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Research Article

Self-Adaptive and Multi Scale Approach for identifying Tumor using Recurrent Neural Network

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Abstract: Brain tumor detection is frequently done using MRI scans. Brain contains several nerve cells and tissues; a tumor occurs when growth of abnormal cells accumulates in region of brain. Early stage of brain tumors is classified into either benign (noncancerous) or malignant (cancerous). To identify tumor in brain comes with it's challenges, with new technology of improved image screening, it is becoming elementary to detect brain tumor.

This research paper suggests an automated approach where MRI images are used for brain tumor detection. The proposed system initially improves the brain scan by reducing color variations and is known as segmentation is performed on the original image alongside with threshold binary, which is done to segment objects from the background. The method incorporates adaptive mean thresholding, which is essential method to calculate threshold value at any pixel. Also, Otsu's thresholding is used in the proposed system to perform automatic image thresholding.

In the method majorly 3 filters are used to facilitate improved segmentation of brain scan image. Kalman filter is one of the most important and widely used estimation algorithms, that produces estimations of hidden variables based on imprecise and uncertain dimensions. Median filter provides result by computing each output sample as median value of the input samples. Gaussian filter here is used to reduce noise and contrast.

This proposed method enables reduction in size and better performance using an architecture known as Xception also reduces computational cost of diagnosis of brain tumor using MRI scans. As the final assessments of the model, we achieve high accuracy and superior performance.

Keywords:

1. Introduction

Tumor is a mass of abnormal cells, where brain tumor is one which is formed in the brain and can be life threatening. India has around 1 million cases per year. There are two types of tumor; *malignant* and *benign,* and the signs and symptoms vary greatly depending on the brain tumor's size. Diagnosis is conducted by a CT scan or an MRI scan. This paper illustrates the identification of brain tumors using MRI scans. This proposed paper has a multi-module model for brain tumor screening in the MRI scan, and also integrates an automated approach that enhances the MRI scans to better assist in the identification of tumors.

The initial stage of segmentation is used on brain tumor images to extract multiple features from these images for analysis. The earlier models use the segmentation technique *Gaussian distribution* which assumes the image is a symmetric histogram, however, if the histogram is non-symmetric this paper depicts more generic technique known as *Gamma distribution.* This paper proposes the use of faster R-neural network, for brain tumor image classification, segmentation and for feature selection process which helps in extracting the best features from multiple features and also reduction in computational time and memory space.

2.Existing System

MRI images are obtained as two-dimensional multislice images, and reformatting them into orthogonal planes has many obstacles because of sparse sampling in the perpendicular direction of the plane. The major focus of existing system is to reinstate the lost through-plane regions in an MRI scan. The existing system suggests an *edge-guided GAN* to be used in reconstructing images of brain MRI scan, by separating it into two methods: contrast completion and edge connection.

The existing system uses dataset acquired from the Human Connectome Project to perform artifact rectification on clinical data and simulated datasets, also training and testing on it. In comparison with the traditional imputation tools, our method has higher SSIM, PSNR, signal quality and clarity.

The existing system follows adversarial model comprised of a generator and discriminator, having two major steps: contrast completion and edge connection.

In the first step, EGGAN combines edge generator along with low resolution images, using two-dimensional scans of missing slices as input along with the edges obtained from the original images. Then for second step, the existing system saturates the contrast based upon the first step, original contrast from 2D images, and also as directed by the original images.

After the above two steps, on generator and discriminator, spectral normalization is applied to enhance the stabilization of network by increasing weight matrices and using their highest values.

Spectral and instance normalization are both applied on all parts of edge generator layers,

conversely only instance normalization is used in contrast generator, this is because grasping high frequency information prescribes more restrictions

in order to maintain network stability. Whereas spectral normalization is not required for low frequency information, hence is not used with contrast generator.

3.Proposed System

Goal of proposed system is brain tumor detection without human interference. Image processing used in the medical field has numerous major challenges. Our proposed model assists in classification and detection of brain tumor from the MRI scans. The very first step is extracting multiple features for examining and interpreting the scans is known as *segmentation*.

