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Automatic Prediction of Tp53 Mutation in Pancreatic Cancer Using PSO Based Convolution Neural Network (CNN)

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ABSTRACT

This project proposes an automatic prediction of Pancreatic Cancer including TP53 Mutation using a new artificial neural network. The image to be tested is segmented by Fuzzy C Means segmentation algorithm. Process of feature extraction is carried out with Gray Level Co-occurrence Matrix Method and optimized using PS optimization algorithm. An effective classifier, (PSO based CNN) is used and final results are accurately predicted. By using CNN Classifier, the obtained results were accurate. This project is implemented with MATLAB simulation software.

1 Introduction

Endoscopic light scattering spectroscopy with light gating has a great deal of potential for the early and precancerous cancer detection range of digestive tract organs, the pancreatic and biliary channels in particular [1]. This method of deduction has been demonstrated to be significantly more effective, rapid, and accurate than the current detector by deep convolutional neural networks (ConvNets). ConvNets are used to forecast subsequent involvement regions of a tumour as well as to graphically illustrate and educate about cell invasion and mass effect [2]. The VHR picture scene classification model's Deep Feature Fusion for VHR Remote Sensing model beats state-of-the-art which provides a better representation of a low dimension image scene [3]. The deep analytic network (DAN) and its kernelization (K-DAN) model retrains multilayer features, resulting in the ridge regression-based S-DNN, which is formed utilising baseline features . This reduces the complexity of the network and enhances CPU training and CPU interference times [4]. Image-derived motion, elastic-growth decomposition, and FDM-FEM-Based Pancreatic Tumor Growth Prediction By combining each of these, it is possible to examine more pathologic biomechanical aspects and reduce the customizable time, which helps with independently customising the growth and elastic [5].

Radiomics Analysis of Pancreatic Neuroendocrine Neoplasms Using Deep Learning-Based Semi-Automatic CT Segmentation is more precise and useful, despite its constrained scope [6]. Comparing the efficacy and cost-effectiveness of 2D and 3D segmentation for the use of CT texture analysis relies on machine learning to assess presence of HPV in oropharyngeal squamous cell cancer, it was shown that the 3D segmentation exhibited superior CT texture feature repeatability [7]. For multimodal face anti-spoofing, a unique pipeline-based multi-

stream CNN architecture called PipeNet has been developed. With continuous frame input, this architecture has the potential to be adaptable, practical, stable, and accurate [8]. The construction of deep learning-based multimodal fusion architecture protects against performance deterioration brought on by partial data absence, handles cross-modal information, and provides compatibility with all learning models for machines [9]. A practical method to produce realistic images from simulated XCAT phantoms is to synthesise Used CycleGAN, CT scans from digital body phantoms. This also aids in segmentation network performance enhancement [10].
Training for Unbalanced Image Data with Balanced Mini-batch Improved classification performance using a Neural Network [11]. Sparse Group Learning and Heterogeneous Feature Selection Using Multi-Modal Deep Neural Networks Lasso has shown. its efficacy in identifying the pertinent even group and achieving competitively ranked performance [12]. Geographic picture annotation is improved using a multi-modal feature fusion-based approach and outperforms the current one in terms of performance [13]. Lower grade gliomas' EGFR expression can be predicted by MRI characteristics: With the aid of this model, a voxel-based radiomic analysis with lower grade glioma was created, indicating that it is possible to predict genetic information using tumour-derived radiological properties [14]. Treatment options for cancer in humans when mutant p53 proteins are expressed, the therapeutic targeting will be considerably more precise, increasing the likelihood of the study's significant success [15]. Pancreatic cancer is a malignant digestive tract tumor that is hard to detect and treat at an initial stage. Therefore, a novel image processing approach is proposed to extract the desired features from the clinical images.

