively.

Later on, the combinations of different ML algorithms called ensemble classifiers are introduced by different researchers to achieve good accuracy. Amasyali et al. [16] proposed the ensemble classifier to improve the accuracy of the approach. They set two criteria such as accuracy and execution time while selecting the classifiers. In these experiments, the comparison of 12 different ensemble algorithms and 11 machine learning classifiers has been presented according to their accuracy.

J. Seetha et al. [17] proposed brain tumor classification using CNN classifier. In this approach, the FCM algorithm is used to segment out the brain tumor, GLCM used to extract the features while SVM and Deep Neural Network algorithm to classify the features. This approach shows low complexity, low computation time but accuracy is less. Hence another approach is introduced in this approach i.e. CNN based normal and tumorous brain MRI classification. The ImageNet pretrained model is used to reduce training time. This approach achieved the training accuracy of 97.5%.

S. Deepak et al. [18] used the transfer learning approach to extract the features from brain MRI. This paper is focused on three-class classification i.e. Meningioma, Glioma, and pituitary. The GoogLeNet transfer learning model is used to extract the features from input brain MRI. The extracted deep CNN feature then classified using SVM and KNN algorithm. This approach achieved an accuracy of 98% for 5 fold cross-validation.

Muhammad Sajjad et al. [19] presented an approach to classify multigrade brain tumor classification using deep learning. In this approach firstly, the brain tumor is segmented using the CNN model then segmented data is augmented using several parameters to enlarge the training samples and finally trained the model using the pretrained VGG-19 CNN model. This system achieved an accuracy of 87.38% for original data while 90.67% after data augmentation.

Javaria Amin et al. [20], proposed brain MRI classification into the tumor and non-tumor region through image fusion technique. First, structural and texture information of MRI sequences T1C, T1, Flair, and T2 are combined for brain tumor detection. The fusion approach is carried out by using the Daubechies wavelet kernel of Discrete Wavelet Transform (DWT). The fusion process provides a more informative tumor as compared to an individual sequence. After this, the partial differential diffusion filter (PDDF) is applied over the fused image to remove noise. Global thresholding method segment the brain MRI into the background (non-tumor) and foreground (tumor) region. This approach is performed on five publicly available datasets i.e., BRATS 2013, BRATS 2015, BRATS 2018, Brats challenge, BRATS 2012 image dataset, and 2013 BRATS Leader Board Dataset. The method got good accuracy on the fused images such as 0.97, 0.98, 0.96, 1.00, and 0.97 on BRATS 2012 Image, BRATS 2013 Challenge, BRATS 2013 Leader board, BRATS 2015 Challenge, and BRATS 2018 Challenge datasets respectively.

From the literature review, it is observed that most of the brain MRI classification using machine learning algorithms extract the texture features using GLCM and GLRLM algorithms. Some of the approaches used CNN for classification of the brain MRI into normal and abnormal.

III. PROPOSED SYSTEM

Fig. 1. shows the block diagram of the proposed method. This system is divided into two parts; training and testing.

A. Database

In this approach, the clinical database of brain MRI is used. The database contains Malignant and Benign MR images [12].

The detailed distribution of the database is as shown in Table I. The database contains raw images that are preprocessed, segmentation and augmentation technique after splitting training and testing data. The structure of the proposed by hyper tuning the parameter and optimize the algorithm. Finally, training and testing performance are presented.

