

Available online at http://www.journalcra.com

International Journal of Current Research Vol. 8, Issue, 08, pp.36002-36006, August, 2016 INTERNATIONAL JOURNAL OF CURRENT RESEARCH

# **RESEARCH ARTICLE**

## EXPOSURE WITH CREDENTIALS OF BRAIN TUMOR USING IMAGE MINING MICCAI PERFORMANCE (MELANOMA)

## \*Prof. P. Senthil

Department of Computer Science, Kurinji College of Arts and Science, Tiruchirappalli-620002, India

ARTICLE INFO	ABSTRACT		
<i>Article History:</i> Received 18 <sup>th</sup> May, 2016 Received in revised form 21 <sup>st</sup> June, 2016 Accepted 05 <sup>th</sup> July, 2016 Published online 20 <sup>th</sup> August, 2016	This tabloid presents a discovery with proof of identity of brain tumor, now It is use an image mining using development performances for a segmentation of image with engendered segmented image authorization to Multivariate division algorithm. Using MICCAI (Medical Image Computing and Computer Assisted Intervention) dataset segmented image is alienated hooked on protuberances, a this time perceive accurate with dishonest protuberances with concurrence to factual lump proposal sapling then the leap protuberances are mingling with engendered a result. Catching wit		
Key words:	network is use for result but in neural network result in the form of 0 and 1 so clamor in result. Hence using the prearrangement progress the result and performance with great accuracy. More over all get a		
Image Mining, Brain tumor, Multivariate division algorithm, Neural network result.	result ten time faster than executing Result.		

*Copyright©2016, Senthil.* This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Citation: Prof. P. Senthil, 2016. "Exposure with credentials of brain tumor using image mining MICCAI performance (Melanoma)", *International Journal of Current Research*, 8, (08), 36002-36006.

# **I. INTRODUCTION**

Today's world many people are living with brain tumor and different type of cancer. Survey represent estimated a one lack peoples are live with cancer. There are 30 to 35 % people are live with cancer. Different type's algorithms and methods are used to analyze tumor. Images' developing for checking a brain tumor but it is not sufficient to analyze a result. Getting a final result is not enough to accurate analyzing and gets any decision on it.MRI scan image are used to analyze a result they segmented image and result pass to random forest tree technique. Image is segmented using an image processing algorithm. They segmented each and every point of image. Features provide by a segmented image is (a) mutual exclusion and (b) exhausted regions. Many algorithms to improve the result such as bagging, boosting, C4.5. RFT is use to classify the image segmented result and analyze the result of brain tumor. Result is complex because the leap nodes are combining each other and give three buckets as an output. Here we use a bagging technique to simplify the result and boosting technique is use to improve speed of processing. Using given algorithms techniques the result is improve with accuracy and better performance compare to exiting.

#### \*Corresponding author: Prof. P. Senthil,

Department of Computer Science, Kurinji College of Arts and Science, Tiruchirappalli-620002, India.

# **II. MATERIALS AND METHODS**

Mohammad Havaei, Axel Davy, David Warde-Farley, Antoine Biard, Aaron Courville, YoshuaBengio, Chris Pal, Pierre-Marc Jodoin, Hugo Larochelle et al. (2017) cascade architecture in which the output of a basic CNN is treated as an additional source of information for a subsequent CNN. Results reported on the 2013 BRATS test data-set reveal that our architecture improves over the currently published state-of-the-art while being over 30 times faster. Marieke Anna de Ruiter, JaapOosterlaan, Antoinette Yvonne Narda Schouten-van Meeteren, Heleen Maurice-Stam, Dannis Gilbert van Vuurden, Corrie Gidding, Laura Rachel Beek, Bernd Granzen, Huib N. Caron, Martha Alexandra Grootenhuis (2016) A total of 82 children were enrolled (mean age 13.9 years, standard deviation = 3.2, 49% males); 80 participants were randomised (NF: n = 40, PF n = 40); 71 participants completed the training (NF: n = 34, PF: n = 37); 68 participants completed training and 6 months post-training assessment (NF: n = 33, PF: n =35). Similar improvements were found over time for the two treatment groups on the primary outcomes (all p's > 0.15). Wenhua Ma, Na Li, Yonghui An, Changpeng Zhou, Changwen Bo, Guangyu Zhang et al. (2016) Total 19 publications of RCTs were included, and there was no allocation concealment or blinding in any of them. Six of the 19 were multicenter RCTs. Overall response rate (ORR) was in favor of radiotherapy plus temozolomide (risk ratio (RR) = 1.35, 95%