2 Proposed System

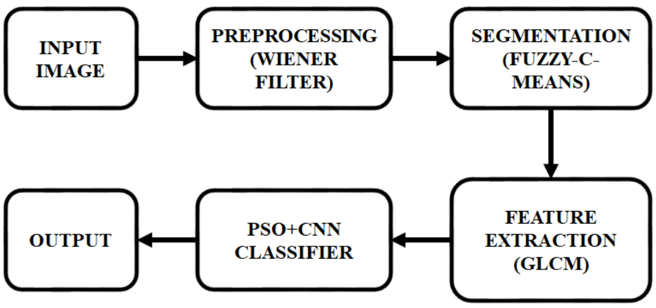

Figure 1: *Proposed system Block Diagram*

The input image is pre-processed with a Wiener filter for eliminating the noise. After pre-processing, the noise removed image is fed into the segmentation block for segmenting the image into several segments for further process. Here, fuzzy-c-means clustering method is being followed. A fuzzy filter is used for Edge detection. The segmented regions are processed by the feature extraction technique for extracting several features and selecting the required features to make the classification easier. In this project, GLCM is used for feature extraction and feature selection. At last, the selected attributes are stuffed into Deep CNN classifier for classifying portrait accurately. Quantitative accuracy of classified image is more accurate.

2.1 Wiener Filter

Weiner filter is used in order to balance the distortion insertion and noise reduction. These filters were used in the pre-processing phase of the ASR system. For AWGN, the effect of noise rather than the effect of distortion was utilized to degrade the recognition performance. The purpose of using Wiener filter is to eliminate the noise from the distorted signals. The filters are configured to achieve a proper frequency response, but process of configuration of Wiener filter is not easier to achieve. The two main aspects of Wiener filter, one having the knowledge about spectral attributes of original signal and other seeks linear time invariant filter, and then the results obtain from both would be probably similar to the original signal. The main function of Wiener filter is to specify frequency of dominant chirp signal over the noise signal and to make the frequency of the weak chirp signal less effective If noise is present in the chirp signal, then the noisy chirp signal is given as,

$$R\ (u) = \frac{H(u)^*}{|H\ (u)|^2 + K} \tag{1}$$

Where R (u) is the output and H (u) is the Fourier transform of the signal. A high pass filter is the counterpart to a blurred image. The low frequency aspect of the parameter K is coupled to Wiener filter .The Wiener filter acts as a band pass filter in the low pass and high pass filters, respectively, due to the inverse filter and parameter K.

The Wiener filter, tends to separate the signals on the basis of their frequency spectra. At some frequencies, the signal predominates, whilst at others, the noise does. It seems sense that the filter should let in frequencies those are "largely signal," while blocking the frequency that are tends to be "primarily noise." This concept is expanded upon by the Wiener filter, which bases its gain at each frequency on the relative amounts of signal and noise present at that frequency.The Wiener filter is prime in the sense that it the most apparent ratio value of the signal power to the noise power.

Main property that is of the Wiener filter is to make the time-dependent noise factor is inversely dependent on SNR and permits it to change from frame to frame. This will assure the stronger suppression of noise-only frames and weaker suppression during the segment process of the chirp signal. This filter thus removes the noisy regions in the given input image.

2.2 Fuzzy C Means Segmentation

Segmentation is the process of breaking up an image into various smaller groups (pixels) known as Image Objects. This system uses the fuzzy-c-means technique for segmentation, which reduces the complexity of the image. Popular data clustering algorithm, fuzzy ISODATA is otherwise known as fuzzy c-means algorithm, considers each data point to be a member of a cluster to a degree determined by a membership grade. A cluster centre is located in each of the c fuzzy groups that FCM creates collection of n vectors, X j, j = 1,..., n, in order to minimise the distance-based cost function. Fuzzy clustering allows for partial belongingness of the object to all groups and accounts for cluster overlapping. In other words, any group having a degree of membership between ° and 1 can have a specific data point as a member. The process, which employs an iterative clustering technique, aims to produce an ideal c partition by minimizing the objective function for weighted within-group squared error J FCM. The following equation describes fuzzy c-partition, the result of a fuzzy clustering.

$$J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q \, d^2(x_k, v_i) \quad (2)$$

- The data set in p-dimensional vector space is represented by X = x1, x2, xn, and R p.
- n is the number of data items.
- c is the number of clusters with $2 \leq c < n$.
- u_{ik} is the degree of membership of x_k in the i th cluster.
- q is a weighting exponent on each fuzzy membership.
- v_i is the prototype of the Centre of cluster i.
- $d^2(x_k, v_i)$ is a distance measure between object x_k and cluster Centre v_i.

