International Journal of Engineering and Applied Physics (IJEAP)
Vol. 2, No. 2, May 2022, pp. 472~479
ISSN: 2737-8071



# Brain Tumour Detection and Classffication Using CNN

**Neetu Nagar, Nishi Pandey, Abhishek Agwekar**
Dept. of Electronics and Communication.
Truba college of science & technology, Bhopal, MP, India

**Article Info**

***Article history:***

Received Apr 2, 2022
Revised May 5, 2022
Accepted May 16, 2022

***Keywords:***

Segmentation,
Medical image,
CNN, Machine learning,
Classification, Barin tumour

**ABSTRACT**

The goal of this study is to find brain tumours and give better care to those who have them. Tumors are abnormal growths of cells in the brain, and cancer is the word for a type of malignant tumour. Most of the time, CT or MRI scans are used to find areas of cancer in the brain. Positron Emission Tomography, Cerebral Arteriogram, Lumbar Puncture, and Molecular testing are also used to find brain tumours. In this study the dataset has 253 Brain MRI images in two folders called "yes" and "no." The "yes" folder has 155 Brain MRI images of tumours, while the "no" folder has 98 Brain MRI non-tumour images. For classification and segmentation of preprocess augumentated data set we use novel CNN architecture in this paper we have achieved Training accuracy is 98.75% and the validation accuracy is 86.45%. The novel CNN architecture could be used as a useful decision-support tool for radiologists in medical diagnostics.



***Corresponding Author:***

Neetu Nagar,
Electronics & Communication Engineering
Truba College of Science & Technology,
Bhopal, MP, India.
Email: neetunagar.truba@gmail.com

## 1. INTRODUCTION

Image processing is a way to turn a real image into a digital one and then get as much useful information out of it as possible. People think that the picture is one of the best ways to get a message across. The process of getting useful information from an image is an important use of digital image technology. During the image processing step, images are broken up into parts. Image segmentation is the process of breaking an image up into different parts so that it can be studied and explained better.

Brain tumours are easier to diagnose and treat if they are found and treated early. This helps to lower the death rate. In the past few years, image processing has become more and more common, and it has become an important part of the medical field as well. Brain tumours are caused by cells in the brain that grow in an abnormal way. An intracranial neoplasm is another name for a brain tumour. There are two kinds of tumours: those that are cancerous and those that are not. There are many ways to distinguish between different types of brain tumours depending on how they appear and contrast with the surrounding tissues. According to their severity, the WHO has classified more than 120 different forms of brain tumours into four categories [1]. It is important to note that symptoms of all forms of brain tumours are dependent on the location of the tumour. Headaches, seizures, blurred vision, nausea, vomiting, and other mental abnormalities, as well as memory loss and a loss of equilibrium, are among the most common symptoms [2]. There are a variety of variables contributing to the rise in cases of cancer, including hereditary factors, cell phone radiation, extremely low frequency magnetic fields, and head injuries [3], there has been an increase in the incidence of brain tumours.

Both primary and secondary tumours are malignant tumours, or cancerous tumours. Primary tumours originate in the brain, while secondary tumours originate elsewhere and spread there.

Brain tumours can be caused by a variety of reasons, including vinyl chloride exposure, neurofibromatosis, and radiation exposure. Computed tomography, magnetic resonance imaging, tissue biopsy, and other diagnostic procedures are available. Treatment options for brain tumours have improved. It's possible that the treatment will cause specific neurological abnormalities, or faults in the visual field, but this is possible. By monitoring tumour size and the time, it takes for tumour development (TTP), side effects can be prevented. Therapy can be more effective if the density of the affected areas can be estimated.

It is a type of machine learning technology that trains computers to make decisions based like humans when faced with a challenging scenario. Using deep learning, for example, a computer model can be trained to perform classification tasks based on images or voice recordings. Deep learning algorithms can sometimes outperform human abilities. It's not uncommon to see neural networks comprised of simulated neurons in artificial neural networks. Each neuron serves as a node, and these nodes are linked to one another by links [5].

The goal of this paper is to use the convolution neural network to build a system that can help find cancer in MRI images. The proposed method was put to the test and compared to other classification techniques to see how well it worked.

