

Brain Tumor Segmentation from MRI Images using Deep Learning-based CNN with SVM Classifier

S. Nirmala Sugirtha Rajini¹, S. Leena Nesamani², P. Abirami³

¹Professor, Department of Computer Applications

²Research Scholar, Department of Computer Applications,

³Research Scholar, Department of Computer Science,
Dr.MGR. Educational and Research Institute, Maduravoyal, Chennai

Abstract

Brain Cancer is one of the most threatening disease today. It caused due to the uncontrolled growth of unhealthy cells in the brain that could be either cancerous or non cancerous. In today's world a brain tumor are not only a life threatening disease but is also the prominent reason behind numerous deaths. Magnetic Resonance Imaging (MRI) is mostly used in brain tumor analysis. In this work, a new deep learning algorithm that is based on CNN with SVM is presented for efficient and automatic segmentation of brain tumor. The steps involved in the processing include preprocessing of the input image, extracting the important features, performing image classification, and finally segmenting the tumor in the brain. The MRI images are smoothed and the segmented using Watershed segmentation. The important features are then extracted from it based on the shape of the tumor, its position, and feature surface in the brain. Experimental results of the proposed method show that 92.59% accuracy in evaluation when compared to the existing algorithms.

Keywords: Brain Tumor, Segmentation, Deep learning algorithm, CNN, SVM

1. Introduction

Abnormal group of cells in the human brain is formed by uncontrolled division of cells in and around the human brain. These cell groups can influence the normal functioning of the brain and the healthy cells too could be affected by this. The brain tumor disease can cause disability in a person and can become deadly in severe conditions. In general, a brain tumor is of two types: one is benign and the other is malignant. The benign tumors do not spread to other body parts and the adjacent healthy tissues of the brain are not affected by this kind of tumor, but the malignant brain tumor is a type of cancer tumor that can spread to the other body parts and can lead to the patient's death. It can expand to the neighboring healthy cells of the brain and in worst cases can spread to distant organs of the body making the conditions worse. Human lives could be spared when the disease is diagnosed early. The Magnetic Resonance Imaging (MRI) scanning method is being used to identify the tumor in the brain at an early stage and to avoid the increased number of deaths due to brain tumors. The MRI systems provide a good way to view the brain tumors and it is mostly used for the early screening of cancer than the computerized tomography (CT) scans. MRI scans could be used to obtain useful information about the size, shape, metabolism, and position of brain tumors during the diagnosis process.

The segmentation of brain tumors from MRI images is a challenging task due to the structure of the brain and the location of tumors when using multi-modal imaging data. Thus, image segmentation is a very crucial and complex process in tumor detection in MRI images of a human brain. Tumor segmentation process is a very important step in identifying the brain tumor for efficient diagnosis. Quantitative and qualitative data about benign and malignant tumors can be obtained by performing appropriate

segmentation process on the brain MRI images and can be utilized to identify the treatment for patients and may also assist the physicians to make better decisions and plan for effective treatments. Numerous algorithms and methods have been presented so far for manual, semi and fully automated tumor segmentation as the tumor segmentation process in MRI images is a very complicated task. But many of those algorithms were executed on small datasets only [1–2].

For medical diagnosis, collect the information from medical images. The most commonly used medical images are CT scans, X-rays, and MRIs, etc. To obtain the internal structure of the brain, brain scans are also used [3]. There are many advanced methods in ML (Machine Learning) and DL (Deep Learning) which are used for image processing. Algorithms like Support Vector Machine (SVM), Neural Network, or other related models could be used for classification. There are a lot of learning classifiers available such as ANN, CNN, RNN, C4.5 and Multi-layer Perceptron, etc. and each has its advantages as well as disadvantages.

DL Models are widely used for image classification. Its architecture can represent complex relations [4]. It has been competing with other image classification methods that have been established in recent times. In this paper, an automated kernel-based CNN algorithm is employed for the feature extraction along with SVM classifier for classification is been introduced for effective brain tumor segmentation offering low time complexity, high accuracy and low error rate. The algorithm has been compared with Random Forest and KNN algorithms and was found to be a better performer.

2. Materials and Methods

Brain tumor classification is very important for medical diagnosis and high accuracy is also needed when human life is involved. In this section, the brain tumor MRI image classification algorithm is explained based on DL algorithms like CNN with SVM, Random forest, and K Nearest Neighbors classification techniques. The proposed method consists of different steps involved for the classification of brain tumor MRI image which is shown in figure 1.