The most effective FCM solution has been discovered using an iterative method. The FCM method uses fuzzy clustering paradigm. To lessen fuzziness of within-cluster variance, the degrees of membership are changed. FCM is the method that is most frequently used to give pixels in image processing values for multiclass membership. When we are aware of the memberships of each class (cluster) for data points, such as pixels, we can assign pixels to the class with the highest membership. Because it doesn't require an initial set of training data, in terms of developing membership functions for additional processing, the fuzzy c-mean approach is unsupervised.

2.3 GLCM (Gray Level Co-Occurrence Matrix)

In place of texture evaluation, the GLCM is carried out. The reference and neighbor pixels are the two pixels that we take into consideration at once. Prior to evaluating GLCM, one has to define certain spatial relationship between the neighboring pixels and reference. For instance, we may say that the neighbor is any pixel that is 1 pixels right towards the current pixel, 3 pixels above, or 2 pixels diagonally (towards any of the NE, NW, SE, or SW) from the reference. We build a GLCM of size (Range of Intensities x Range of Intensities) with all of its starting values set to zero after a spatial relationship has been established. An 8 bit single channel image, for instance, will possess 256x256 GLCM. Then, as we move across the image, we increment that matrix cell for each pair of intensities we discover for the specified spatial connection. Count of the occurrences of each pair of intensities in an image with specified spatial connection is kept in most of the entries of GLCM [i, j].

Matrix can be made symmetrical so in a way every cell expresses the likelihood of the certain particular pair of intensities occurring in the image by adding it to its transpose and normalizing it. We can represent the textures in the image using the texture characteristics of the matrix after computing the GLCM.

2.3.1 GLCM Algorithm

Input: Image
Output: Vector of textual features
Start
Step 1: The Algorithm of computing GLCM matrix in four direction with distance d=1 is called
Step 2: The Algorithm of normalizing each GLCM matrix is called.
Step 3: For each GLCM matrix in certain angle
Step 4: Evaluate textural features according to their equations.
Step 5: Store computed features in a vector.
Stop

2.4 CNN based PSO Classifier

This method chooses a swarm of particles, which go through a hyperspace in search of a solution. In hyperspace, each particle determines its own solution while retaining both its own best solution and the swarm's collective best solution. The social character of birds serves as the basis for this algorithm. Initializing the particle values and velocity is the first step of the procedure. Then, based on the objective function's minimal value for each particle, we choose the optimal option globally. The position of each particle is updated using a velocity calculation. When the allowed number of epochs is reached, the algorithm is ended.

2.4.1. Hybrid PSO-CNN Training Model(Proposed Method)

An algorithm is carried out as 5 steps.

- Evaluation of Prediction Accuracy and Results
- Appointing weight values from step 4, upgrade CNN.
- PSO Training
- Pre-PSO Training: Weight Capture and Weight to Particle Conversion
- CNN Training

The neural network's predetermined weights are established by the CNN with back propagation. Given that the MNIST dataset taking into account the portrait of size 28x28 pixels, and a CNN with two hidden layers and 784 input nodes is used. Additionally, the CNN has two 2D max pool layers and two 2D convolutional layers. One hot vector is encoded as the output.
“Pre-PSO Training: Capturing Weights and Conversion of Weights into Particles”:- Since the weights must be optimized, train the CNN via back propagation. They are taken in as tensors and transformed into dumpy arrays so that PSO can further optimize them. The acquired weights are transformed into particles for the following stage because particles are optimized by the PSO algorithm.
After determining the memory, cognitive, social, particle, halting condition, and maximum epoch’s parameters. CNN loss function serves as an aim for PSO training in order to ensure consistency when PSO optimization explores the hyper plane for optimum solutions.