CI: 1.23-1.47). Subgroup analysis of non-small cell lung cancer (NSCLC) metastasis brain tumor also showed that ORR was in favor of radiotherapy plus temozolomide (RR = 1.38; 95% CI: 1.17-1.63). Progression-free survival (PFS) or overall survival rate, however, was not significantly different between the 2 treatment groups. In addition, incidence of side effect was significantly higher in the group of radiotherapy plus temozolomide than that of radiotherapy alone (HR = 2.03, 95%CI: 1.56–2.64). Arthur H. Fierman et al. (2016) Combining these new tools can increase diagnostic specificity and confidence. Familiarity with conventional and advanced imaging findings facilitates accurate diagnosis, differentiation from other processes, and optimal patient treatment. This article is a practical synopsis of pathologic, clinical, and imaging spectra of most common brain tumors. EliseeIlunga-Mbuyamba, Jorge Mario Cruz-Duarte, Juan Gabriel Avina-Cervantes, Carlos Rodrigo Correa-Cely, Dirk Lindner, Claire Chalopin et al. (2016) CS method using polar coordinates is generally preferable to CS performed in rectangular shapes. Real medical and synthetic images were used to validate the proposed strategy, through three performance metrics as the Jaccard index, the Dice index and the Hausdorffdistance. Applied specifically to Magnetic Resonance Imaging (MRI) images, the proposed method enables to reach better accuracy performance than the traditional ACM formulation, also known as Snakes and the use of Multi-population Particle Swarm Optimisation (PSO) algorithm.

Heba M. Abdou, Mokhtar I. Yousef, Desouki A. El Mekkawy, Ahmed S. Al-Shami et al. (2016) integral representation of the solution at any time-space point of our problem's domain is independent on any other points of the domain, except of course on initial data, coupled with a simple composite trapezoidal rule, implemented on appropriately chosen integration contours, yields a fast and efficient analyticalnumerical technique capable of producing directly high-order approximations of the solution at any point of the domain requiring no prior knowledge of the solution at any other time instances or space information. Charles W. Huang, Ming-Xiong Huang, Zhengwei Ji, Ashley Robb Swan, Anne Marie Angeles, Tao Song, Jeffrey W. Huang, Roland R. Lee (2016) n 32 patients with brain tumors and/or epilepsies, an objectnaming task was used to evoke MEG responses. Our Fast-VESTAL source imaging method was then applied to the MEG data in order to localize the brain areas evoked by the object-naming task.YazanAbuodeh, Kamran A. Ahmed, Arash O. Naghavi, Puja S. Venkat, SiripornSarangkasiri, Peter A.S. Johnstone, Arnold B. Etame, Hsiang-Hsuan Michael Yu et al. (2016) Between April 2011 and May 2014, 75 patients were treated for 77 metastatic brain lesions with postoperative SRS in 5 sessions. The median planning target volume was 13.8 cm3 (1.93-128.43 cm3) with a median follow-up for all lesions of 9.5 months (range, 1.2–38.2 months). Kaplan-Meier estimates of local control at 1 and 2 years were 88.8% and 83.9%, respectively. On univariate analysis, a trend in decreased survival with multiple brain lesions was noted (hazard ratio (HR) = 2; 95% confidence interval (CI), 0.87-4.53; P = 0.10). There was a trend towards decreased local control with radioresistant tumors (HR = 3.23; 95% CI, 0.7-22.6; P = 0.14) and planning target volume  $\geq 17$  cm3 (HR = 3.07; 95% CI, 0.73–15.23; P = 0.12). Two (3%) patients

