Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

Feature Selection using Multi-Verse Optimization for Brain Tumour Classification

Katkoori Arun Kumar[1], Ravi Boda[2], Dr. Praveen Kumar[3], Dr. Vijendar Amgothu[4]

[1]Research Scholar, Electronics and Communication Engineering Department,
KL University, Hyderabad, India.
e-mail: arun.katkoori@gmail.com
[2]Associate Professor, Electronics and Communication Engineering Department,
KLEF Off Campus, Hyderabad, India.
e-mail: raviou2015@klh.edu.in
[3]Associate Professor, Electronics and Communication Engineering Department,
KLEF Off Campus, Hyderabad, India.
e-mail: prawinpoola@klh.edu.in
[4]Associate Professor, Electronics and Communication Engineering Department,
Malla Reddy Engineering College, Hyderabad, India.
e-mail: amgothu.vijendar@gmail.com

Abstract:

Selecting the feature will reduce the dimensionality of the characteristics and the consistency of the reserved features can be maintained in the choir. The selection of features represents a machine-learning optimization challenge, reducing the number of features, eliminating obsolete, noisy, and repetitive data, and achieving suitable acknowledgement. In this paper, Multi-verse Optimization (MVO) is used to select the features from segmented MR image with Random Forest classifier. The steps involved for feature selection- pre-processing, tumor segmentation, feature extraction, feature selection and classification. Two different objective functions are used- image entropy is used as objective function for tumor segmentation and accuracy function is used as objective function for feature classification. Experimental results show that performance of MVO+RF approach gives high accuracy compared to existing techniques like PSO and BAT.

Keywords:*MR Image, Image segmentation, Feature extraction, feature selection, MVO, Random-Forest classifier.*

Introduction:

Tumors are masses or lumps of tissue that resemble swelling. Although not all aTumors are cancerous, it is a good idea to consult a doctor if one appears. A tumor, according to the National Cancer Institute, is “an abnormal mass of tissue that results when cells divide more than they should or do not die when they should”. Cells in a healthy body grow, divide, and replace one another. The old cells die as new one’s form. When a person is diagnosed with cancer, new cells form even when the body does not require them. When there are too many new cells, a cluster of cells, or tumor, can form. Some tumors are ‘benign’ and made up of non-cancerous cells, while others are ‘malignant’. Malignant tumors are cancerous, and cells can spread throughout the body.

MR Imaging is frequently employed in disease detection, diagnosis, and treatment monitoring and is based on advanced technology that excites and detects changes in the rotational axis of protons found in the water that makes up living tissues[13][17][18][19]. These tissuescan be distinguished by two relaxation times: T1and T2. T1 is called longitudinal relaxation time, is the time constant that governs how quickly excited protons

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

return to equilibrium. It is the time it takes for spinning protons to realign with the external magnetic field. T2 is called transverse relaxation time, is the time constant that governs how quickly excited protons reach equilibrium or fall out of phase with one another. It is the time it takes for spinning protons to lose phase coherence among nuclei spinning perpendicular to the main field.

Feature selection is a hot topic in machine learning, pattern recognition, and data mining [1][2][13]. Irrelevant and redundant features encourage additional search because they make patterns less detectable and rules required for forecasting or classification less obvious, in addition to the high overfitting risk.The selection of feature subsets necessitates determining the most appropriate feature to maximise prediction or classification accuracy. The primary goal of this research was to identify the best feature subset. Typically, features are chosen based on computational time and the quality of the generated feature subset solutions. In fact, fast and accurate classification with the fewest features is frequently chosen. This appears to be achievable through feature selection. In this paper, MVO algorithm was chosen for determining the best feature subsets for classifying brain tumors as benign or malignant[13][17][18][19].

When creating a predictive model, feature selection is the process of reducing the number of input variables. It is preferable to reduce the number of input variables to reduce the computational cost of modelling and, in some cases, to improve model performance. Statistical-based feature selection methods entail using statistics to evaluate the relationship between each input variable and the target variable and selecting the input variables with the strongest relationship with the target variable. Although the choice of statistical measures is dependent on the data type of both the input and output variables, these methods can be quick and effective. As a result, when performing filter-based feature selection, it can be difficult for ML practitioner to choose an appropriate statistical measure for a dataset.

