iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 2017 **Issue:** **Month of publication:** March 31, 2017

DOI:

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Identification of Metastatic Detection Using Ant Colony Optimization and Segmentation Based on PSO-LVQ Method

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Abstract: ***In this modern world, to identify the brain tumors the medical industry utilizes Magnetic Resonance Imaging technique, which is use to discriminate the pathological report of normal and abnormal tissues. The medical care center produces millions of images frequently. The task performed by medical specialists is time consuming and significant data is extracted from tumor segmentation by means of MRI. To obtain the diagnosis of image, the demand increases on computerized image analysis. In computer aided system, the physicians and radiologist uses computer output as a second idea for diagnosing the patient retails in a fast manner compared to manual work. The second stage uses PSO algorithm with the changes in the 'n' value. The third stage uses selection of best images based on the time. The final stage involves extracting the affected region using filtering techniques. The size of tumor is found with the help of PSO algorithm. It also includes swarm intelligence and learning vector quantization in the MRI technique. The swarm optimization eliminates iteration dependent natural and it also trains the LVQ. Finally ACO detects metastasis.***

Index Terms: Particle Swarm Optimization (PSO), LinearVector Quantization (LVQ), Ant Colony Optimization (ACO).

I. INTRODUCTION

Image Processing (IP) is an analysis of picture's unrecognized shape, color and relationship between them using various techniques. IP examines the data using series of equations and stores computational result of each pixel and develops a new image. IP is an approach in which various mathematical operations are applied to the digitized image data to create an enhanced image and widely exists in remote sensing, training, video, film industry, and medical applications. Segmentation is the process of dividing an image into regions having uniform properties such as color, texture, gray level, contrast and brightness. In medical image segmentation, studying untypical structure and analyzing region of interest i.e. locating tumor, lesion and other abnormalities is more essential. Measurement of tissue size helps to plan prior treatment on growing tumors using radiation therapy.

The existing image segmentation methods classified into four categories: first one belongs to threshold segmentation, second is based on the region and third one corresponds to edges and then the final is study. MRI is a non-invasive diagnostic technique that gives the computerized digital images of internal body tissues based on the nuclear magnetic resonance. The images of organs, tissues and structures inside the body are provided by MRI based on the function of radio waves. MRI can diagnose minor harm to tendons, aneurysm, bleeding in the brain, nerve injury, and other problems, such as harm caused by a stroke by its higher spatial resolution.

II. METHODOLOGY

Some existing method carries different methods in detection of blocks in brain (tumor). In this paper, the PSO algorithm is appropriate for the MRI brain data analysis. Brain tumor is a collection of growth of atypical cells in the brain and the closer area to it. The existed brain tumors are of type benign, which is a beginning stage, cannot be spread to the other places and the type malignant spreads over other parts of the body.

In general brain tumors that cannot cause cancer are benign and tumor that spread the cancer cells to the other parts refers to malignant. Further the paper is organized as: The prior work carried out in the analysis of brain tumor and its affected region. Here, the PSO segmentation algorithm and feature extraction methodology are explained in part II along with the LVQ approach. Experimental analysis and results are discussed in part III and finally the paper is concluded in part IV.

The application areas of PSO are system design, classification, pattern recognition, biological system modeling, scheduling, multiobjective optimization, games, robotics applications, decision making, signal processing, simulation and identification.

The MRI brain image data is taken as input to detect the tumor by image segmentation. PSO segmentation is performed with the

input image, from which the features are extracted. The segmented images are classified into LVQ classifier and then finally the metastasis cells are detected using ACO. The proposed workflow is summarized as follows.

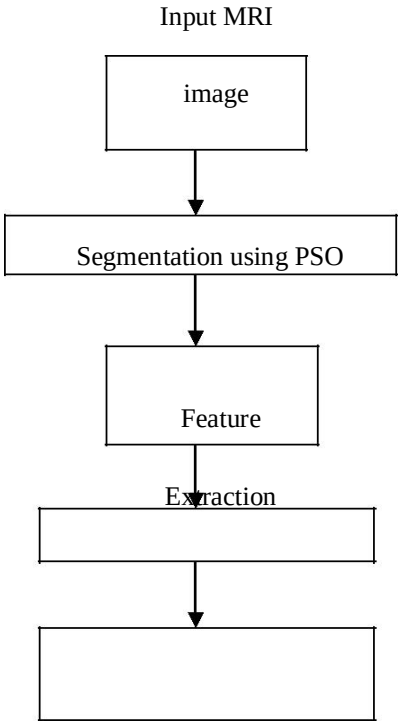


Fig.1 Proposed workflow

Step5: For each particle do if swarm is not developing its performance then punish swarm: delete the swarm/particle: or reduce the swarm life.
Step 6: Extend the swarm to spawn (the swarm is examine for next iteration)
Step 7: Delete the „„aborted"""" swarms.(the swarm will never come into search space) and Reset threshold counter.