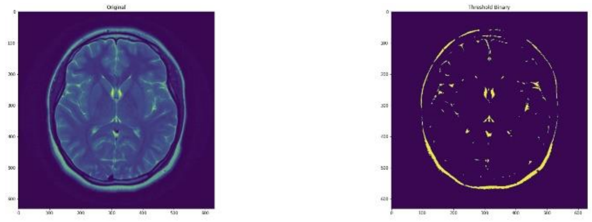


Figure 1.

Above figure shows the original image alongside with threshold binary, which is done to segment objects from the background.

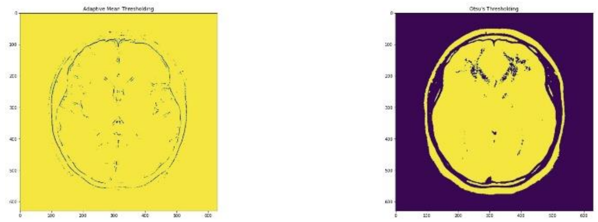


Figure 2.

Figure 2. shows adaptive mean thresholding, which is essential method to calculate threshold value at any pixel. Also, Otsu's thresholding is used in the proposed system to perform automatic image thresholding.

Segmentation helps in detection of any irregularities in MRI scans, and to evaluate image threshold using *gaussian distribution* which assumes that the image histogram has symmetric distribution. In cases where the histogram is non-symmetric, *gamma distribution*, must be used. For brain MRI image segmentation, the paper aims to use the Neural Network method called Faster RCNN, by using Between-Class Variance with Gamma distributions.

Once segmentation is completed, an essential step is performed which reduces computational time and memory space, and is known as feature selection process. It assists in selecting the prime features from the present ones. Variance is calculated for selecting prime features, then the feature with maximum variance is selected.

4.Advantages Of Proposed System

- ❖ Sequencing of data is done, so that every sample is dependent on prior ones.
- ❖ Various convolutional layers along with recurrent neural networks are used to increase the pixels.
- ❖ Enhances the performance in the target domain and also handle non-linear data.
- ❖ Can not only extract specific features adaptively but also aim to learn features of specific scales.
- ❖ A simplified and reconstructed Faster R-CNN with InceptionV3.

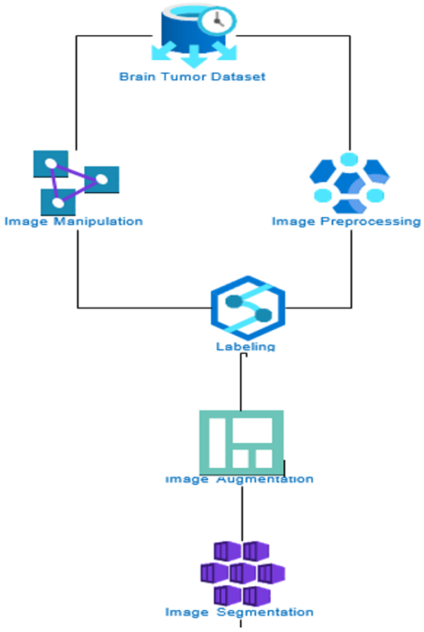
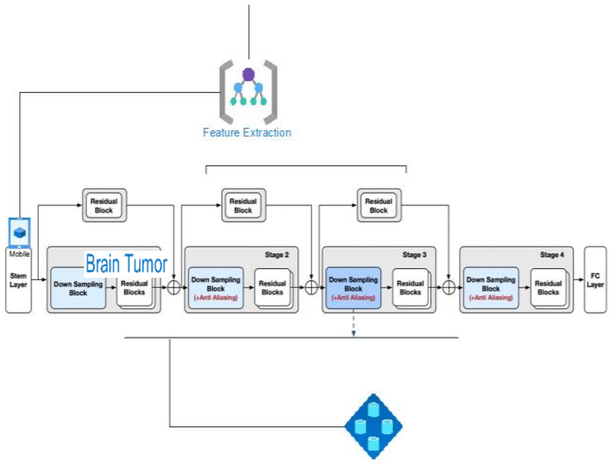


Figure 3. Architecture diagram



5.Algorithm

Fast Regions with Convolutional Neural Network (Faster R-CNN):

The core of faster R-CNN is formed by combination of; RPN (Region proposal network), which is used for generation of,

region proposals and for detecting objects in those regions we use faster R-CNN.