Related work:

There are two popularly used feature selection methods: Filter and Wrapper. Filter approaches score and rank features based on specific statistical criteria, then select the features with highest ranking. Examples for this methods- T-test[4], Chi-Square test [5], PCA [6], etc. Despite the speed, the filter model is not strong against interactions between features and redundancies and may not produce the right subset of features.

The wrapper method considers the feature subset and regression model interactions. It uses a learning algorithm to find the most appropriate subset of features and to evaluate the accuracy of potential subsets in predicting the target. These wrapper methods are classified into two- Greedy and Stochastic. Greedy algorithms seek to find the best possible combination of features that results in the best performing model-which is computationally costly and therefore inefficient by using exhaustive quest. To solve large-scale combinatorial problems, stochastic algorithms are created. The leading function subset selection research problems are PSO, ACO, GA, etc. [7]. These methods are capable of capturing redundancy and interaction in features. It is not constrained by the monotonicity assumption. They produce the best function subset, but they are time-consuming to compute. However, the hybridization of filter and wrapper methods done, these are unreliable since, in the presence of component associations, an isolated significant feature can be as discriminatory as an insignificant one.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

Materials and Methods:

The proposed method architecture is shown in figure 1. In this, input MRI image is given to pre-processing stage to eliminate the noise. Median filter is used in this stage. By using Multi-verse Optimization (MVO), threshold was calculated. And this threshold is used to segment the tumour part in input MRI image. Later then the features are extracted using GLCM (Gray-Level Co-Occurrence Matrix) and LBP (Local- Binary- Pattern) methods. These features are given to the next stage i.e. feature selection. This is done by Multi-verse optimization algorithm. Then the type of tumor was classified by classifier.