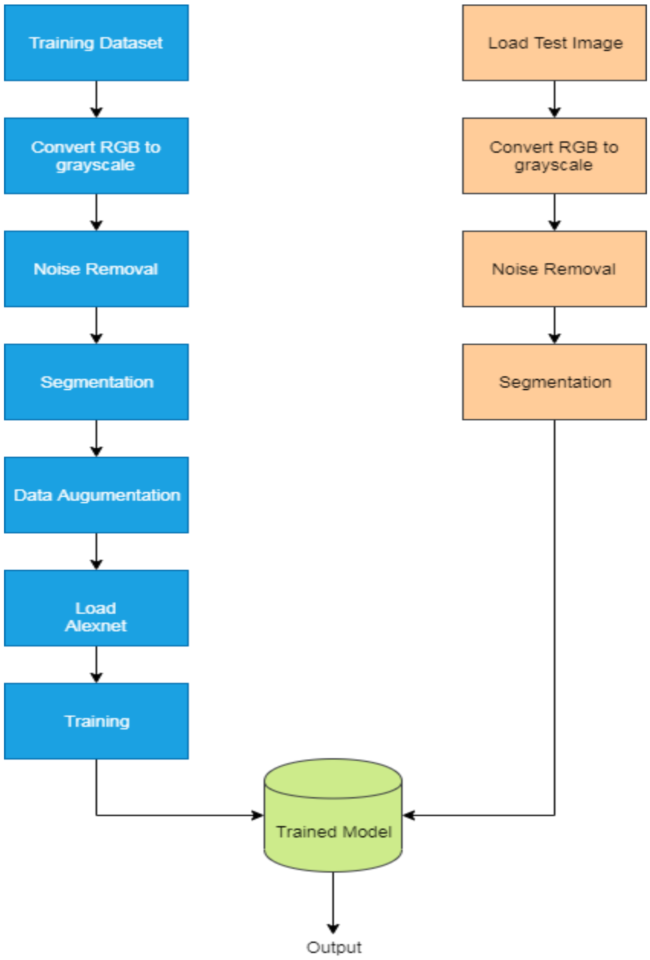

Fig. 1.Block diagram of the proposed methodology

Table- I: Database Distribution

Table Head	Database Distribution		
	Total Images	*Training Images*	*Testing Images*
Benign	100	75	25
Malignant	100	75	25

B. Preprocessing

The database images are raw, noisy and contain patient data text on the image. Firstly, the images are in the RGB color format. The RGB color is converted into grayscale using the weighted average method. Medical images mostly affected by Rician and salt & pepper noise [12]. The median filter is effective in the presence of unipolar and bipolar impulse noise and salt and pepper noise [21]. In this approach, the median filter is used to eliminate noise at an earlier stage to achieve accuracy at the decision stage. Another problem with medical images is poor contrast [22]. The low contrast images can be enhanced by using power-law transformation [23]. It is mathematically given as;

$$S = Cr^{\gamma} \quad (1)$$

where r is the intensities of the input image and γ is called gamma hence it is known as gamma transformation. The value of γ is varied from 0 to 1. S is the gray level of the output image. C is constant.

C. Segmentation

The segmentation is the important steps for extracting the brain part from the skull. In this approach, thresholding is used to segment the brain part. The preprocessed images I(x, y) is segmented using thresholding is defined as:

$$f_{g(x,y)} = \begin{cases} 1 & I(x,y) > T \\ 0 & \text{else} \end{cases} \quad (2)$$

where $I(x,y)$ is the grayscale value of the pixel and $f_{g(x,y)}$ is the binary image. If the grayscale pixel value is greater than the defined threshold value then assign value 1 to that pixel otherwise set to 0. Then the thresholded image again processed by a morphological operation such as erosion and dilation to get proper boundary and shape. Finally, the binary mask is convolved with the original image.

D. Data Augmentation

The deep learning architecture needs large data with a variation. Data augmentation is a major part of the pre-processing in transfer learning. When the dataset is relatively small, then a deep learning model might start to memorize the features very specific to your dataset this is called overfitting. To overcome the overfitting problem, the dataset needs to be large with large variation but this is very challenging in case of medical images. Another solution is to artificially augment the current dataset. This is a good practice method when working with image data [24]. Data augmentation involves different operations such as scaling, rotation, translation, flipping, resizing, adding noise, perspective transform, etc. Details of data augmentation parameters used in this proposed approach with their values are tabulated in Table II.

Table- II: Database Distribution

Parameter	Value
FillValue	0
RandXReflection	1
RandYReflection	0
RandRotation	[0,0]
RandXScale	[1,1]
RandYScale	[1,1]
RandXShear	[0,0]
RandYShear	[0 0]
RandXTranslation	[-10 10]
RandYTranslation	[-10 10]

E. Training using Deep Learning Algorithm

DL is extensively used for classification in recent years. Among the DL algorithm, CNN is the most trendy algorithm for the classification of medical images. CNN learns the spatial correlation between the pixels in a hierarchical way. This is performed by convolving the image with feature maps. Then reduce the size of features by max-pooling layer and finally flatten the features for feeding to the dense layer.

In this proposed work, the pretrained CNN network called 'AlexNet' is used. AlexNet is one of the famous architecture consist of five convolutional layers, three max-pooling layers, and three fully-connected layers. This architecture is trained for 1000 different object classification [25]. The network can also have certain layers retrained to identify the object which does not belong to the original dataset. The architecture of the AlexNet is as shown in Fig. 2.