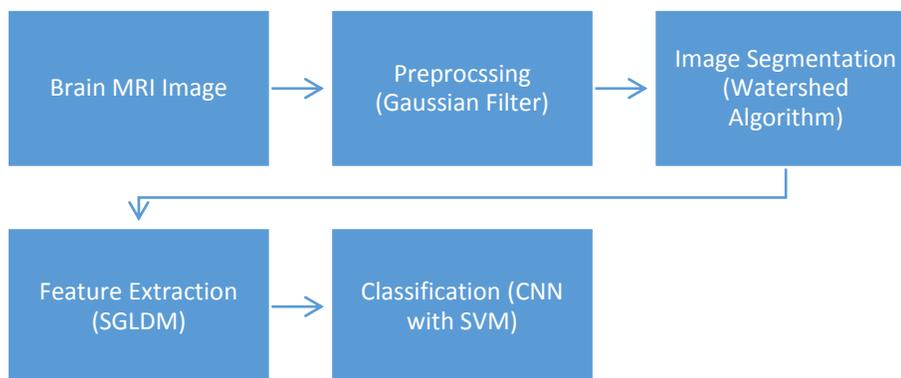


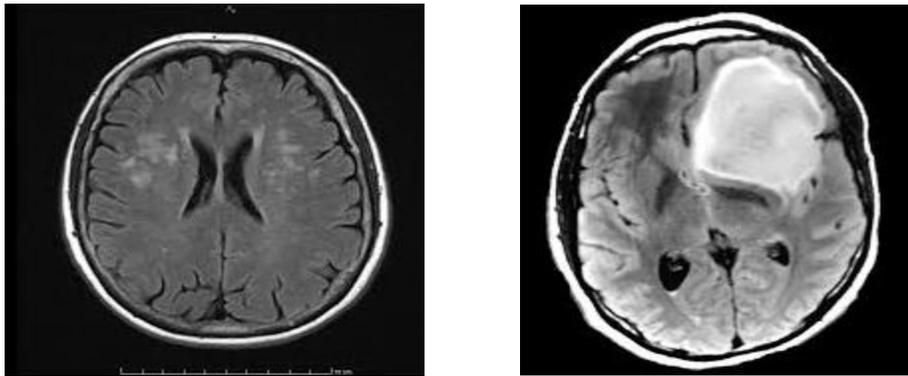
Figure.1 Proposed framework of brain tumor classification

It involved pre-processing of the image which is followed by image segmentation and feature extraction, then the process of classification, and finally the performance evaluation of classifiers. The important features are extracted from the segmented image using the SGLDM (Spatial Gray Level Dependency Matrix) method. It is a very fast and an adaptive method to find the texture features using the SGLM. The texture features are extracted from the selected features. Then, the selected features are

then fed into the SVM classifier to classify them as either normal or abnormal type. If an MRI image is abnormal, then a DL-based CNN has been applied to segment the tumor region in the image. Finally, the tumor is classified as either benign or malignant tumors.

2.1. Dataset description

The data set images used in this work comprises of the brain MRI images of 153 patients, including both normal patients and brain tumor patients who were referred to imaging centers due to the presence of headaches. After thorough examination and diagnosis by the physician, the collected image consists of brain MRI images of 80 healthy patients which contains a total of 1321 images, which include 56 images for testing data, and 515 images for the training data. Images collected from 73 patients with tumors resulted in 571 images which have been separated into 170 images for test data and 1151 images for the train data. The collected images had an initial size of 512 x 512. The appearance of the brain MRI image has been generated with the help of an MRI scanner. The strong magnetic fields and radio waves help to generate MRI images. MRI directly affects the treatment of patients. The tumor highlighted part in the MRI image with white color are shown in figure.2.