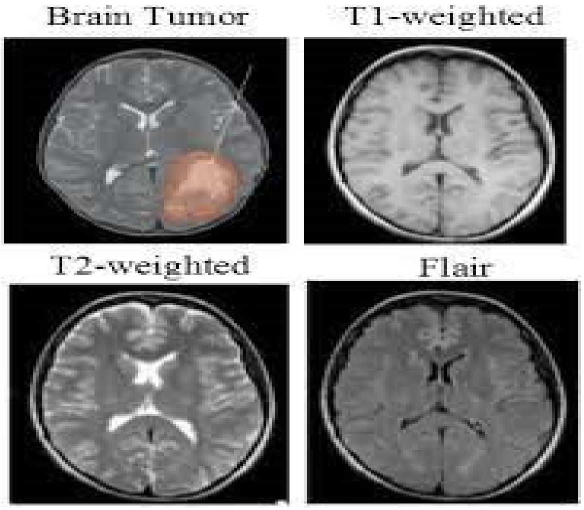



Figure 1. Diffrent brain MRI images.

## 2. RELATED WORK

Segmentation and classification of images, a key component of machine learning, are used in clinical diagnostics. Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and Support Vector Machine (SVM) were introduced [6]. In order to distinguish between cancerous and non-cancerous tumours, wavelets of differing levels are used. An issue with the new approach is that it takes longer to compile.

Somasundaram S. and Gobinath R et al. [7] present an in-depth analysis of the current level of tumour diagnosis and segmentation using deep learning models. The use of 3D-based CNN, ANN, and SVM for further segmentation is applied. Tumor images are classified using Neural Networks based on key features retrieved from each segmented tissue, including tumour, white matter, grey matter, and cerebrospinal fluid (CSF) (NN).

An early diagnosis of tumours can be achieved with the appropriate application of data mining classification algorithms [9]. The CNN network is used as the segmentation algorithm. This can be done on an MRI scan [10]. Radiological tests can be used to identify the size and location of tumours. It's a laborious process to do this by hand. For the pre-processing, an anisotropic diffusion filter is employed.

Using support vector machines, we may divide and classify the data into many categories. For example, in Wei Chen et al. [11], isolated local squares might be used as a basis for an innovative strategy. Segmentation, feature extraction, and the building of a model for brain tumour segmentation are all part of this suggested method.

Table 1 compares different image segmentation approaches. It discusses the pros and cons of each strategy.

Table 1. Comparison of various image segmentation methods.

| Method of Segmentation | Description of Method | Pros | Cons |
|---|---|---|---|
| Edge Based | Dependency on discontinuity detection | This method works best with images that have small changes across the various regions. | It has a lower noise resistance and is mostly dependent on peaks. |
| Region Based | As they're processed, images are being divided up into portions that are all the same color. Other techniques include dividing and combining regions and increasing the size of regions. | The impact of noise is greater. | In terms of memory and time, it is expensive. |
| Clustering | It is based on the division of the population into homogeneous groups. | Real-time problem-solving apps benefit greatly from this capability. | Trying to figure out what the membership function is in the method is tough. |
| Thresholding | It is possible to find threshold values that are dependent on the histogram peaks. | A straightforward procedure that does not necessitate any prior knowledge. | Peaks are based on the situation. |
| Fuzzy based Fuzzy | This method makes use of mathematical concepts and operators. | When describing the degree of similarity between two linguistic expressions, the fuzzy membership function is used. | This method necessitates a significant amount of computing. |

## 3. PROPOSED METHOD

Figure 2 shows how the proposed system is put together. Image acquisition, preprocessing, segmentation, feature extraction, and classification are the parts that make up the system.

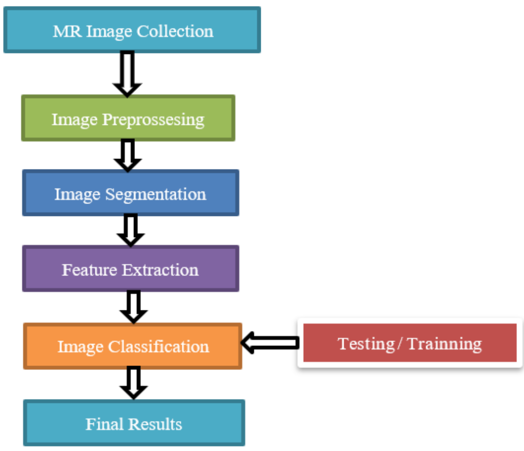
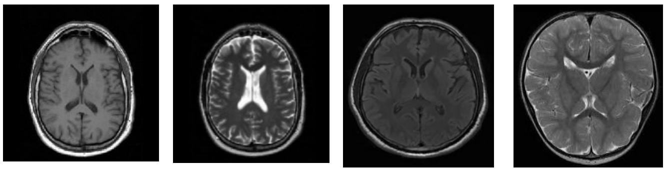