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A new CNN with specific weight values must be created in the results computation's final stage using the weight values obtained from phase 4.This CNN won't be trained using the output. Our final output is the CNN output in its original form, an accuracy and cost value are calculated from that. After CNN training, the system receives weights and utilizes PSO to optimize them in order to increase accuracy. From CNN model the weight vectors may be extracted as tensors using tensor flow, a free open-source framework created specifically for machine learning. After that, values are sent to PSO training module, which updates and trains them. When PSO training model converges, updated weight values matrix is turned back into a tensor to update CNN weights.

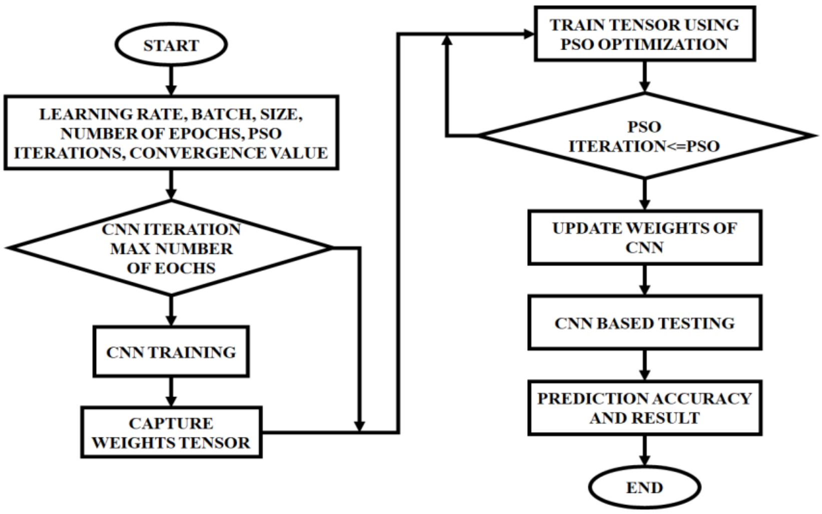

Figure 2: *Diagram showing the suggested method's control flow.*

2.4.2. Architecture

There are three layers in a convolutional neural network: input, hidden, and output. The term "hidden layers" refers to any intermediate layers in a feed-forward neural network that, by their activation function and final convolution, conceal the inputs and outputs of the network. The hidden layers of a convolutional neural network contain convolutional layers. ReLU is usually employed as that layer's activation function, and this frequently includes a layer that performs multiplication or another dot product. Following this are further convolution layers, such as connected, pooling, normalization and completely layers.

A CNN's input is a tensor with the following dimensions: (count of images) x (image length) x (image breath) x (input channels). The image is abstracted into a feature map after going through a convolutional layer, and it has the following dimensions: (count of images) x (feature map length) x (feature map breadth) (feature map channels). A convolutional layer in a neural network needs to meet the requirements listed below:

- Convolutional filters/kernels have width and height specifications.
- The quantity of input and output channels.

- Number of channels in an input feature map must match the number of channels (depth) in convolution kernel/filter.
- The convolution operation's hyper parameters, such as padding size and stride.

Convolutional layers integrate input before send the combined data to the layer below. This is similar to the way a visual cortex cell reacts to a specific stimulus. Data processing for unique receptive field of each convolutional neuron. In order to categorise data and learn features, fully connected feed forward neural networks can be utilised; however, this design is not appropriate for portraits. Even with a deep structure, it would need a very high number of neurons because to the enormous input sizes associated with images, where each pixel is a major variable. Using a (small) image of size 100 by 100 as an example, the second layer of a fully linked layer has 10,000 weights for each neuron. Contrarily, convolution restricts number of free parameters, allowing for a deeper network. No matter how big the image is, tiling 5 5 regions with identical shared weights only needs 25 learnable parameters. Using regularised weights across fewer parameters prevents the vanishing gradient and inflating gradient problems that might occur during back propagation in conventional neural networks.