A. Feature Extraction

Gray Level Co-Occurrence Matrix (GLCM) is a statistical method of extracting texture based features based on the spatial relationship between the pixels in an image. According to co-occurrence matrix, Haralick defines fourteen textural features of remote sensing images [1]. In this paper, six important parameters, such as Mean, Standard deviation, Energy, Entropy, Variance and Correlation are represented.

1) Mean: Measurement of mean combinations between reference pixel and its neighboring pixels with gray level values.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} A_i.$$

2) Standard deviation: Measurement of dataset dispersion from its mean having higher deviation.

$$S = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} |A_i - \mu|^2},$$

B. PSO segmentation algorithm is given below

Step 1: Read the input image to be segmented.

Step 2: Select PSO method to be applied on that image with a particular threshold level
Step 3: For each particle in the population do update particle's fitness in the surfing space and it is best in the search space move particle in the population
Step 4: For each particle do if swarm gets better then reward the swarm spawns the particle: extend the swarm/particle life.
Entropy: Measurement of disorders of an image with respect to reference pixels and neighboring pixels. When the image is not

$$f_3 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)\log\left(p_{d,\theta}(i,j)\right)$$

having uniform texture, then the value of other GLCM features have smaller values, but entropy may have larger values.
Variance: Measurement of dispersion around the mean values of combinations in reference and neighboring pixels.

$$f_4 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} (i-\mu)^2 p_{d,\theta}(i,j)$$

Correlation: Measurement of linear dependencies among gray levels of neighboring pixels. The value of correlation represents how a reference pixel is correlated with its neighboring pixel and often used to measure rearrangement, deformation and strain of an image.

$$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right]$$

Energy: Measurement of closeness of gray levels with respect to spatial distribution of reference pixels and
neighboring pixels of an image. Sometimes, energy may be a negative measure or positive measure which is minimized and maximized respectively.

$$\sum_{i,j=0}^{N-1} P_{i,j}^{\,2}$$

C. Learning Vector Quantization

LVQ is a specialized version of vector quantization that uses the class information having labeled input data to replace the Voronoi vectors slightly, tends to improve the quality of the classifier decision regions and it is widely used in complemented pattern classification.
The first step refers to feature choice in which the unsupervised identification of small set features, where the input data content is fixed. The second step involves distribution of feature domains which are assigned to individual classes.
LVQ systems can be applied to multi-class classification problems for practical applications. The steps included in this algorithm as

1) Step 1: Initialize the cluster centers by a clustering method
2) Step 2: Label each cluster by the voting method \
3) Step 3: Randomly select a educate input vector x and find k such that ||x-wk|| is a minimum
4) Step 4: If x and wk belong to the same class update bywk

The parameters used for the training process of a LVQ add the following
Where x = training vector (x, x2,……, xn)
T = category or class for the training vector x Wj = weight vetor for jth output
Cj = cluster or class or category associated with jth output unit.
The Euclidean width of jth output unit is expressed as D (*j*) =Σ (*xi-wij)* ^{2}

D. Ant Colony Optimization (ACO)

Any discrete optimization problems have solution by the application of ACO, which is constructed as follows.

1) *Artificial ants are stochastic solution construction heuristics:* The probabilistic solution obtained by adding solution components to partial solutions with heuristic knowledge on the problem, which changes dynamically at run-time with acquired search experience. Initially, each ant is randomly put on a city, where ants are frequent through a probabilistic rule during the construction of a feasible solution. When an ant k states in city I for constructing partial solution, the probability of moving next city j to neighboring city i is given by

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{u \in J_k(i)} [\tau_{iu}(t)]^{\alpha}[\eta_{iu}]^{\beta}} & if\ j \in J_k(i) \\ 0 & otherwise \end{cases}$$

Where τij is the intensity of trails between edge (i,j) and ηij is the heuristic visibility of edge (i, j)

ηij = 1/dij.