6.Modules

6.1.Data Augmentation:

To build a powerful image classifier and detector our model uses an effective method called Data Augmentation, using only very limited training dataset from each class it was able to recognize the data.

To make the most of our limited training data, our model will Augment the data using various transformations like whitening the image, rotating, flipping the images horizontally and vertically, increasing brightness and rescaling the images so that our model never sees the same images twice. This helps us avoid overfitting and helps the model simplify and generalize better.

Finding the correct tool for an image classification job can be challenging, for that reason our model is trained to use data as an initial baseline. Since the amount of data is limited, our main concern is to avoid overfitting in the model, which occurs when a model is trained with very limited amount of data and learns the patterns and cannot recognize new information.

Supposing, if a human can identify ten people who are loggers and ten as mariners from the images, where out of them only two loggers have a hat, then one may falsely assume that having a hat is considered as being a logger and this pretense will result in being an imperfect classifier.

Augmenting data is one of the ways to prevent overfitting, but that is still not that enough

because, the augmented examples might still be immensely associated with each other. Entropic capacity of our model will be our prime focus for avoiding overfitting, along with to what extent data and information our model is qualified to store and utilize.

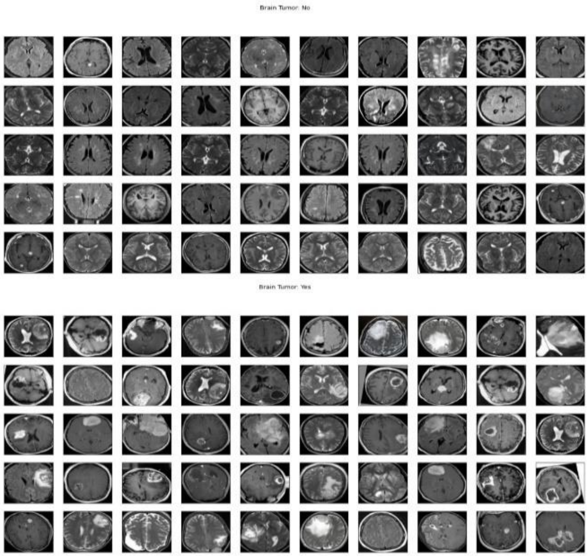


Figure 3.

The above Figure 3. Shows Augmented MRI scans of brain with and without tumors.

Higher the capacity of storing information, more precise the model will be as it can use additional features, contradictorily, it can also store inappropriate features which may result in decreased performance. As to avoid both scenarios, building a model which stores limited features enables it to emphasize on most relevant features and has better chance in being highly precise

One among the multiple ways to control entropic capacity is to choose the optimal number of parameters for the model, i.e., the number of sizes of each layer and the number of layers.

Another technique is to penalize the network and using weighted regularization to reduce overfitting in various deep learning models, such as L1 or L2 regularization, which

optimizes the network by forcing it to take smaller values.

6.2.Data Import and Preprocessing:

Pre-processing is a technique which is used to convert the raw and preprocessed inputs into a useful and efficient form. The main aim of pre-processing is to improve the image using different types of filters and to reduce the redundant distortions in the data and also to enhance some features important for further processing of data.

First, we Convert the color images into grayscale images to reduce space complexity or computational complexity. This is because, in many objects and images, colors aren’t necessary to identify and interpret an image. Using Grayscale can be better option to create and recognize different type of objects. Because colored images contain extra materials and information than black and white images, they can further add redundant data and can increase the time and space complexities.

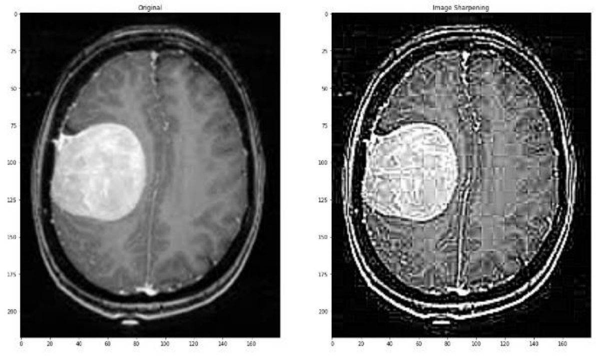


Figure 4.

The above image (Figure 4.) exhibits image sharpening performed onto the original image. The reason it is done is that, image sharpening is a high-end filtering process which aims to amplify high frequency details in the input image.