2.4.3. CNN Algorithm

Pancreatic Cancer Classification Using Convolutional Neural Network
Feed in: load all CT images *I* that is available in the dataset
Out turn: Segregated Pancreatic Cancer images into ischemic and hemorrhagic
Step 1: Function CI=Classify (I)
Step 2: The Contrast stretching method is used.
Step 3: Use an average filter to perform image filtration and sharpening.
Step 4: the quad tree-based technique is appointed to combine filtered and contrasted images.
Step 5: the combined images are segregated into testing and training set.
Step 6: Feed the training dataset of 512 × 512 × 1 into P_CNN network

1. 2-D convolutional layer with 96 filters of [11 11] size where stride is 4.
2. ReLU layer
3. Max Pooling layer
4. 2-D convolutional layer with 10 filters of [5 5]
5. ReLU Layer
6. Max Pooling layer
7. Layer fully connected with 512 output pixels
8. ReLU Layer
9. Dropout layer through 0.1 possibility of dropout
10. Fully connected layer with an output size of two to distinguish between ischemia and hemorrhagic stroke
11. Apply soft max layer
12. Employing a classification layer, categories the image dataset.

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3 Results and Discussion

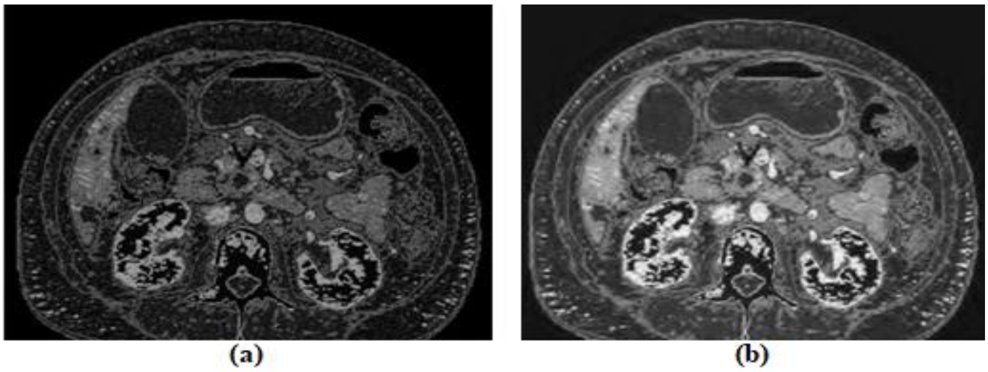

Figure 3: *Input Image of Pancreas* ***(b)*** *Image of Preprocessing*

The above figure 3 (a) shows the pancreas image, which is to be tested.

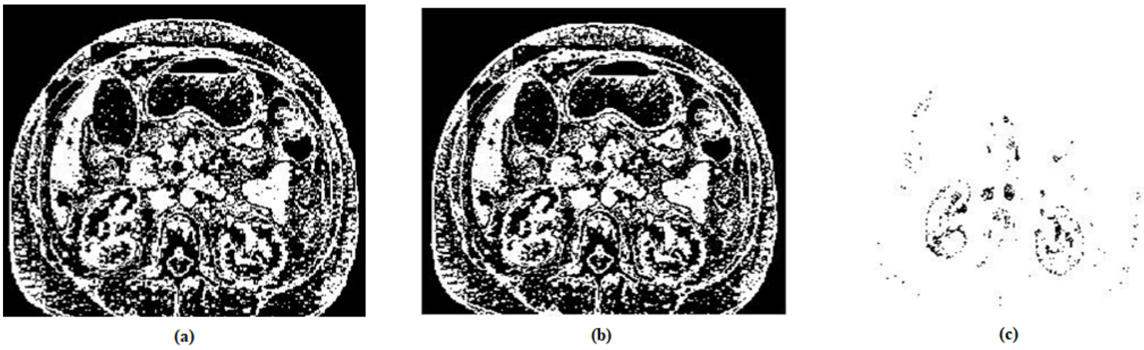

Figure 4: *Filter Image* ***(a)*** *Noise removed,* ***(b)*** *Adaptive Binarization,* ***(c)*** *Outline Filter*