Jk(i) is a set of cities which remain to be visited when the ant is at city i. The two flexible positive parameters α and β are able to control the relative weights of the pheromone trail and the heuristic visibility respectively. After the completion of each ant's tour, the pheromone amount on each path will be adjusted with equation as follows.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t)$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t)$$

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \dfrac{Q}{L_k}, & \text{if (i, j) } \in \text{ tour done by ant k} \\ 0 & \text{otherwise} \end{cases}$$

2) *Steps for implementing ACO*: Step 1: Initiation. The amount of the pheromone on each side is initiated into a tiny stable value; allot m ants randomly to n cities. □

Step 2: In ACS, the so-called pseudorandom proportional rule is used: the probability for an ant to move from city i to city j depends on a random parable q uniformly given over [0, 1], and a predefined parameter q0 □

□

$$j = \begin{cases} \arg\max_{u \in allowed_k(i)} \{ [\tau_{iu}]^{\alpha} . [\eta_{iu}]^{\beta} \} & \text{if } q < q_0 \\ J & \text{otherwise} \end{cases}$$

Step 3: The local pheromone update is performed by all the ants after each construction step. Each ant applies it only to the chosen city □

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho.\tau_0$$

Where 0< ρ<= 1 is a decay parameter, τ0=1/n. Lnn is the initial values of the pheromone trails, which is cost produced by the nearest neighbor heuristic, where n is the number of cities in the TSP.

Equation (2) is derived to avoid strong pheromone paths which is to be chosen by other ants tends to increase the explorative probability for other paths.

Once the edge between city i and city j has been visited by all ants, the local updating rule provides pheromone level which diminishes edge. So, the effect of local updating rule is less desirable for the following ant.

Step 4: Computation of optimal path. After m ants transmit through all the cities, compute the length of the optimal. □

ants have transmitted through all cities, update only the volume of the pheromone on the optimal path with equation (8)□

$$\Delta\tau_{ij}(t) = \begin{cases} \dfrac{1}{L_{gb}}, & \text{if } (i, j) \in \textit{global best tour} \\ 0 & \text{otherwise} \end{cases} \quad \square$$

Where ρ is constant and Lgb refers to the length of global best course.

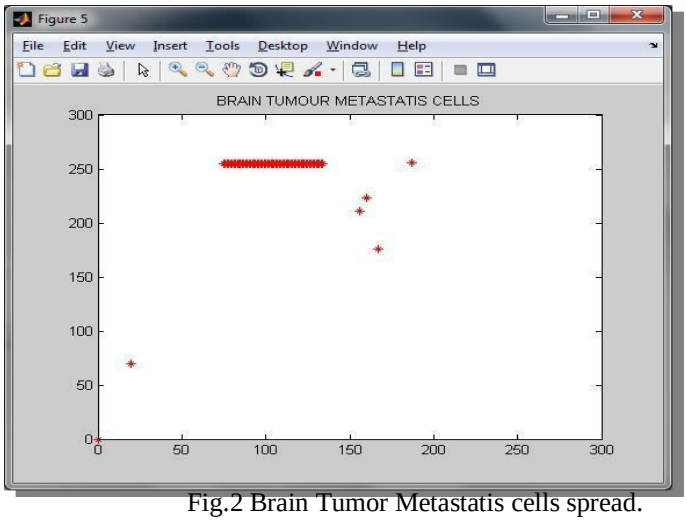


Fig.2 Brain Tumor Metastatis cells spread.

Step 6: If the designated search number is not obtained, then repeat the above steps. □