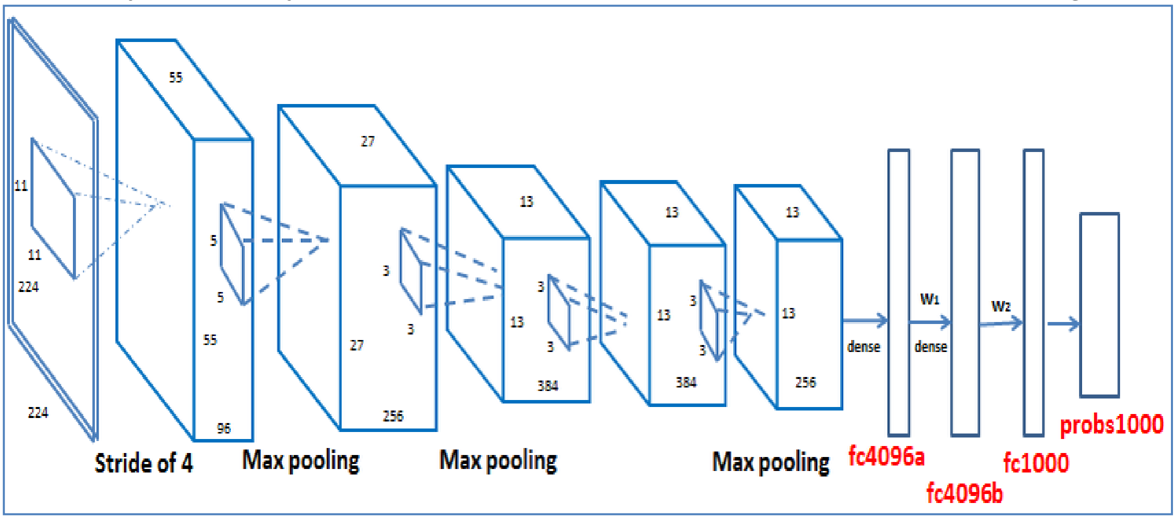

Fig. 2.Architecture of AlexNet

Instead of the large increase in the number of trained images, the existing size of the dataset is inadequate to train a deep learning model from scratch. To overcome this problem, transfer learning is applied to the pretrained AlexNet architecture in two different ways. First, the classification layer of the AlexNet is replaced by the softmax layer with two classes i.e. benign and malignant. second, the weight is fine-tuned and back-propagate to train the new weights. A learning rate is initialized to a small value so that the weights of the convolutional layer does not change dramatically while the weights of dense layer initialize randomly. The stochastic gradient descent (SGD) algorithm used to update the weight of the network based on the input augmented dataset of brain MRI. This process gives the optimal weights of the highly accurate network model.

IV. RESULTS

The experiments are performed using the Acer computer equipped with 8GB DDRAM. The MATLAB 2018aX64 bit version is used for the implementation of the code.

Table- III: Database Distribution

Parameter	Value
Network	'AlexNet'
Gradient Decay Factor	0.9000
Squared Gradient Decay Factor	0.9900
Epsilon	1.0000e-08
Initial Learn Rate	3.0000e-05
L2 Regularization	1.0000e-04
Gradient Threshold Method	'l2norm'
Gradient Threshold	Inf
Max Epochs	100
Mini Batch Size	64
Verbose	0
Verbose Frequency	50
Validation Data	Augmented Image Datastore
Validation Frequency	3
Validation Patience	5
Shuffle	'every-epoch'
Execution Environment	'auto'
Plots	'training-progress'
Sequence Length	'longest'
Sequence Padding Value	0

The clinical dataset of 75 images of benign and 75 images of malignant in RGB format is used for this experiment. The AlexNet transfer learning architecture is used to train the training images. The training parameters used in the proposed approach are as tabulated in Table III.

The training progress at each iteration is as shown in Fig.3. The plot describes the accuracy vs iteration. In this process, 80% of data is used for the training while 20% of data is used for validation. The data is shuffle at every iteration. From Fig. 4., it is observed that AlexNet is capable of achieving more accurate and generalizable power on unknown data. However, the training required a large number of epochs to achieve good accuracy. CNN required more epoch and time than the transfer learning model. Generally, networks that tend to learn additional descriptive and diverse levels feature leads to good performance, as the high-quality information acquired in the unsupervised pre-training contributes to superior fine-tuning and categorization.

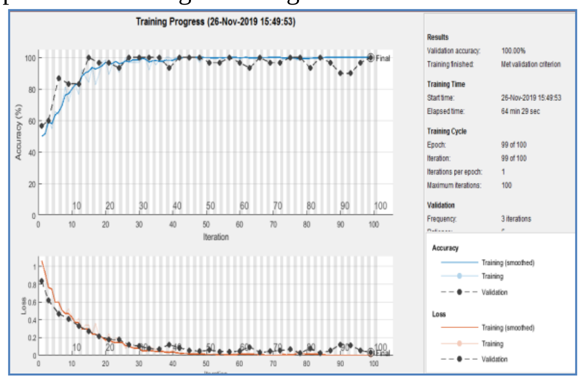

Fig. 3.Training progress of the proposed architecture

The proposed approach is trained four times. Each time the data were shuffled and evaluate the performance. Table IV shows the cross validation accuracy of each stage.