Brain MRI without tumor

Brain MRI with tumor

Figure. 2 Sample brain MRI images

2.2. Image Preprocessing

Pre-processing is a very important step in image processing for improving the quality of the image. Removing noise, resize an image is the basic step in image pre-processing. The first step of the pre-processing is converting MRI images into the Grayscale image. Skull masking and image noise removal is a very important step in brain MRI image classification it will help to improve classification accuracy rate. Skull Masking is the process of removing brain tissues from non-brain tissue from the brain. It improves the accuracy of diagnosis and also helps in improving the classification result. False segmentation is caused by the presence of Rician noise in the MRI images. There are a bunch of denoising algorithms available to remove the noise from the image. Various filters such as Low Pass Filter or Median Filter can be applied to remove the noise. Gaussian Filter is one of the best among them and are used here in this method. Gaussian filters are less sensitive to extreme values and provide good results in detecting outliers without compromising on the method sharpness. Further, the contrast of the image is enhanced to have better segmentation. It has been proven that best results can be obtained by employing an adaptive filtering technique such as Bayesian filtering, nonlinear isotropic diffusion filtering and filtering with wavelets transformations. Preprocessing of MR images is a very important step in image processing as improper usage of the noise removal may result in increased noise or removal of minute details in the image.

2.3. Watershed segmentation

In the segmentation stage, images are separated into multiple slices and object regions. The major advantage of using Image segmentation is a way to change the image into an easier recognizable and analyzable format. The watershed transform applies the segmentation techniques to the gray-scale images to solve a variety of image segmentation problems. Watershed segmentation is edge-based segmentation which first uses image acquisition technique and then gradient magnitude of the image is performed as shown in the figure.3

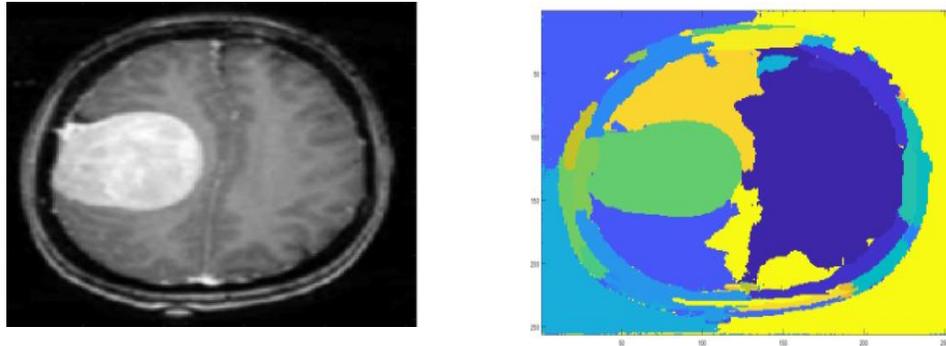


Figure.3 Segmented image using Watershed image segmentation

The gradient of ‘f’ at coordinates (x, y) is defined as a two-dimensional column vector shown in Equation (1). And the magnitude of vector ∇f denoted as $M(x,y)$ as in Equation (2). g_x and g_y are Sobel operators, called mask coefficient, shown in Equations (3) and (4).

$$\nabla f = \text{grad} (f) = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (1)$$

$$M(x,y) = \text{mag} (\nabla f) = \sqrt{g_x^2 + g_y^2} \quad (2)$$

$$g_x = \frac{\partial f}{\partial x} = (Z_7 + 2Z_8 + Z_9) - (Z_1 + 2Z_2 + Z_3) \quad (3)$$

$$g_y = \frac{\partial f}{\partial y} = (Z_7 + 2Z_8 + Z_9) - (Z_1 + 2Z_2 + Z_3) \quad (4)$$

Where f is a brain MRI image. The watershed transform is often preferred to separate the objects that are touching each other in an image; it is very effective than other methods because it can also segment non-homogenous tumors thereby providing non-homogeneity within the tumor region. There are various watershed transforms like watershed segmentation using distance transform, watershed segmentation using gradients, marker-controlled watershed segmentation, etc. Here due to noise and other irregularities of gradient over-segmentation has been occurred. To avoid the situation area opening is done so that irregularity will not affect the segmentation.

2.4. Feature extraction using SGLDM

After the segmentation, the features were extracted from the MRI images using the SGLDM method for image classification. SVM classifier is used to for classification and dimensionality reduction technique is employed for better accuracy in image classification. Before MRI image classification, the features were extracted using the SGLDM technique. The features are based on the

shape, structure and the surface of the tumor in the MRI images. This technique employs a function of the co-occurrence matrix to extract the features from the preprocessed MRI images. The second-order statistical texture features are extracted by this method. From the given sample MRI image, the co-occurrence matrix extracts the statistical data according to the pixel pairs. The pixel pairs in MRI images are estimated with the angle θ and the distance d . The distance d separates the pixel pairs during the feature extraction. The pixel pairs are counted for the extraction of features depending on the gray level values of a given MRI image. The co-occurrence matrices can be executed to four various distances d in the directions of vertical, horizontal, and the two diagonals. Angle θ can be any one of the degrees - 0° , 45° , 90° and 135° . The distance d and angle θ can be described to estimate the co-occurrence matrix. In this paper, six features such as contrast, entropy, mean, variance, homogeneity and energy, and were selected for the MRI images. The features were selected from the extracted list of features based on tumor structure for the classification process.