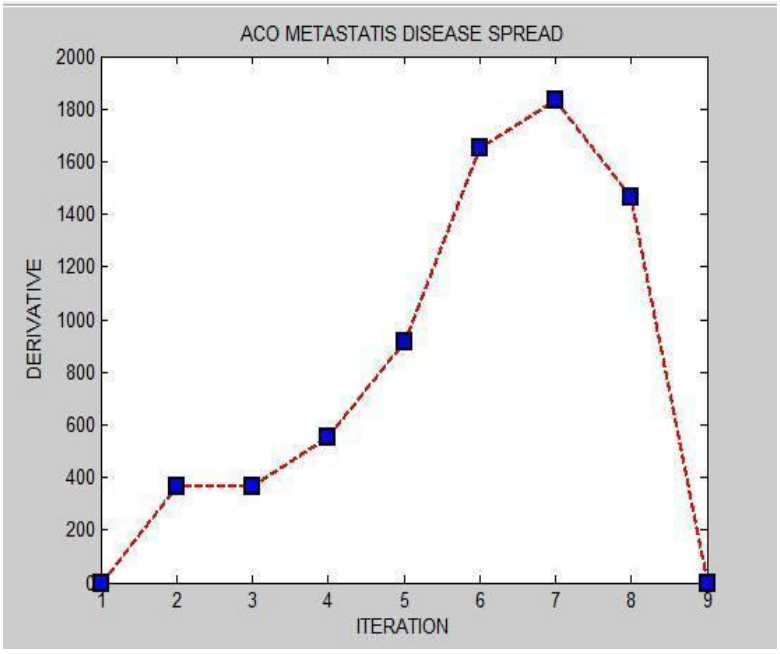


Fig.2 Metastatis Disease Spread

III. Experimental Results and Discussions

TABLE I Different Types of Database and Size of Tumour

DATASET	SIZE OF TUMOUR
1	78
2	80
3	39
4	92
5	48
6	30
7	37
8	52
9	18
10	23

The software used for the implementation is MATLAB. The training data and testing data are taken in a same level for all the images. Thus, the textural features are extracted from the training data. The qualitative analysis of the PSO-LVQ-based tumor detection in MR brain images are show in Fig.5.The experiments are conducted on 10 images, but only samples are shown in Fig.3. Fig.3 shows the input images in which the abnormal tumor portion is seen in white color. A visual analysis reveals that PSO-LVQ has successfully segmented the tumor portion from the abnormal input image.