Noise in the input image is removed using Wiener filter. The above figure 4 shows the noise removed image i.e., filtered image.

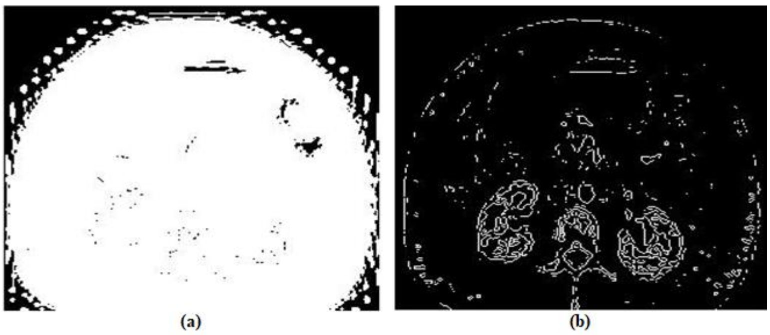

Figure 5: (a) *Segmented Image* **(b)** *Edge detection*

The filtered portrait is then segmented with the help of Fuzzy-C-Means segmentation method. Thus, segmented portrait is shown in figure. 5 (a)

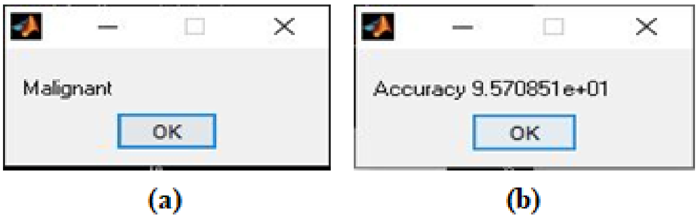

Figure 6: ***(a)*** *Output image* ***(b)*** *Accuracy*

4 Conclusion 0

iIn this project, we propose a PSO based CNN classification approach to detect TP53 mutation in pancreatic cancer cells. The noise in the image is removed using wiener filter. Thus, the enhanced image is segmented using fuzzy c means segmentation algorithm. By using GLCM, the textural features are extracted. In order to enhance the classification performance the whale optimization is used for the feature selection. The final result demonstrates that the suggested technique is efficient and performs better than the other approaches.