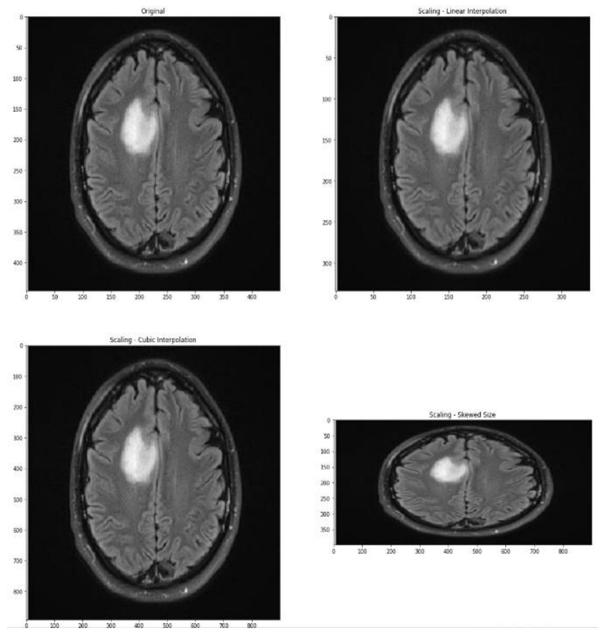


Figure 5.

The above image (Figure 5.) shows as a part of pre-processing, input image goes through multiple scaling to avoid blurring. Linear

interpolation desires an amplification into two dimensions and is used when you have very small image, while cubic interpolation is preferably used for most images keeping the edges smooth.

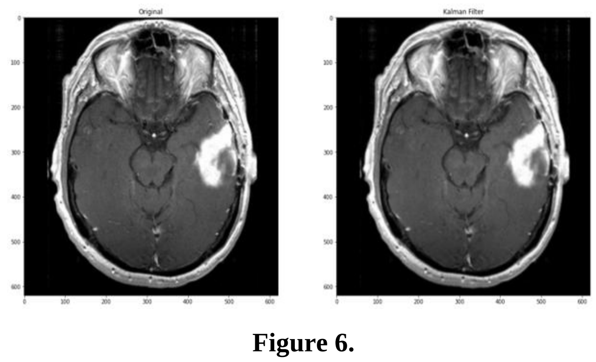


Figure 6.

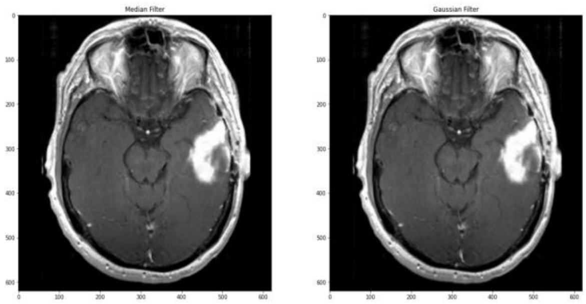


Figure 7.

Our proposed model is using 3 main filters; Kalman filter is one of the most important and widely used estimation algorithms, that produces estimations of hidden variables based on imprecise and uncertain dimensions. Median filter provides result by computing each output sample as median value of the input samples. Gaussian filter here is used to reduce noise and contrast.

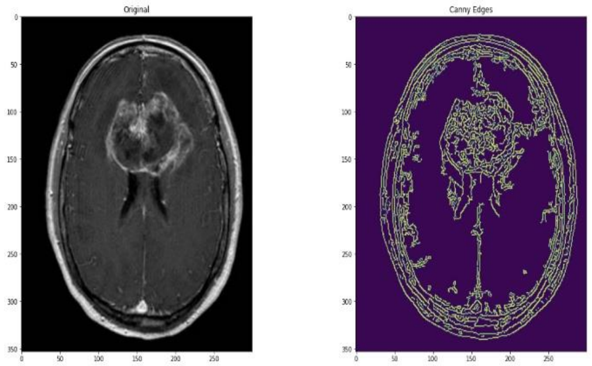


Figure 8.