INPUT IMAGE PSO SEGMENTATION SEGMENTED IMAGE

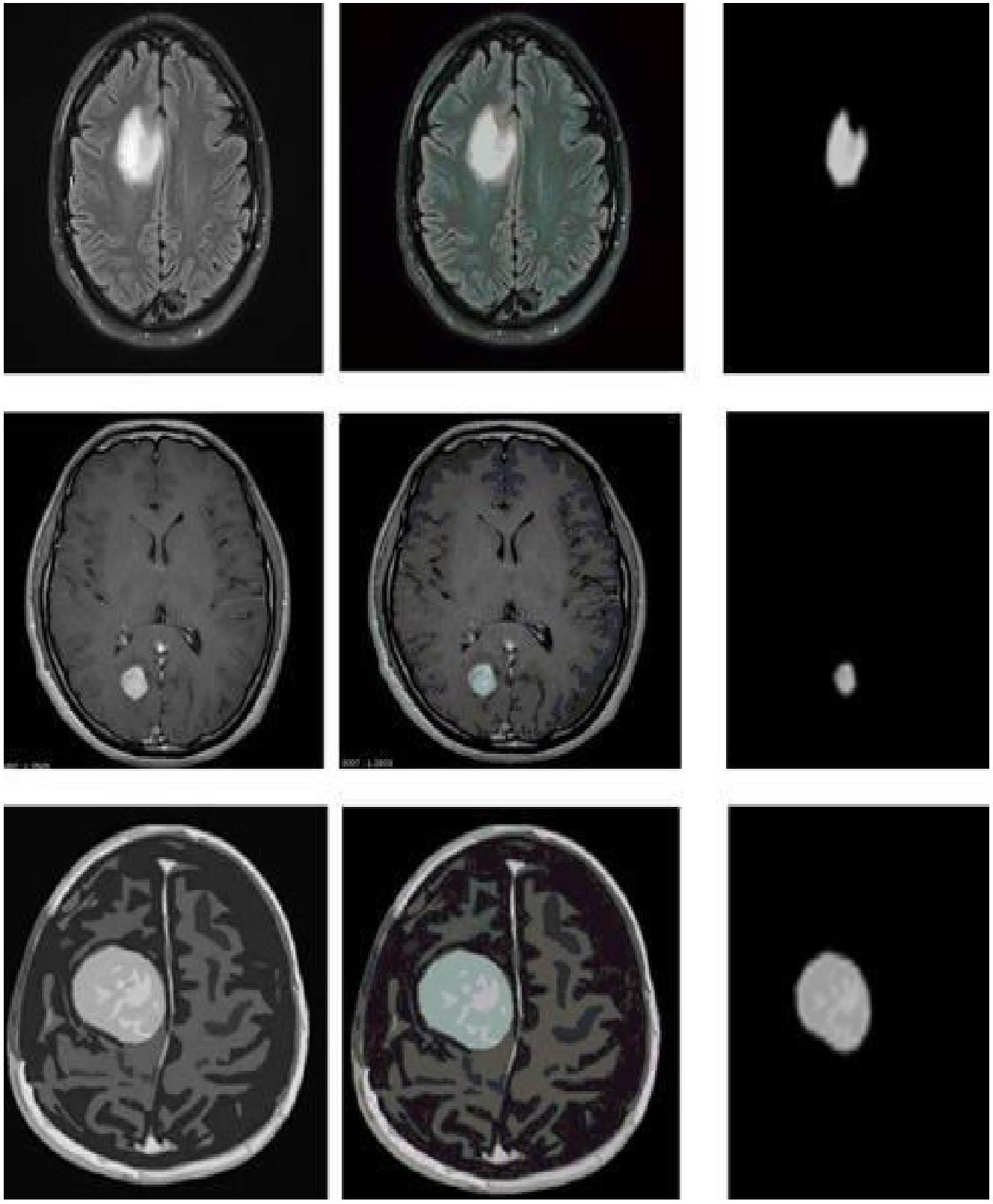


Fig.3 Brain Image Fig.4 Segmentation based on PSO Fig.5 Tumor region

IV. CONCLUSION

Manual brain segmentation is probably more accurate than automated segmentation, but having major defects such as time exhausting and subjectivity of human segmentation. It is important to develop a reliable automated segmentation of the MRI brain images given rise to many different approaches and the methodology carries some automotive metrics. Hence, it is concluded that the automation of MRI brain images to detect the brain tumor is based on the criteria of elapsed time and segmentation level. The process of segmenting the MRI brain image by PSO algorithm is better in the axial plane. In addition to the ACO, detection of metastasis area in brain images gives the information about spreading cancer cells in other regions of the brain.

REFERENCES

[1] Mohammad Majid al-Rifaie1, Ahmed Aber, Duraiswamy Jude Hemanth,' Deploying swarm intelligence in medical imaging identifying metastasis, micro calcifications and brain image segmentation'
.Institution of Engineering and Technology 2015.

[2] Zhang W, Zhou C, Bao X. investigation on digital media image processing algorithm based on asynchronous and inertia adaptive particle swarm optimization. International Journal of signal processing, Image processing and pattern recognition. 2015;8(2):65-76.

[3] Sheejakumari V, SankaraGomathi B. MRI brain images healthy and pathological tissues classification with the aid of improved particle swarm optimization and neural network.2015; 15(1):1–12.

[4] Das A, Jain N. Optimum approach of detecting abnormalities in MRI of brain image using texture feature analysis. Int J AdvEngg Res Studies. 2015; 4(2):305–7.

[5] Saini A, Verma SK. 3D image segmentation by hybridization of PSO and BBO. History. 2015;29(1):82– 7.

[6] Rifaie, M.M., Aber, A., Sayers, R., et al.: 'Deploying swarm intelligence in medical imaging'. 2014 IEEE Int.
Conf. on Bioinformatics and Biomedicine (BIBM), 2014, pp. 14–21

[7] Rifaie, M.M., Aber, A., Raisys, R:Swarming robots and possible medical applications'. Int. Society for the
Electronic Arts (ISEA 2011), Istanbul, Turkey,2011

[8] Rifaie, M.M., Aber, A., Bishop, M. 'Swarms search for cancerous lesions: artificial intelligence use for accurate identification of bone metastasis on bone scans'. 13th EFORT Congress, Berlin, Germany, 2012

[9] Rifaie, M.M., Aber, A.: 'Identifying metastasis in bone scans with stochastic diffusion search'. IEEE Information
Technology in Medicine and Education (ITME), 2012.

[10] N. C. for Health Statistics: 'Deaths, percent of total deaths and death rates for the 15 leading causes of death: United States and each State,2000 (National Center for Health Statistics, 2001)

[11] Cassar, K., Godden, D., Duncan, J.: 'Community mortality after ruptured abdominal aortic aneurysm is unrelated to the distance from the surgical centre',
Br. J. Surg., 2001, 88, (10), 1341–1343

[12] Brown, L., Powell, J.: 'Risk factors for aneurysm rupture in patients kept under ultrasound surveillance', Ann. Surg., 1999, 230, (3), p. 289