Table- IV: Cross-Validation Accuracy

Stage	Precision	Recall	F-measure	Accuracy (%)
I	100	100	100	100
II	100	88.23	93.7471	93.33
III	100	100	100	100
IV	100	100	100	100
Average	**100**	**97.05**	**98.4367**	**98.3325**

The Precision, Recall, and F-measure at each stage is evaluated. The average of each stage is taken as the overall performance of the system. From Table IV, it is observed that the validation accuracy of the system is founded to be 98.33% and F-measure is 98.44%.

In the testing phase, the unseen images of the brain MRI test with the training model. The output of the test images is as shown in Fig.4. The input benign and malignant images are shown in Fig 4(a) and Fig 4(c) respectively while their respective output images with the label are as shown in Fig. 4(b) and Fig. 4(c).

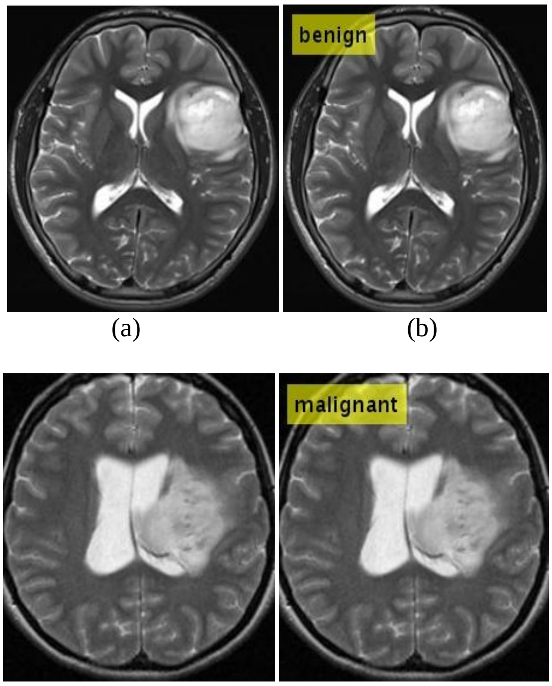

Fig. 4.Qualitative Analysis of the proposed algorithm (a)(c) Input Image (b)(d) Output Image

The proposed algorithm is compared with the existing machine learning approach presented in [12]. In this approach, the same database is used as [12]. Table 3. shows the comparative analysis of deep learning algorithms proposed in this approach with the machine learning-based approach presented by Vijay Wasule et al. [12] in terms of Precision, Recall, and F-measure which are mathematically represented as.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

$$F-measure = 2\ X\ \frac{Precision\ X\ Recall}{Precision + Recall} \quad (5)$$

where TP is the true positive value which defines the benign is predicted as benign. TNis the true negative value that defines malignant detected as malignant. FP is a false positive value that defines occurred benign detected as malignant. FN is a false negative value that defines malignant detected as benign. The quantitative analysis of the proposed approach is as shown in Table V.

Table- V: Quantitative analysis of the proposed brain tumor classification algorithm

Method	Precision (%)	Recall (%)	F-measure (%)
SVM [12]	100	76	86.36
KNN [12]	88	73.33	79.99
Proposed Method	100	97.05	98.4367

Based on the F-measure value as shown in Table 3, it is observed that the proposed methodology gives better results compared to the existing method.

V. CONCLUSION

In the last decade, most of the approaches used traditional machine learning algorithms for classification based on texture features. It is observed that the performance of the machine learning algorithm depends on the feature extracted from the brain MRI. There are lots of efforts required for feature engineering. Hence to avoid the efforts in the feature engineering, a system for classification for brain tumors into benign and malignant using CNN has been presented.

In this approach, the clinical MRI dataset of 75 images of benign and 75 images of malignant are used for training. The image augmentation techniques are used to generate the data artificially by different techniques such as rotation, scaling translation, flipping, resizing, adding noise, perspective transform, etc. to get a rid of limited availability and variability of the medical image dataset. Also, this technique helps to overcome the overfitting problems. AlexNet strength lies in its ability to recognize the diverse and extensive range of classification but it stumbles when faced with less diversity and more subtle classification. The proposed system was able to mark the strong classifier with high accuracy. The strength of the proposed customized CNN algorithm shows the much better F-measure value of 98.44%.

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AUTHORS PROFILE

Sunita M. Kulkarni, is working as an Assistant Professor in the Department of Electronics and Communication Engineering, MITWPU, Pune. She has completed her BE and ME in Electronics. She is currently pursuing a Ph.D. degree in Electronics Engineering at Sathyabama Institute of Science and Technology (Deemed to be University) Chennai.

Dr. G. Sundari, is working as a Professor in the Department of Electronics and Communication Engineering, Sathyabama Institute of Science and Technology, Chennai. She has 22 years of teaching and research experience in the field of wireless sensor networks and image and video processing. She has more than 50 publications in reputed journals and conferences.