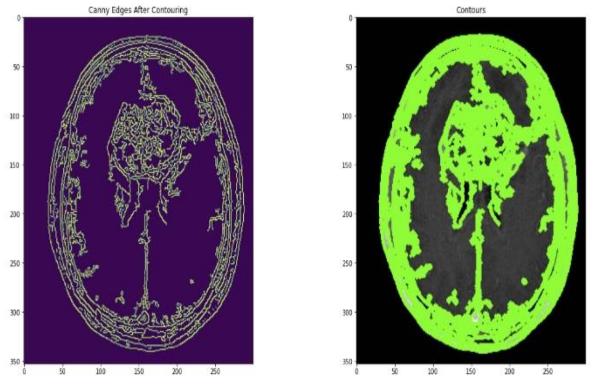


Figure 9.

Figure 8 & 9, are describing conversion of original image into edges and contour, here Canny Edges are used which is a multi-stage detector and helps to detect edges in the image. Contour is used to identify different structural outlines of the object and which can in turn help us identify the shape of the object. The canny edges then help us find different contours in the image.

One significant limitation present in a few algorithms of machine learning, like Convolutional Neural Networks, is the necessity of resizing the images into unified dimensions and size. Thus, before being used in the algorithm, the images should be preprocessed and reformatted to have similar heights and widths.

To further classify only the important parts in our image, the biggest contour is used from the image and then the extreme points on those contours are pointed out. Cropping the image is done using the extreme points on the contour so that only the important parts of the image are used for building our model and all the noise and redundant data are discarded from the images.

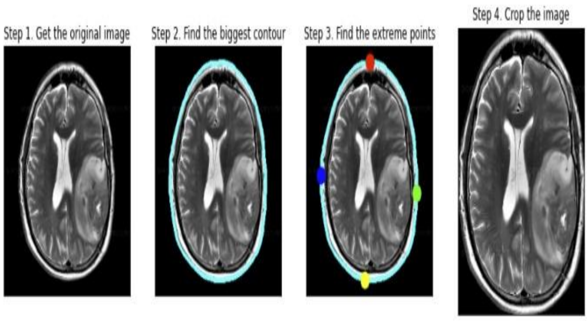


Figure 10.

6.3.Model Building:

A total of 5781 images were result after doing data augmentation and applying different filters on our data, consisting both images having brain tumor and not having brain tumor. 2934 images were of images having brain tumor and 2838 images were of images not having brain tumor.

```
Number of examples: 5781
Percentage of positive examples: 50.908147379346113%, number of pos examples: 2943
Percentage of negative examples: 49.09185262065387%, number of neg examples: 2838
```

Figure 11.

Figure 11. is an image of the number of images in our model.

```
Training Data:
Number of examples: 4046
Percentage of positive examples: 51.458230350963916%, number of pos examples: 2082
Percentage of negative examples: 48.541769649036084%, number of neg examples: 1964
Validation Data:
Number of examples: 868
Percentage of positive examples: 49.193548387096776%, number of pos examples: 427
Percentage of negative examples: 50.806451612903224%, number of neg examples: 441
Testing Data:
Number of examples: 867
Percentage of positive examples: 50.05767012687428%, number of pos examples: 434
Percentage of negative examples: 49.94232987312572%, number of neg examples: 433
```

Figure 12.

The above figure shows, 70% (4046) of the data was for Training the model and 15% (868) for Test Data and 15% (867) of the data for Validation.

The input size to the first convolutional layer is 240 x 240 RGB colored image. The input is being passed from various convolutional layers, then different types of filters were used with a size of: 3×3 (to capture the view of left, right, up, down, and center the smallest size filter is used). Now input is passed through several Activation and Batch Normalization layers. Model uses Sigmoid activation function and max-pooling being performed on a 2×2-pixel window, with a stride of 2.

Model is trained on total 21,876,513 parameters with loss function as Binary Cross entropy, and the optimizer function being RMSprop with a learning rate being 0.0001.

```
Total params: 21,876,513
Trainable params: 21,842,081
Non-trainable params: 34,432
```

Figure 13.

Model Checkpoint help the model in monitoring a particular parameter. Here, validation accuracy is monitored by passing Validation accuracy into Model Checkpoint. Now, if the validation accuracy in our current epoch is higher than the last epoch of the model, only then the model will be saved.

6.4,Model Performance:

After training our classification predictive model, an assessment was performed to check the performance. Python package called scikit-learn is used by majority of the machine learning and deep learning practitioners for predictive and classifier modeling. With multiple functions that Scikit-learn provides us,

are used for interpreting and calculating performance of models.