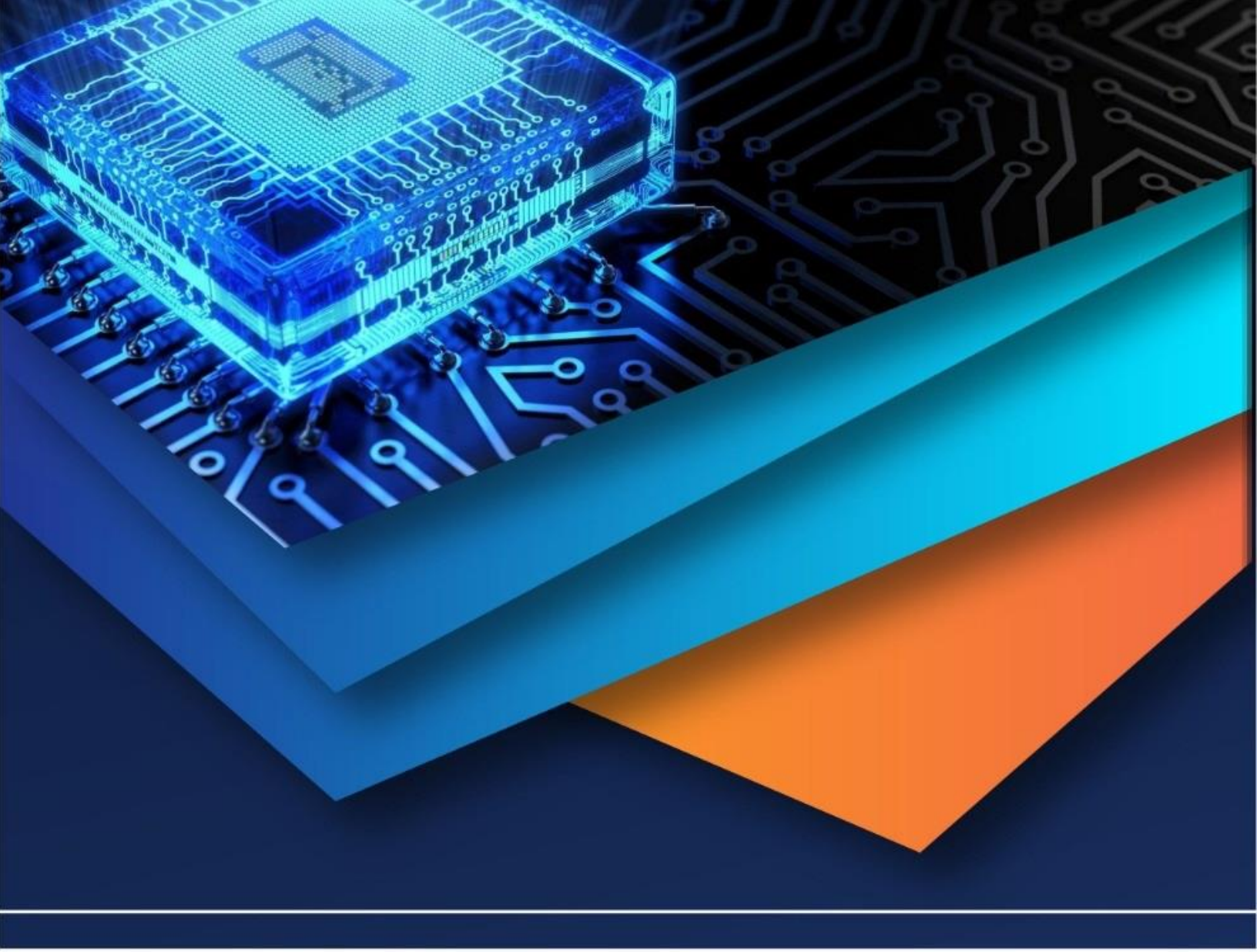
[13] Zhang, Y., Wang, S., Phillips, P., et al.: 'Binary PSO with mutation operator for feature selection using decision tree applied to spam detection', Knowl.-Based Syst., 2014, 64, (0), PP 22–31

[14] Wang S, et al. Feed-forward neural network optimized by hybridization of PSO and ABC for abnormal brain detection. Int J Imaging Syst Technol. 2015;25(2):153–64.

[15] Puranik P, et al. Human perception-based color image segmentation using comprehensive learning particle swarm optimization. Eme,'rging Trends in Engineering and Technology (ICETET). 2011; 2(3):227–35.

[16] Punithavathy Mohan*, Vallikannu. AL*, B.R.Shyamala Devi*,B.C.Kavitha*,'Intelligent Based
Brain Tumor Detection Using ACO'. International Journal of Innovative Research in Computer and Communication Engineering, Vol. 1, Issue 9, November 2013.

[17] N Zhang, Feature Selection based Segmentation of Multi-Source Images: Application to Brain Tumor Segmentation in MultiSequence MRI, Ph.D. Thesis,
L'Institut National des Sciences Appliquées de Lyon 2011.



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