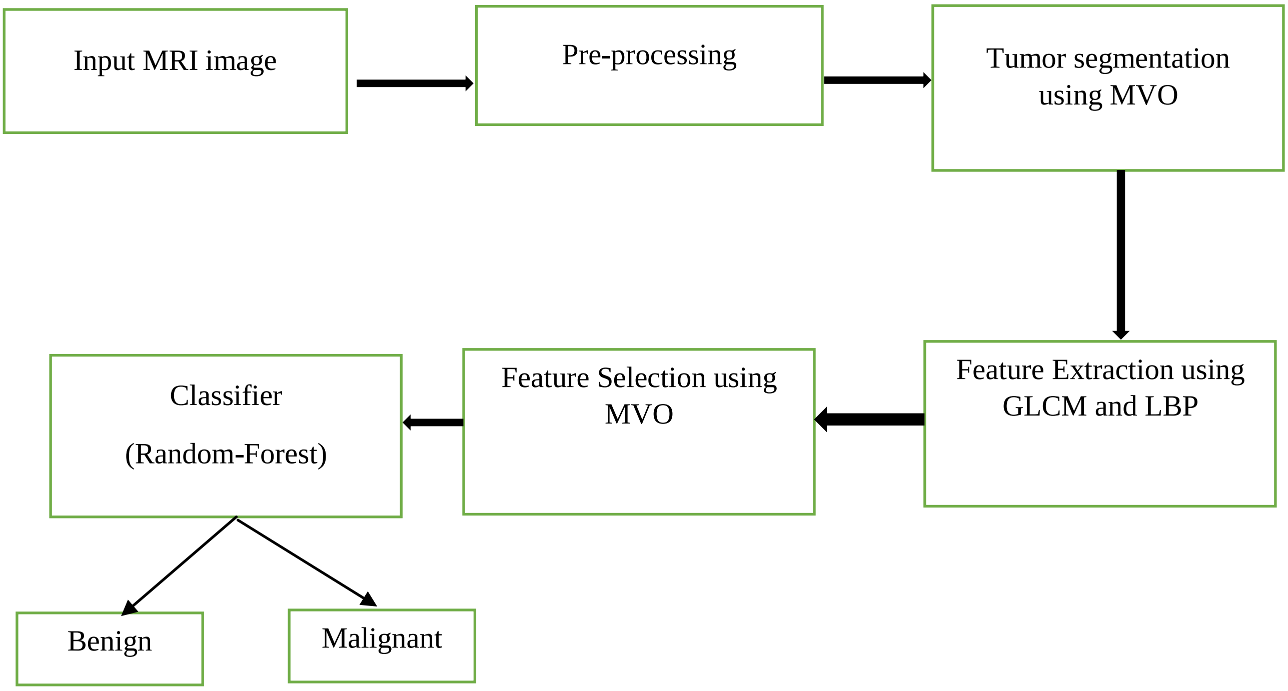


Figure 1. Proposed Method Architecture

Feature extraction using GLCM:

It is a well-known texture feature extraction tool that can be used for image segmentation, image retrieval, image classification, pattern recognition, etc. [8] [9] [10][11].This feature is extracted using GLCM by using the joint condition probability distribution of the image gray-level to reflect texture and calculating the local correlation of pixels to obtain the texture feature value. The authors [12] derived multi-scale texture features from very high-resolution panchromatic imagery by measuring various GLCM directions and window sizes.

It is a 2-D matrix at which two pixels in the image, divided by a certain vector, exist. Gray-Level Co-occurrence Matrix is represented as below

$$G_{jk}(\triangle w, \triangle x) = KS(j, k \mid \triangle w, \triangle x) \tag{1}$$

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

where $$K = \frac{1}{(D-\triangle w)(H-\triangle x)} \tag{2}$$

$$S(j,k \mid \triangle w, \triangle x) = \sum_{h=1}^{H-\triangle x} \sum_{d}^{D-\triangle w} B \tag{3}$$

Where B= 1, if f(d,h)=j and f(d+△w, h+△x) = k
0, otherwise. (4)

It is M * M matrix in size, which means that rows and columns reflect the range of possible pixel values.

This matrix is calculated using two parameters- 'dis' and 'theta'. 'dis' is the pixel pair's relative distance (measured in pixel numbers 1,2,3, …….). The 'theta' is the rotational angle or relative orientation (0^o, 45^o,90^o,135^o, etc.) as shown in figure 1.

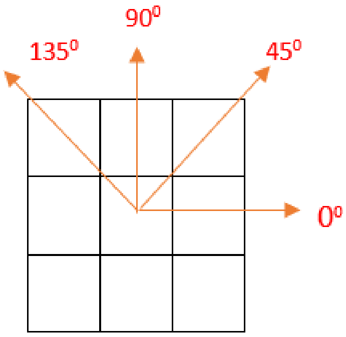


Figure 2.Adjacencydirections (theta)

The statistic of pixel shifts within an area that represents the similarity and regularity of the pixel gray value in different directions is known as image texture directionality. According to this, the statistic of pixel gray shift in different directions will represent the directional function of texture images [13]. This function is the union of structural and statistical characteristics at the large and small scales. As a result, the path calculation must represent the configuration of the image data to some degree, but it should also reflect the statistical properties of the image pixels. The direction measurement is used to divide the image in various directions and the gray-scale image value is measured in each direction, resulting in the quantitative difference in pixels in each direction.

The texture measure is dependent on second order statistical parameters by using GLCM to define texture characteristics. Table 1 lists thedifferent categories of statistics that were mentioned.

Table I.Features extracted using GLCM matrix

Parameter	**Description**	**Mathematical formula**
ASM- Angular Second Moment	Not have distinguishing ability	$f1 = \sum_{j} \sum_{k} g2_{jk}$