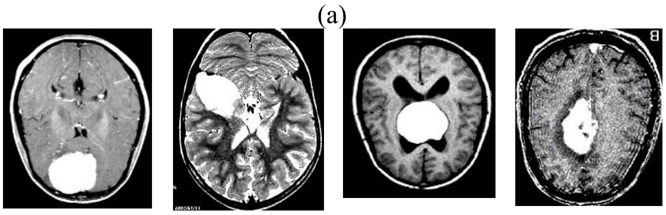

Figure 2. Conventional approach of toumor detection

### *A. Image Collection*

For the investigation of brain tumour identification, many bio-medical imaging records are provided. Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) are two of the most common procedures (MRI). Particle Emission Tomography (PET), Cerebral Arteriogram (CAG), Lumbar Puncture (LP), and molecular testing are all methods of detecting brain tumours. The downside is that they are costly. It is based on the idea that the presence of a water molecule in the body may be detected by both a magnetic field and radio waves. In contrast to CT scans, MRIs have higher resolution and carry more data. This research utilised the magnetic resonance imaging (MRI) dataset from Navoneel Chakrabarty's kaggle submission [12]. A total of 98 images of normal brain function and 155 images of abnormal brain function are contained within this collection. Tumor images are represented by the letter "yes," while healthy images are represented by the letter "no." The augmentation procedure is also used in this instance to increase the number of samples. One of the steps in the augmentation process includes rotating the image by 10 degrees, shifting the image by 0.1 width and 0.1 height, shifting the image by (0.3,1.0 brightness), and flipping the image vertically or horizontally. From the supplemented data, a total of 2530 photos were chosen for inclusion. 980 normal photos and 1550 aberrant images make up the final dataset.



(a)



(b)

Figure 3. Brain image dataset (a) Non tumour images (b) Tumour imgaes

### B. Preprocessing

Image preprocessing is intended to ensure that brain images are ready for further analysis after they have been acquired. Data processing devices have their own set of inherent parameters, and these factors play a key role in this process. If the original data is in three dimensions, a conversion to grayscale or two-dimensional (2D) is required. For biological photos, median filtering is the most effective way to reduce noise. Images of varying resolutions can be found in the database. It is common practise to rotate and resize each image before to augmenting it. Histogram equalisation improves the quality of the image. To improve the photos, we used a contrast constrained adaptive histogram equalisation approach.

### C. Image Segmentation

A digital image is divided into many sections in this process. Separation is taking place in an area of a picture that is distinct from the rest. A digital image is divided into several segments at this step, which is why it's important. A certain area of the image is being isolated from the rest of the image. In order to extract features, this phase is critical.

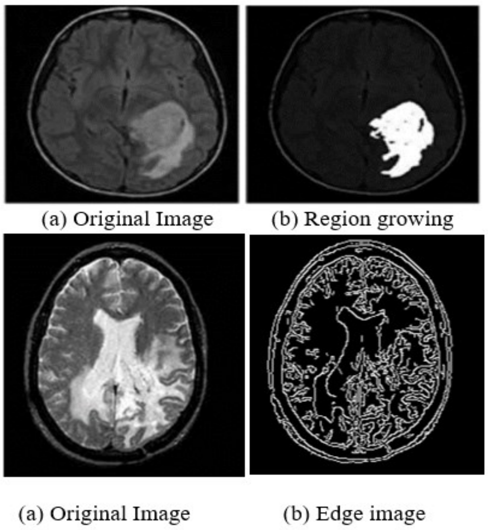



Figure 4. Region growing and Edge based segmentation

There are two easy phases to segmenting disease: thresholding and morphological procedures (e.g., eroding, diluting, opening). However, when it comes to brain tumour imaging, the segmentation procedure at this level does not reveal the specific locations of tumours. There is also a similar intensity in the healthy photos that resembles the tumour area. That's why it's possible to separate the skull from the brain via segmentation. The tumour is located inside this area of special interest (ROI). Skull masks can be generated using an OTSU thresholding algorithm [14]. The boundary of the region is drawn using the active contour approach. To produce the mask for the tumour area, it is possible to apply the second stage of segmentation to the ROI as well as the ROI itself. This approach may not produce the greatest results in images of people who are in good health. This segmented image can be used to analyse the characteristics of the tumour region in order to estimate its density for density estimation.