2.5. Image classification using DL based CNN with SVM

The selected features are then fed into the SVM classifier to classify the MRI image as either normal or abnormal. In general, the SVM classifier is a binary classifier and it is mostly used for classifying the two-class classification problems. It is supervised learning method, where a hyper-plane is employed to divide the two classes of data in the given MRI images. Support vectors can act on the input data elements that can describe the individual data points and discover the decision boundaries that separate the training data for MRI images into different classes. The SVMs work faster and can be more deterministic than the traditional neural network algorithms. A decision plane divides a set of data points into various memberships of class. The SVM classifier is utilized in two fundamental steps: training and testing of images. During the training process, the support vectors that clearly distinguish the two classes from all the training data are identified. Hence, the MRI image can be classified as a normal image or abnormal image by the SVM classifier depending on the extracted features from the images. If any image is classified as abnormal, then it indicates that the image has a tumor area in it.

When the SVM classifier classified an MRI image as an abnormal one, then the deep learning method CNN method is applied to segment the tumor region from the brain MRI image efficiently based on the kernels with lower error rate in a shorter time. The CNN classifier is combined with the SVM classifier to perform classification. The kernel-based CNN can be utilized to segment the tumor region from the given image and the SVM classifier is used for classifying the tumor into benign or malignant type. In this work, the neural networks are trained at two steps to assist two levels of the deep learning process in tumor segmentation in MRI images. The first step is focused and applied to the convolution layer of network and the second step is applied to the completely related layer. During the initial learning process, the weights of the neural network are copied and the training samples of the MRI image that has spectrum mixing is added to the primary kernel in order to add flexibility to the tumor segmentation process, that assist the SVM classifier to classify the target classes. During the second level of transfer deep learning, the connected layers are trained entirely from the non-target class of MRI images. In this segmentation process, a novel technique is presented here which combines CNN, SVM, and the Kernel to progress the performance of the DL model for segmentation of brain tumor and for the further classification of the same. To tune the hyper parameters, random weights are used. Hence, the kernel-based CNN segments the tumor from the MRI image and the segmented tumor is classified into the benign or malignant tumor by SVM classifier.

3. Results and discussions

In this section, the performance of the existing methods and the proposed system is evaluated based on the tumor segmentation in MRI images. The features like a binary weight have been learned from

MRI brain images of training data and the features are obtained by segregating 80% of the train and 20% of the test dataset that gets classified using the proposed model. The deep learning-based CNN with SVM classifier for testing after the successfully training images. The features were extracted from the dataset for training the model to perform brain tumor classification. The proposed method shows the results for benign and malignant images with a good accuracy rate. The test image classification results are shown in figure.4. The difference in the accuracy based on the brain tumor dataset used for training the model can be viewed. The two lines used in the graph represent the training and the validation accuracy. Validation accuracy is the precision.