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

Contrast	It is rotationally variant and has discriminating ability	$f2 = \sum_{r=0}^{M-1} r^2 [\sum_{j}\sum_{k} g_{jk}]$
Correlation	It has rotational-dependant feature and has strong discriminating ability	$f3 = \frac{\sum_j \sum_k (jk) g_{jk} - \mu_w \mu_x}{\sigma_w \sigma_x}$ where μ_w and μ_x are means, σ_w and σ_x are standard deviations
Variance	It is rotational-invariant and has discriminating ability	$f4 = \sum_j \sum_k (j-\mu)^2 g_{jk}$
IDM- Inverse Difference Moment	It is like angular second moment	$f5 = \sum_j \sum_k \frac{g_{jk}}{1+(j-k)^2}$
Sum average	It is similar to variance and rotationally-variant	$f6 = \sum_{r=0}^{2M-2} r g_{j+k}(r)$
Sum variance	It is similar to variance.	$f7 = \sum_{r=0}^{2M-2} (r - f6)^2 g_{j+k}(r)$
Sum entropy	It’s characteristics similar to entropy	$f8 = -\sum_{r=0}^{2M-2} g_{w+x}(r) \log(g_{w+x}(r))$
Entropy	It is almost rotationally variant and has strong discriminating ability	$f9 = -\sum_j \sum_k g_{jk} \log(g_{jk})$
IMC-1	It is similar to sum average but is different for different groups and significant rotational variant	$f10 = \frac{f9 - H_{wx1}}{max\{Hw, Hx\}}$ where $H_{wx1} = -\sum_j \sum_k g_{jk} \log(g_w(j) g_x(k)$
IMC-2	It is rotation variant and costly compared to others	$f11 = \sqrt{1 - exp(-2(H_{wx2} - f9}$ where $H_{wx2} = -\sum_j \sum_k g_w(j) g_x(k) \log(g_w(j) g_x(k)$

Feature Extraction using LBP:

The LBP operator marks the pixels in a decimal image, which is called LBPs or LBP codes that are coded around each pixel in the local structure. [14] The resulting purely negative values are labelled with ‘0’, while others are enclosed with ‘1’. Each pixel is equivalent to its 8 neighbours in the 3 * 3 neighbourhood by subtracting the centre value of a pixel. A binary is achieved for each pixel, as all these binary values are concatenated in a clockwise direction, starting from one on the left top. For marking the given pixel then the corresponding decimal value of the binary number produced. The resulting binary numbers are LBP Codes.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

One constraint for LBP operators is that they cannot catch dominant features of larger architectures in the smaller 3 * 3 neighbourhood [15]. This operator was later expanded to use neighbourhoods of varying sizes to cope with texture at various scales. A local area is characterised as a collection of sample points uniformly spaced on a circle centred on the pixel being marked, and the sampling points not flowing in the pixels are interpolated using bilinear interpolation such that any radius and number of sample points are permitted in the neighbourhood.

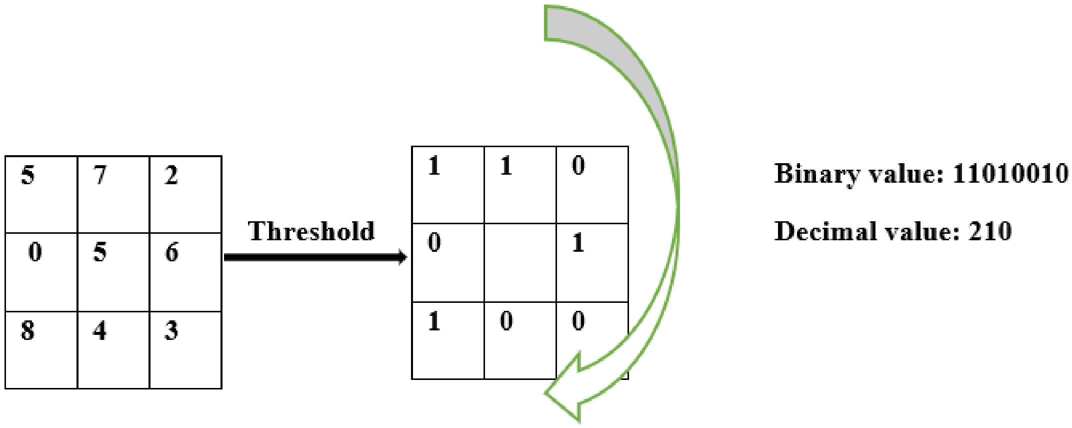


Figure3.Example of LBP operator

For a given pixel at (x,y), the LBP is defined as below

$$LBP^{P,R}(x,y) = \sum_{P=0}^{P-1} w\,(gl_n - gl_c)\,2^P \quad (5)$$

Where gl_c is the gray-level of central pixel.

gl_n is the gray-level of its neighbours.