### *D. Feature Extraction*

It is possible to analyse the disease's behaviour or symptoms with the use of actual data. It is the feature selection that has the most impact on the categorization. Diameter and border irregularity are further common characteristics [15].

### *E. Clasiffication*

There are a variety of machine learning techniques being used to diagnose disease from brain image. If the features are extracted sequentially, it is possible to use artificial neural networks to classify [16]. Features that are not connected to each other are assumed by an ANN classifier. It is possible to categorise a tumour image without segmentation by using deep learning techniques. Using the Convolutional neural network technique, a deep neural network can be built. Figure 5. depicts the overall structure of onvolutionary neural networks. The feature is automatically taken from the complete image via deep learning. This is accomplished using convolution in the CNN architecture. CONV layer increases the number of feature maps. To begin training, it is necessary to reduce the dimensions. The feature dimension is sampled by pooling layer down. Each label's score can be altered by using multiple connected layers. Feature and class scores are calculated using Softmax layers. The dimensions of the CNN architecture are slightly altered in order to train images of brain tumours. Table 1 shows the prameters of updated model architecture.

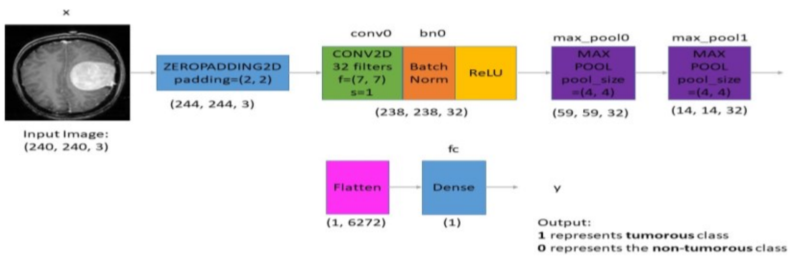



Figure 5. Architecture of CNN model

It was constructed in Keras utilising the 'Adam' optimizer and the loss function of binary cross entropy (BCE). There is a default rate of 0.001. In order to train the model, a batch size of 32 is used for a total of 24 iterations. Using the test photos, our trained model is 95.6 percent accurate. Multilevel thresholding, morphological procedures and contour extraction are used to identify the tumor's location in images that have been categorised as having a brain tumour.

$$g(x,y) = \begin{Bmatrix} 1, f(x,y)\} > T \\ 0, f(x,y)\} \leq T \end{Bmatrix} \quad (1)$$

With respect to image brightness, T is the average of the image's maximum and minimum values. Segmenting the regions is accomplished by the usage of the Morphological Open function. There are contours for all regions, and the largest area contains the tumour region.

$$f(x) = \frac{1}{n\sigma\sqrt{2\pi}} \sum_{i=0}^{n} e^{\frac{-1}{2}} \left(\frac{x_{i-x}}{\sigma}\right)^2 \quad (2)$$

Table 1. Parameters of model architecture

| Layer (type) | Output Shape | Param # |
|---|---|---|
| input_1 (InputLayer) | [(None, 240, 240, 3)] | 0 |
| zero_padding2d (ZeroPadding 2D) | (None, 244, 244, 3) | 0 |
| conv0 (Conv2D) | (None, 238, 238, 32) | 4736 |
| bn0 (BatchNormalization) | (None, 238, 238, 32) | 128 |
| activation (Activation) | (None, 238, 238, 32) | 0 |
| max_pool0 (MaxPooling2D) | (None, 59, 59, 32) | 0 |
| max_pool1 (MaxPooling2D) | (None, 14, 14, 32) | 0 |
| flatten (Flatten) | (None, 6272) | 0 |
| fc (Dense) | (None, 1) | 6273 |

Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64

## 4. Implementation Results

Classifying cancerous brain tumours from MRI images is the primary goal of the proposed approach. From the Kaggle dataset, 253 MRI pictures were collected." To model a deep neural network, you need a lot more data than you have. With this procedure, 2530 images were generated. This process is repeated for each of the cropped images. The model is built using the Keras (TensorFlow backend) library. In order to evaluate the system's performance, two alternative methods of segmentation are used at different levels of segmentation. Classification came first, then segmentation. According to the results of the performance investigation, segmentation after classification is more effective.