References

1. Le Qiu; Lei Zhang; Vladimir Turzhitsky; Umar Khan; Yuri Zakharov; Douglas K. Pleskow; Mandeep Sawhney; Tyler M. Berzin; Jeffrey D. Goldsmith; Kanchan Kantekure; Edward Vitkin; Irving Itzkan; Lev T. Perelman, Year: 2019, "Multispectral Endoscopy With Light Gating for Early Cancer Detection", IEEE Journal of Selected Topics in Quantum Electronics, Vol: 25, no: 1, pp. 1-9.
2. Zhang Ling; Le Lu; Ronald M. Summers; Electron Kebebew; Jianhua Yao, Year: 2018, "Convolutional Invasion and Expansion Networks for Tumor Growth Prediction", IEEE Transactions on Medical Imaging, Vol: 37, no: 2, pp. 638-648.
3. Chaib Souleyman; Huan Liu; Yanfeng Gu; Hongxun Yao, Year: 2017, "Deep Feature Fusion for VHR Remote Sensing Scene Classification", IEEE Transactions on Geoscience and Remote Sensing, Vol: 55, no: 8, pp. 4775-4784.
4. Low Cheng-Yaw; Jaewoo Park; Andrew Beng-Jin Teoh, Year: 2020, "Stacking-Based Deep Neural Network: Deep Analytic Network for Pattern", IEEE Transactions on Cybernetics, Vol: 50, no: 12, pp. 5021-5034, doi: 10.1109/TCYB.2019.2908387.
5. Wong Ken CL; Ronald M. Summers; Electron Kebebew; Jianhua Yao, Year: 2017, "Pancreatic Tumor Growth Prediction with Elastic-Growth Decomposition, Image-Derived Motion, and FDM-FEM Coupling", IEEE Transactions on Medical Imaging, Vol: 36, no: 1, pp. 111-123.
6. Bingsheng Huang; Xiaoyi Lin; Jingxian Shen; Xin Chen; Jia Chen; Zi-Ping Li; Mingyu Wang; Chenglang Yuan; Xian-Fen Diao; Yanji Luo; Shi-Ting Feng, Year: 2021, "Accurate and Feasible Deep Learning Based Semi-Automatic Segmentation in CT for Radiomics Analysis in Pancreatic Neuroendocrine Neoplasms", IEEE Journal of Biomedical and Health Informatics, Vol: 25, no: 9, pp. 3498-3506.
7. Ren Jiliang; Ying Yuan; Meng Qi; Xiaofeng Tao, Year: 2020, "Machine learning–based CT texture analysis to predict HPV status in oropharyngeal squamous cell carcinoma: comparison of 2D and 3D segmentation," European Radiology, Vol: 30, no: 12, pp.6858-6866.

8. Yang Qing; Xia Zhu; Jong-Kae Fwu; Yun Ye; Ganmei You; Yuan Zhu, Year: 2020, “PipeNet: Selective modal pipeline of fusion network for multi-modal face anti-spoofing”, Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pp. 644-645.
9. Jun-Ho Choi; Jong-Seok Lee, Year: 2019, “EmbraceNet: A robust deep learning architecture for multimodal classification”, Information Fusion, Vol: 51, pp.259-270.
10. Russ Tom; Stephan Goerttler; Alena-Kathrin Schnurr; Dominik F. Bauer; Sepideh Hatamikia; Lothar R. Schad; Frank G. Zöllner; Khanlian Chung, Year: 2019, “Synthesis of CT images from digital body phantoms using CycleGAN”, International journal of computer assisted radiology and surgery, Vol: 14, no: 10, pp.1741-1750.
11. Shimizu Ryota; Kosuke Asako; Hiroki Ojima; Shohei Morinaga; Mototsugu Hamada; Tadahiro Kuroda, Year: 2018,“Balanced Mini-Batch Training for Imbalanced Image Data Classification with Neural Network,” 2018 First International Conference on Artificial Intelligence for Industries (AI4I), pp. 27-30.
12. Zhao Lei; Qinghua Hu; Wenwu Wang, Year: 2015, “Heterogeneous Feature Selection with Multi-Modal Deep Neural Networks and Sparse Group LASSO,” IEEE Transactions on Multimedia, Vol: 17, no: 11, pp. 1936-1948.
13. Ke Li; Changqing Zoub; Shuhui Bud; Yun Liang; Jian Zhang ; Minglun Gong, Year: 2018, “Multi-modal feature fusion for geographic image annotation”, Pattern Recognition, Vol. 73, pp.1-14.
14. Li Yiming; Xing Liu; Kaibin Xu; Zenghui Qian; Kai Wang; Xing Fan; Shaowu Li; Yinyan Wang; Tao Jiang, Year: 2018, “MRI features can predict EGFR expression in lower grade gliomas: a voxel-based radiomic analysis,” European radiology Vol: 28, no: 1, pp. 356-362.
15. Blandino Giovanni; Silvia Di Agostino, Year: 2018, “New therapeutic strategies to treat human cancers expressing mutant p53 proteins,” Journal of Experimental & Clinical Cancer Research Vol. 37, no. 1, pp. 1-13.