P is surrounding pixels in the circle neighbourhood.

R is radius of neighbourhood.

The function w(x) is defined as

$$w(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases} \quad (6)$$

In the clockwise direction, the sampling is normal around the central pixel according to a certain radius value, which defines the scattered sampling point's spatial resolution. If the "R" grows, an LBP has more general knowledge on the pattern of texture and therefore requires more neighbors. When a big radius is combined with a small P, the re-sampling can lead to extreme artifacts.In this paper, the number of neighbours is set to 8 for the purpose of balancing knowledge and calculation, and the radius is 1.

Multi-Verse Optimization (MVO):

The evolution of the universe was a massive eruption, according to Big Bang Theory. There was not even one organism in the universe, according to the mentioned hypothesis. The big bang theory is the explanation behind all the world's things. A recent and popular

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

hypothesis called 'multiverse' has been suggested by physicians [16].The multiverse hypothesis says that there was not only one big bang, but a lot of big bangs, and that all bore a new world. It has been concluded that there are many other worlds other than our universe. There is also a chance that these various universes could hit each other.

There are three types of holes exist in the universe- white holes, black holes and worm holes. The 'white holes' are supposed to be the key factor in the world's creation, and they were never observed. The big bang is the white hole itself. when two competing universes merge, a big bang is formed. White holes vary completely from 'black holes'. These hole's property is that with its overwhelming gravitational strength it draws every little thing into itself. Due to 'worm holes', different worlds remain in contact. In multiverse theory, objects are moved from universe to universe or in the same universe with the help of worm holes.The world is expanding in space due to inflation, which is a continuous rate of expansion. In the meantime, the fast inflation rate is required when building various bodies, such as planets and stars. To achieve a peaceful state in various worlds, the black, white and worm holes must be kept in touch.

The following guidelines for optimization should be followed by the MVO algorithm.

- If the rate of inflation is high, there would be a lot of white holes.
- Where the rate of inflation is greater, the existence of black holes would be less possible.
- If the universe's inflation rate is high, objects will be sent into white holes.
- If the universe's inflation rate is minimal, objects will be obtained from black holes.
- Objects will travel to the best universe through wormholes at random, regardless of inflation rate.

All concepts like white, black, and tunnels can be mathematically modelled by using the Roulette-Wheel mechanism. At each iteration, organise the worlds in order to choose a white hole using the Roulette-Wheel mechanism.

Let

$$Z = \begin{bmatrix} z_1^1 & z_1^2 \cdots & z_1^t \\ \vdots & \ddots & \vdots \\ z_m^1 & z_m^2 \cdots & z_m^t \end{bmatrix} \tag{7}$$

where t- number of parameters
m- number of universes.

And $$Z_i^j = \begin{pmatrix} z_k^j, & rand\ 1 <= NOR(ZI) \\ z_i^j, & rand\ 1 >= NOR(ZI) \end{pmatrix}$$ is the j^{th} term of the i^{th} universe (8)

Where ZI- i^{th} universe

NOR(ZI)- normalized inflation rate.

rand1- random variable is either 1 or 0

z_k^j- j^{th} term of the k^{th} universe

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

Each universe is given an objective function, and the objective value is used to calculate the inflation rate. This algorithm explores the search spaces with black and white holes, while exploiting the search spaces with worm holes.

The process of objects inter-universe trade is that high inflation universes often try to disposal objects and return them with low inflation to the receiving universes. In addition, low-inflation universes use high inflation universes as objects to achieve a stable and inflation-modified world. The inflation rates in all universes are at the end of this mechanism and all universes are stable. The universes are initialised as normal and then ordered according to their inflation during this process. At each point, the exchanging of particles between the local universes through worm hole tunnels is sustained towards the best universe. This can be represented as shown below

$$Z_i^j = \begin{cases} \begin{cases} z_j + T_{DR} * ((u_j - l_j) * rand4 + l_j) & rand3 < 0.5 \\ z_j - T_{DR} * ((u_j - l_j) * rand4 + l_j) & rand3 >= 0.5 \end{cases} & (rd2) < WHEP \\ z_i^j & (rd2) >= WHEP \end{cases} \quad (9)$$