Numerous research has relied on the same database to categorise brain tumours, which has proven to be reliable. Previously published research was only considered comparable if it used entire images as input for classification and employed a CNN approach to validate its results (Table 2). With our results, A comparison is made between researchers that used Convolution neural networks (CNN) and a bigger dataset.

Figure 6 (a) shows the Training accuracy and Validation accuracy, and Figure 6 (b) Training loss and Validation loss. This lets us see that the Training accuracy is 98.6.2% and the validation accuracy is 86.4%. We've used data as follows: 70% for training, 15% for testing, and 15% for validation. In this case, the "Adam" optimizer was used.

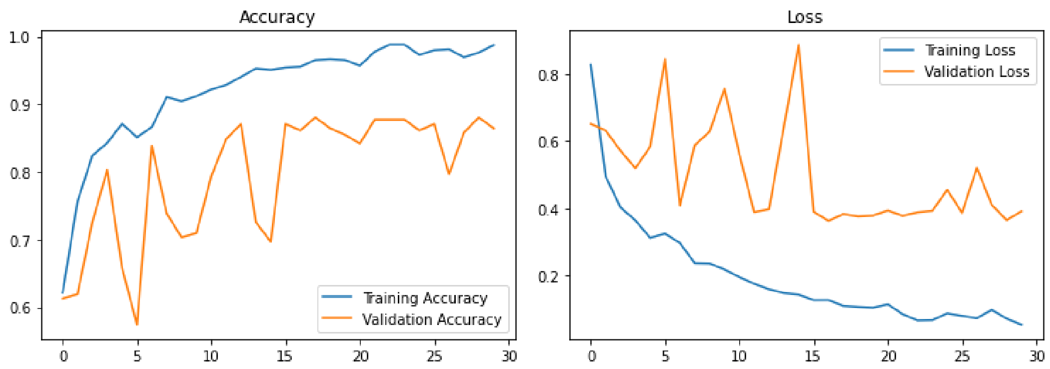



Figure 6. (a) shows taining and validation accuracy (b) shows training and validation loss

Google Colab is being used to train a deep neural network structure that has been proposed. We use a CNN model and a single GPU to figure out what kind of brain tumour it is. 2530 images were trained in 10 minutes and 51 seconds over 30 epochs.

Table 2. Comparison of previous work to our Proposed work.

| Authors | Overall Accuracy |
|---|---|
| Nandpuru [18] | 96.77% |
| Ibrahim [20] | 96.23% |
| Rajini [21] | 90.% |
| Proposed Techniques | 98.75% |

*4.1. Evaluation Metrics*

- *TP: True Positive:* When the model correctly predicts a much positive class, it is positive.
- *TN: True Negative:* If the model correctly says the negative class, it is a real negative.
- *FP: False Positive:* When the model incorrectly says the positive class, it is a false positive.
- *FN: False Negative:* When the model incorrectly says the negative class, it is known as a false negative.

Also, the model describes such concepts as sensitivity, accuracy, precision, and specificity.

*ACCURACY:* The optimistic predictions and the sum of negative and positive predictions are called accuracy.

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

*PRECISION:* The ratio of true positive and the sum of a genuinely positive and false positive.

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

*SENSITIVITY:* It is calculated by dividing true positives by the sum of true positives and false negatives.

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

*SPECIFICITY:* It is calculated by dividing true negatives by the sum of false positives and true negatives.

$$Specificity = \frac{TN}{TN + FN} \tag{6}$$

## 5. CONCLUSIONS

In this study, a machine learning algorithm is presented for the detection of brain tumours. Early cancer identification is critical to getting the right treatment at the right time. The MRI images in the Kaggle dataset are of high quality and can be used for study. There were several different segmentation algorithms tried out. As a result of this, the dataset benefits most from segmentation of region growing edge detection and thresholding with a modified technique, the Convolutional Neural Network (CNN) produced an outcome with a Training accuracy is 98.75% and the validation accuracy is 86.45%. A web-based interface can be added to this system in the future. MRI images can also be used to detect certain disorders. Some other factors can also be evaluated for therapeutic purposes.

**REFERENCES**


[1] David N. Louis, Arie Perry, et al., “The 2016 World Health Organization Classification of Tumors of the Central Nervous System: a summary”, Acta Neuropathol, Springer may 2016

[2] Salander, P., Bergenheim, A. T., Hamberg, K., & Henriksson, R. (1999). Pathways from symptoms to medical care: a descriptive study of symptom development and obstacles to early diagnosis in brain tumour patients. Family Practice, 16(2), 143-148.