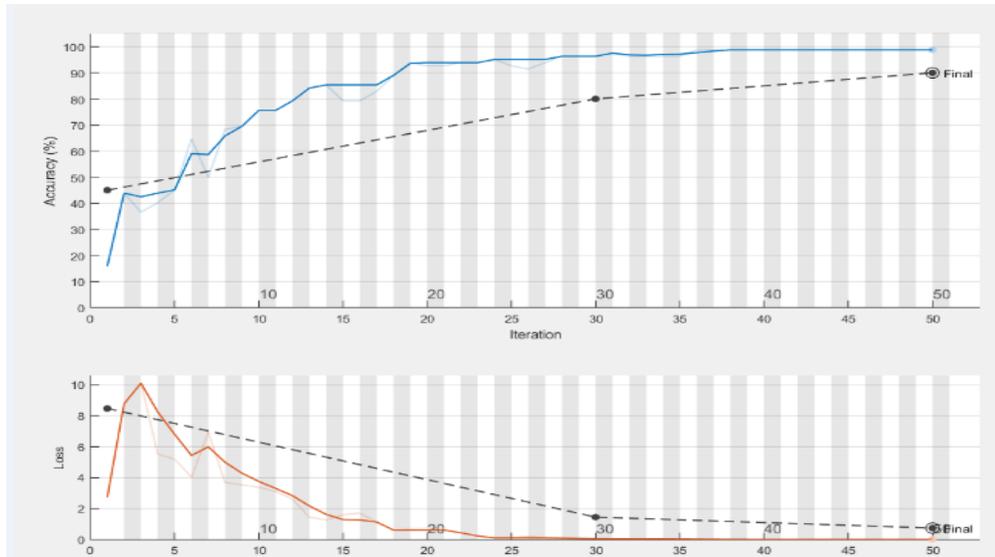


Figure 4. Training and testing accuracy of deep learning-based CNN with SVM

Once the model is trained, the test dataset obtained an accuracy of 92.59% which is graphically represented in the figure. 4. The proposed method has been compared with existing methods in terms of tumor segmentation accuracy and time complexity are the two important metrics that are used to compare the proposed system .

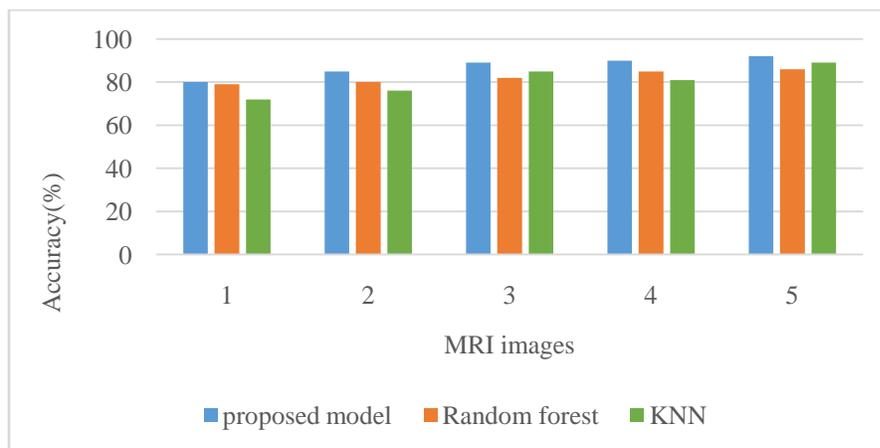


Figure 5. Accuracy for tumor segmentation

The number of tumor cells detected and segmented correctly out of the total number brain cells present in the brain image determines the accuracy of tumor segmentation in MRI images. Figure.5 shows the accuracy level of the proposed and existing methods for the segmentation of tumors using MRI images. The proposed method shows a higher accuracy level than the existing methods.

Time complexity

The segmentation time is the total time required to perform thesegmentation of tumor cells from the MRI images. The time taken forsegmentation process is calculated in milliseconds.The tumor segmentation time of the proposed system and existingmethods have been compared in Figure.6.

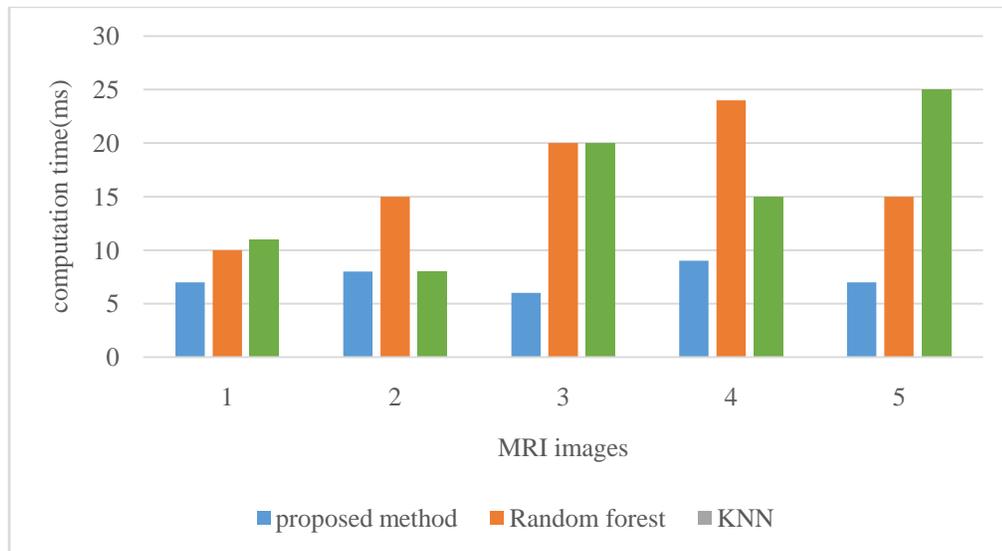


Figure.6 Computation time for tumor segmentation

From figure 6, it can be clearly seen that the proposed method has performed the tumor segmentation and tumor classification with less time when compared to the existing methods.