Where z_j – j[th] universe

z_i^j - j[th] term in i[th] universe

u_j - upper bound of j[th] variable

l_j – lower bound of j[th] variable

WHEP- wormhole existing probability and is defined as

$$WHEP = min - q * (\frac{min - max}{Q}) \quad (10)$$

T_{DR} - Travelling distance rate

$$T_{DR} = 1 - (\frac{q^{1/w}}{Q^{1/w}}) \quad (11)$$

rd1, rd2, rand3, and rand4 - random variables in the interval [0 1]

q- current iteration

Q- maximum number of iterations

w- the accuracy of exploitation and is taken as 1.

Pseudo code of MVO algorithm

Initialize population's maximum size, WHEP, T_{DR} *,Maximum number of iterations;*

Initialize uj,lj;

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

```
 Initialize BestUniverse;

S_U = sorted universe;
NOR= Normalized universe's inflation rate;
While iter≤ max_iter do
        Find the universe's cost;
for every universe 'i' do
 for every particle 'j' do
        rd1=rand [0 1];
       if rd1 < NOR (Ui) then
            white_hole index = Roulette Wheel selection (-NOR);
U(black_hole index, j) = S_U(white_hole index, j);
      end
rd2= rand [0 1];

        if rd2 < WHEP then
                rand3= rand [0 1];
                rand4 = rand[0 1];
         if rand3 < 0.5 then
```

$$Z_j^i = z_j + T_{DR} * ((u_j - l_j) * rand4 + l_j);$$

```
        else
```

$$Z_j^i = z_j - T_{DR} * ((u_j - l_j) * rand4 + l_j);$$

```
        end
        end
     end
  end
end
```

Detailed steps of Tumor segmentation using MVO algorithm are shown below:

1. Consider input MR image which is to be segmented. (Tumor)
2. Perform pre-processing using median filtering.
3. Initialize MVO parameters like WHEP, T_{DR}, population's maximum size, number of iterations, etc.
4. Define cost function i.e. entropy.
5. By optimizing the cost function, the optimal threshold value can be obtained using MVO technique. (see MVO pseudo code above)
6. Best universe describes the Global threshold (G_{best}) with the best cost value.
7. Using G_{best}, the tumour is segmented.

Detailed steps of feature selection using MVO algorithm are shown below:

1. Consider the segmented MR image as input.
2. Using GLCM, get the texture features.
3. Using LBP, get the texture features.
4. Concatenate the features of step 2 and step 3.
5. Initialize MVO parameters like WHEP, T_{DR}, population's maximum size, number of iterations, etc.
6. Define cost function i.e. Accuracy.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 3970 - 3982
Received 25 April 2021; Accepted 08 May 2021.

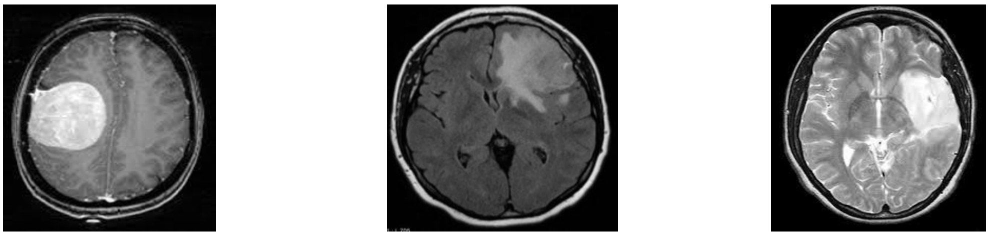
7. By optimizing the cost function, the optimal threshold value can be obtained using the formulae. (see MVO pseudo code above)
8. Best universe describes the G_{best} with the best cost value.
9. Apply to Random-forest classifier to know the given input MR image is benign or malignant.

Experimental Results:

We have taken different slices of the human brain and single patient's MRI images are analysed. The MRI images are taken from different datasets of the same patient at different times and in different view-focuses. These are taken from Kaggle dataset, using the link htttp://www. kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection/.