[3] McKinney, P. A. (2004). Brain tumours: incidence, survival, and aetiology. Journal of Neurology, Neurosurgery & Psychiatry, 75(suppl 2), ii12-ii17.

[4] Heimans, J. J., & Taphoorn, M. J. (2002). Impact of brain tumour treatment on quality of life. Journal of neurology, 249(8), 955-960.

[5] Suresh, M., Sinha, A., & Aneesh, R. P. (2019). Real-Time Hand Gesture Recognition Using Deep Learning. International Journal of Innovations and Implementations in Engineering, 1.

[6] Gurbină, M., Lascu, M., & Lascu, D. (2019, July). Tumor detection and classification of MRI brain image using different wavelet transforms and support vector machines. In 2019 42nd International Conference on Telecommunications and Signal Processing (TSP) (pp. 505-508). IEEE.

[7] Somasundaram S and Gobinath R, “Early Brain Tumour Prediction using an Enhancement Feature Extraction Technique and Deep Neural Networks”, International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278- 3075, Volume-8, Issue-10S, August 2019.

[8] Damodharan, S., & Raghavan, D. (2015). Combining tissue segmentation and neural network for brain tumor detection. International Arab Journal of Information Technology (IAJIT), 12(1).

[9] Hemanth, G., Janardhan, M., & Sujihelen, L. (2019, April). Design and implementing brain tumor detection using machine learning approach. In 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI) (pp. 1289-1294). IEEE.

[10] Mathew, A. R., & Anto, P. B. (2017, July). Tumor detection and classification of MRI brain image using wavelet transform and SVM. In 2017 International conference on signal processing and communication (ICSPC) (pp. 75-78). IEEE.

[11] Mathew, A. R., & Anto, P. B. (2017, July). Tumor detection and classification of MRI brain image using wavelet transform and SVM. In 2017 International conference on signal processing and communication (ICSPC) (pp. 75-78). IEEE.

[12] Chakrabarty, N. (2019). Brain mri images for brain tumor detection. Kaggle.

[13] Poornachandra, S., & Naveena, C. (2017, March). Pre-processing of mr images for efficient quantitative image analysis using deep learning techniques. In 2017 International Conference on Recent Advances in Electronics and Communication Technology (ICRAECT) (pp. 191-195). IEEE.

[14] Al Okashi, O. M., Mohammed, F. M., & Aljaaf, A. J. (2019, October). An Ensemble Learning Approach for Automatic Brain Hemorrhage Detection from MRIs. In 2019 12th International Conference on Developments in eSystems Engineering (DeSE) (pp. 929-932). IEEE.

[15] Soumya, R. S., Neethu, S., Niju, T. S., Renjini, A., & Aneesh, R. P. (2016, July). Advanced earlier melanoma detection algorithm using colour correlogram. In 2016 International Conference on Communication Systems and Networks (ComNet) (pp. 190-194). IEEE.

[16] J. A. Akhila, C, Markose, et al. "Feature extraction and classification of Dementia with neural network," 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), Kerala, India, 2017, pp. 1446-1450

[17] Sinha, A., & Aneesh, R. P. (2019). Real time facial emotion recognition using deep learning. International Journal of Innovations and Implementations in Engineering, 1.

[18] Nandpuru, H. B., Salankar, S. S., & Bora, V. R. (2014, March). MRI brain cancer classification using support vector machine. In 2014 IEEE Students' Conference on Electrical, Electronics and Computer Science (pp. 1-6). IEEE.

[19] El-Dahshan, E. S. A., Hosny, T., & Salem, A. B. M. (2010). Hybrid intelligent techniques for MRI brain images classification. Digital signal processing, 20(2), 433-441.

[20] W. H. Ibrahim, A. A. A. Osman, and Y. I. Mohamed, ‘‘MRI brain image classification using neural networks,’’ in Proc. Int. Conf. Comput., Electr. Electron. Eng. (ICCEEE), Aug. 2013, pp. 253–258.

[21] Rajini, N. H., & Bhavani, R. (2011, June). Classification of MRI brain images using k-nearest neighbor and artificial neural network. In 2011 International conference on recent trends in information technology (ICRTIT) (pp. 563-568). IEEE.