Our model is trained for 20 epochs and 127 steps per epoch. From the start itself the model started performing well and was able to get good Test and Validation Set Accuracy. The model managed to generate a validation loss as low as 0.00000041952

but when the best model was selected from all the epochs it had validation loss of 0.1316. The test accuracy was 98.70%.

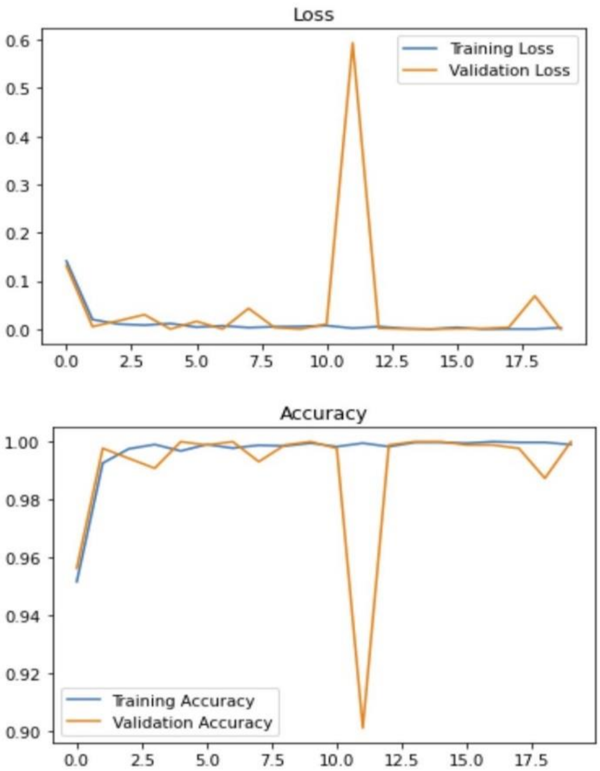


Figure 14.

In Figure 14, a plot is shown below to help visualize model's performance while training.

7.Result

After completing the training and selecting the best model, resulted in Test set accuracy of 98.70% and Test loss of 0.026. Since the model was somewhat imbalanced, F1 score was used as metric for our model and it managed to achieve 98.71% f1-accuracy for Testing data

and 99.36% f1-accuracy on Validation data which also shows that the model is good and there is no sign of overfitting.

Accuracy of the best model on the testing data:

```
print (f"Test Loss = {loss}")
print (f"Test Accuracy = {acc}")
```

```
Test Loss = 0.026624836027622223
Test Accuracy = 0.9870796027183533
```

F1 score for the best model on the testing data:

```
y_test_prob = best_model.predict(X_test)
```

```
f1score = compute_f1_score(y_test, y_test_prob)
print(f"F1 score: {f1score}")
```

```
F1 score: 0.9871192660550459
```

```
y_val_prob = best_model.predict(X_val)
```

```
f1score_val = compute_f1_score(y_val, y_val_prob)
print(f"F1 score: {f1score_val}")
```

```
F1 score: 0.9936635514018692
```

Figure 15.

The above figure is a snapshot of the accuracy achieved using our best model.

8.Conclusion

This paper proposes a Faster R-neural network aimed for categorizing the MRI brain tumor images which were acquired from Jansons MRI diagnosis center, and determining if tumor is present or not. The features which have highest dissimilarities are used for classification, and were classified as global feature using faster R-CNN along with Inception V3. This paper proposes an enhancement to the method for image thresholding. While training the model it took around 7 seconds per step. Our model was trained using different filters like Kalman Filter, Median Filter and Gaussian filter. It also used Image Interpolation to avoid image blur and increasing the pixel quantity in the image for maximum results.

In our method Gamma distribution is used which resolves the problem of a nonsymmetric histograms of brain MRI images, also optimal value is obtained from threshold value by applying faster RCNN algorithm in the method.