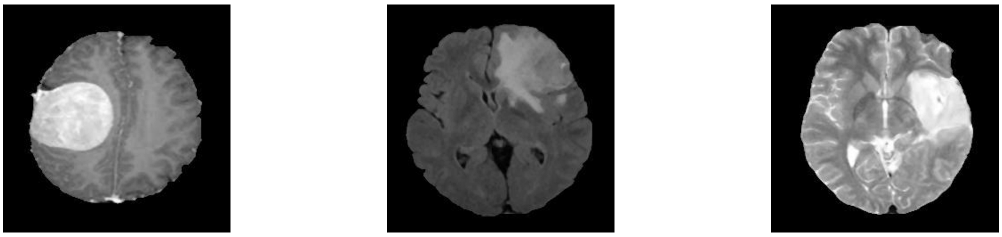
In this, 240 datasets are considered. Among them, 100 datasets are related to malignant and140 are related to benign type of tumor. The extensive simulation has been done to validate the significance of the proposed algorithm. These MRI images are T1-weigthed type, which are widely considered in medical diagnosis of tumor. These experiments are done in MATLAB on PC.

First, the input MRI image is pre-processed using median filter and then using MVO algorithm, a threshold was found. This threshold is applied to segment the tumour from the input MRI image. We run this algorithm for 30 times.



(a) (b) (c)

Figure 4. Input MRI images



(a) (b) (c)

Figure 5. Pre-processed MRI images

(a) (b) (c)

Figure 6. Tumor segmentation using MVO

The MVO parameters are set as follows:

- Population size=20 (i.e. 20 universes are considered)
- Maximum number of iterations=30
- ‘w’ is chosen as <0.05
- WHEP is increased linearly from 0.2 to 1
- T_{DR} is decreased from 0.6 to 0

In figure 4, three input MRI images are considered. These are given to the pre-processed stage. The outputs after median filter and skull stripping, are shown in figure 5.Then by using MVO, a threshold was selected. Threshold values of figure 6 (a), (b), and (c) are 158, 162, 149 respectively.

Later, the features are extracted using GLCM and LBP techniques. A total of 42 features were extracted using the above-mentioned texture-based methods.Then, features are selected using the MVO technique. The performance is calculated using Random-Forest classifier. Total 30 experiments were done. During this, the parameters like execution time, training accuracy, testing accuracy, and number of features selected are observed. Here three optimization techniques are considered- PSO, BAT, and MVO. This is shown in following table.

Table II. Performance Analysis of 3 optimization techniques.

Optimization technique	Experiments	Execution time(sec.)	Training Accuracy (%)	Testing Accuracy (%)	Number of selected features
PSO	Exp. 1	4.80	88.30	82.41	30
	Exp. 30	3.90	87.13	82.41	32
BAT	Exp. 1	5.43	88.73	84.71	28
	Exp. 30	4.62	87.73	83.50	31
MVO	Exp. 1	3.51	88.5	84.71	29
	Exp. 30	3.68	87.7	83.67	28

From the above table, it is observed that training and testing accuracies are good for proposed MVO techniques compared to existing PSO and BAT algorithms. And the number of features selected are also less. So proposed MVO-RF technique takes less computing time with less features, more accuracy is obtained.

Conclusion:

The construction of an effective classification model is essential for problems of classification with various dimensions and sample sizes. Choosing attributes and choosing the grouping system are the key activities. In this paper, the MVO method is used for feature selection and then fitness values were tested by a Random-Forest classifier. Experimental findings indicate that this MVO+RF approach efficiently streamlined the collection of features and total number of required parameters, which achieves an increased classification accuracy in comparison with standard PSO and BAT algorithms. This approach will provide the optimization of the selection process as an excellent pre-processing technique, since it improves classification accuracy and, at the same time, minimizes the computing time required.