4. Conclusion

In this research work, three different traditional classification techniques were used for brain tumor classification as either benign or malignant, and normal MRI images. In this work, a new deep learning method that is based on CNN along with SVM classifier has been examined to efficiently perform classification and segmentation of tumor in the human brain. In this process, the brain MRI images have been preprocessed and segmented using the watershed algorithm. The relevant features were then retrieved by the SGLDM method. The MRI image has been differentiated into either as normal brain image or abnormal brain images by the SVM based on the extracted features of the MRI images. To assist the doctors who treat the patients the tumor region is segmented by the proposed deep learning method from MRI image effectively. The proposed algorithm performs accurate tumor segmentation. The proposed work has attained an accuracy of 92.59% to segment and classify the tumor region as malignant, benign or normal when compared to the existing methods such as Random Forest and KNN. Hence, the proposed research has taken lesser time to segment and classify the tumor from the MRI image compared to the other existing methods. Moreover, the proposed research has also obtained low time complexity than the existing methods. Therefore, this research work can be used to identify the brain tumor at a very

early stage and is predominantly very helpful to prevent deaths that have been occurred due to delayed diagnosis.

References

- [1] B. Bavani, S. Nirmala Sugirtha Rajini, M.S. Josephine and V. Prasannakumari (2019), “Heart Disease Prediction System based on Decision Tree Classifier, *Jour of Adv Research in Dynamical & Control Systems*, Vol. 11, 10-Special Issue, , pp. 1232-1237.
- [2] Heba Mohsen, El-Sayed A., El-Dahshan, El-Sayed M. El-Horbaty, and Abdel-Badeeh M. Salem, “Classification using deep learning neural networks for brain tumors”, *Future Computing and Informatics Journal, ScienceDirect* 2018.
- [3] Leena Nesamani.S and Nirmala Sugirtha Rajini.S, “Evaluation of Ensemble Machines in Breast Cancer Prediction, *Advances in Parallel Computing*”, Vol. 37 *Intelligent Systems and Computer Technology*, 2020, 37, 391-395.
- [4] Leena Nesamani.S, Nirmala Sugirtha Rajini.S, M. S. Josphine and J. Jacinth Salome, “Deep Learning-Based Mammogram Classification for Breast Cancer Diagnosis Using Multi-level Support Vector Machine”, *Advances in Automation, Signal Processing, Instrumentation, and Control, Lecture Notes in Electrical Engineering*, 2021, 371-383.
- [5] P. G. Rajan and C. Sundar, “Brain Tumor Detection and Segmentation by Intensity Adjustment”, *Journal of Medical Systems*, 2019, 43.
- [6] Parthasarathy, P, and Vivekanandan, S., “Urate crystal deposition, prevention and various diagnosis techniques of GOUTarthritis disease: A comprehensive review”, *Health Inf. Sci. Syst*, 2018, 6, 19.
- [7] S. Leena Nesamani and S. Nirmala Sugirtha Rajini, “Evaluation Of Machine Learning Classifiers In Breast Cancer Diagnosis”, *Turkish Journal of Computer and Mathematics Education*, 2021, 12, 1331-1337.
- [8] Shen, D., Wu, G and Suk, H.-I., “Deep learning in medical image analysis”, *Annu. Rev. Biomed. Eng*, 2017, doi:10.1146/annurev-bioeng-071516-044442.
- [9] Sourabh Hanwat and Chandra J, “Convolutional Neural Network for BrainTumor Analysis Using MRI Images”, *International Journal of Engineering and Technology*, 2019.
- [10] Varadharajan, R., Priyan, M. K., Panchatcharam, P., Vivekanandan, S., and Gunasekaran, M., “A New approach for prediction of lung carcinoma using backpropagation neural network with decision tree classifiers, *J. Ambient Intell. Humaniz. Comput*, 2018, 1–12.