References

1. Siegel, R. L., Miller, K. D. and Jemal, A. (2017), Cancer statistics, 2017. CA: A Cancer Journal for Clinicians, 67: 7–30. doi:10.3322/caac.21387.
2. Jain S. 2013. Brain Cancer Classification Using GLCM Based Feature Extraction in Artificial Neural network. International Journal of Computer Science & Engineering Technology, IJCSET, 4(7): 966-970.
3. Nandpuru H B, Salankar S S, & Bora V R. 2014 March. MRI brain cancer classification using Support Vector Machine. in Proc. of IEEE Students' Conference Electrical, Electronics and Computer Science (SCEECS):1-6. DOI:10.1109/SCEECS.2014.6804439.
4. B. Schouten, J. Hellings, P. Vankrunkelsven, J. Mebis, P. Bulens, F. Buntinx, D. Vandijck, and E. Van Hoof, ‘‘Qualitative research on the belgian cancer rehabilitation evaluation system (CARES): An evaluation of the content validity and feasibility,’’ J. Eval. Clin. Pract., vol. 23, no. 3, pp. 599–607, Jan. 2017, doi: 10.1111/jep.12681.
5. S. B. Sakri, N. B. A. Rashid, and Z. M. Zain, ‘‘Particle swarm optimization feature selection for breast cancer recurrence prediction,’’ IEEE Access, vol. 6, pp. 29637– 29647, 2018, doi: 10.1109/ACCESS.2018.2843443.
6. Y. Sun, J. Zhang, G. Li, Y. Wang, J. Sun, and C. Jiang, ‘‘Optimized neural network using beetle antennae search for predicting the unconfined compressive strength of jet grouting coalcretes,’’ Int. J. Numer. Anal. Methods Geomech., vol. 43, no. 4, pp. 801–813, Jan. 2019, doi: 10.1002/nag.2891.
7. J. Zhang, Y. Jia, D. Zhu, W. Hu, and Z.
8. Tang, ‘‘Study on the situational awareness system of mine fire rescue using faster ross Girshickconvolutional neural network,’’ IEEE Intell. Syst., to be published, doi: 10.1109/MIS.2019.2943850.

9. Q. Zhang, J. Lu, D. Wu, and G. Zhang, ''A cross-domain recommender system with kernel-induced knowledge transfer for overlapping entities,'' IEEE Trans. Neural Netw. Learn. Syst., vol. 30, no. 7, pp. 1998–2012, Jul. 2019, doi: 10.1109/TNNLS.2018.2875144.
10. Yang, Y. Li, C. Liu, J. Li, Y. Zhang, and J. Wang, ''Research on logistics supply chain of iron and steel enterprises based on block chain technology,'' Future Gener. Comput. Syst., vol. 101, pp. 635–645, Dec. 2019, doi: 10.1016/j.future.2019.07.008.
11. G. Xu, M. Zhang, H. Zhu, and J. Xu, ''A 15-gene signature for prediction of colon cancer recurrence and prognosis based on SVM,'' Gene, vol. 604, pp. 33–40, Mar. 2017, doi: 10.1016/j.gene.2016.12.016.
12. Z. Yue, S. Ding, W. Zhao, H. Wang, J. Ma, Y. Zhang, and Y. Zhang, ''Automatic CIN grades prediction of sequential cervigram image using LSTM with multistate CNN features,'' IEEE J. Biomed. Health Informat., to be published, doi: 10.1109/JBHI.2019.2922682
13. X. Jiang and S. Li, ''BAS: Beetle antennae search algorithm for optimization problems,'' 2017, arXiv:1710.10724.
14. H. Turabieh, M. Mafarja, and S. Mirjalili, ''Dynamic adaptive network-based fuzzy inference system (D-ANFIS) for the imputation of missing data for Internet of medical Things applications,'' IEEE Internet Things J., vol. 6, no. 6, pp. 9316–9325, Dec. 2019, doi: 10.1109/JIOT.2019.2926321.
15. Wakchaure S L, Ghuge G D, & Musale D S. 2014. The Detection and Visualization
16. of Brain Tumors on T2-Weighted MRI
17. Images Using Multiparameter Feature Blocks. International Journal of Emerging Technology and Advanced Engineering, 4(2):127- 131.
18. Kothavari K, Arunadevi B, & Deepa S N. 2014. A Hybrid DE-RGSOELM for Brain Tumor Tissue Categorization in 3D Magnetic Resonance Images. Mathematical Problems in Engineering: 2014.
19. Ojala T, Pietikainen M. 1999. Unsupervised texture segmentation using feature distributions. Pattern Recognition, 32: 477-486.