References:

1. Xuan Z, Xin G, Jiajun W, Hui Y, Zhiyong W, Zheru C.Eye tracking data guided feature selection for image classification. Pattern Recognition 2017;63(2):56-70.
2. Bischl B, Lang M, Kotthoff L, Schiffner J, Richter J, Studerus E, Casalicchio G, Jones Z M.mlr: Machine learning in R. Journal of Machine Learning Research 2016;17(170):1-5.
3. Dash M, Choi K, Scheuermann P, Liu H. Feature selection for clustering-a filter solution.In Proceedings of the Second IEEE International Conference on Data Mining, 2002, pp.115-122.
4. Deqing W, Hui Z, Rui L, Weifeng L, Datao W. t-Test feature selection approach based on term frequency for text categorization. Pattern Recognition Letters 2014;45(2):1-10.
5. Jin X, Xu A, Bie R, Guo P. Machine learning techniques and chi-square feature selection for cancer classification using SAGE gene expression profiles. Lecture Notes in Computer Science 2006;3916:106-115.
6. Yijuan Lu, Cohen Ira, Xiang S Z, Tian Qi. Feature selection using principal feature analysis. In Proceedings of the 15th ACM international conference on Multimedia, 2007, pp. 301-304.
7. Chuan L, Wenyong W, Qiang Z, Xiaoming S, Martin K. A new feature selection method based on a validity index of feature subset. Pattern Recognition Letters 2017;92:1-8.
8. Zhang, Y. Optimisation of building detection in satellite images by combining multispectral classificationand texture filtering. ISPRS J. Photogramm. Remote Sens. **1999**, 54, 50–60.
9. Sahoo, M. Biomedical Image Fusion and Segmentation using GLCM. In Proceedings of the 2nd NationalConference-Computing, Communication and Sensor Network (CCSN), Orissa, India, 29–30 October 2011;pp. 34–39.
10. Kekre, H.; Thepade, S.D.; Sarode, T.K.; Suryawanshi, V. Image retrieval using texture features extracted fromGLCM, LBG and KPE. Int. J. Comput. Theory Eng. **2010**, 2, 695–700.
11. De Almeida, C.W.D.; De Souza, R.M.C.R.; Candeias, A.L.B. Texture Classification Based on Co-OccurrenceMatrix and Self-Organizing Map. In Proceedings of the IEEE International Conference on Systems, Man andCybernetics, Istanbul, Turkey, 10–13 October 2010; pp. 2487–2491.
12. Pacifici, F.; Chini, M.; Emery, W.J. A neural network approach using multi-scale textural metrics from veryhigh-resolution panchromatic imagery for urban land-use classification. Remote Sens. Environ. **2009**, 113,1276–1292.
13. Pravin Kshirsagar and Sudhir Akojwar (2017), "Classification of ECG-signals using Artificial Neural Networks", Researchgate.net
14. S. Liao, M. W. K. Law and A. C. S. Chung, "Dominant Local Binary Patterns for Texture Classification," in IEEE Transactions on Image Processing, vol. 18, no. 5, pp. 1107-1118, May 2009.

15. Shihab Hamad Khaleefah1, Salama A. Mostafa2, Aida Mustapha3, Mohammad Faidzul Nasrudin, “Review of localbinary pattern operators in image feature extraction” in Indonesian Journal of Electrical Engineering and Computer Science Vol. 19, No. 1, July 2020, pp. 23~31
16. Mirjalili, S.; Mirjalili, S.M.; Hatamlou, A. Multi-Verse Optimizer: A nature-inspired algorithm for globaloptimization. Neural Comput. Appl. **2016**, 27, 495–513.
17. Pravin R Kshirsagar, Anil N Rakhonde, Pranav Chippalkatti, “ MRI IMAGE BASED BRAIN TUMOR DETECTION USING MACHINE LEARNING”, Test Engineering and Management, January- February 2020 ISSN: 0193-4120, Vol. 81, Page No. 3672 – 3680.
18. Pravin Kshirsagar et.al (2016), “Brain Tumor classification and Detection using Neural Network”, DOI: 10.13140/RG.2.2.26169.72805.
19. Pravin R. Kshirsagar, Arpit D. Yadav, Kirti A. Joshi, Pranav Chippalkatti, Rinali Y. Nerkar (2020) “Classification and Detection of Brain Tumor by using GLCM Texture Feature and ANFIS” Journal of Research in Image and Signal Processing, 5(1), 15- 31 http://doi.org/ 10.5281/zenodo.3732939.