developed radionecrosis, one of whom required craniotomy. Dominik Sturm, Brent A. Orr, Umut H. Toprak, Volker Hovestadt, David T.W. Jones, David Capper, Martin Sill, Ivo Buchhalter, Paul A. Northcott, Irina Leis, Marina Ryzhova, Christian Koelsche, Elke Pfaff, Sariah J. Allen, GnanaprakashBalasubramanian, Barbara C. Worst, Kristian W. Pajtler, Sebastian Brabetz, Pascal D. Johann, Felix Sahm, JüriReimand, *et al.* (2016) Highly malignant primitive neuroectodermal tumors of the CNS (CNS-PNETs) have been challenging to diagnose and distinguish from other kinds of brain tumors, but molecular profiling now reveals that these cancers can be readily classified into some known tumor types and four new entities with distinct histopathological and clinical features, paving the way for meaningful clinical trials.



Fig.1. Architecture of our proposed system



Fig.2. Dataset Analysis Methods

### **III. IMPLEMENTATION**

The basic techniques to detection and identification of brain tumor and classify in normal and unmoral condition. A modified image segmentation to analyze the result for brain tumor classification uses a modified PNN, using this technique result show in the form of 0 and 1. Brain tumor classification is 100% correct to applying a PNN on MRI image. Using these techniques LVQ-based PNN for brain tumor result time is more to classify approximately 79%. In this approach result is in the form of normal and abnormal. Here use an 18 data set for a detection and identification of result. Drawback of this system is result; result show in 0 or 1 manner example - result is 0.000235 so it is calculate as a 0.

## A. Boosting

Another technique is Artificial Neural network to detect and classify brain tumor. Getan input MRI image is segmented then find a result. For image segmentation here use a histogram equalization technique. The result of this technique is in two a level first is gray level1 and gray level 0 is background segmentation. 2) Feature extraction using this trained data set for image classification. The result is dividing between normal and abnormal. 3) ANN classifier to identify brain tumor.

## **B.** Random forest

Computer aided diagnosis is based on MRI image. A classification framework describe four type of different features extracted from structural MRIimage.AS vs. MCI vs. CN is a classification of different classes. Classification rate is a subset of ADNI1-2database and they achieve 51 to 59 % features sets. An artificial intelligence, different types of algorithms like random forest tree, neural network and support vector machine. The result –

### C. Analysis of processing

Proposed System Include Following Stages.

- A. Image Preprocessing
- B. Classification Using
- C. Random Forest
- D. Bagging
- E. Boosting

### **D.** Image preprocessing

Proposed system using image segmentation brain tumor image is segmented. Features of image are extracted for classification. Using random forest tree algorithm classify the image is in three condition normal, pre and post condition. Segmented image is classified and compare to these three conditions, get result. Result is display in the form of all deep details. Bagging and boosting algorithms are used to improve the result of classification.

## E. Sushisen Algorithms

- 1. P = D-S Image > 0;
- 2. P sparse Image>dataset;
- 3. If (Py= $\lambda y$ )
- 4. Lanczos used for efficiency;
- 5.  $\lambda 1$ ,  $\lambda 2$  first 2 eigenvalues;
- 6.  $\lambda 1 = 1$ ; use  $\lambda 2$  instead;
- 7. y1,y2 first 2 eigenvectors;
- 8. y2 Fiedler eigenvector;

- 9. Pixels iI = vertices of graph G;
- 10. Edges ij = pixel pairs with Sij> 0;
- 11. Similarity matrix S = ( Sij );
- 12. Given a partition (A,B) of the vertex set V;
- 13. Final Classification Result;

## F. Classification

The C4.5 algorithmic program extension of his own ID3 algorithmic program for generating call trees. Textile and Boosting area unit general methods for up classifier and predictor accuracy. suppose that we have a tendency to area unit a patient and would really like to own a diagnosing created supported the symptoms. rather than asking one doctor, we have a tendency to could opt to raise many. if a definite diagnosing happens over any others, we have a tendency to could select this because the final or best diagnosing. It's the ultimate diagnosing is created supported a majority vote wherever every doctor gets associate equal vote. Currently replace every doctor by a classifier, we/ve got the essential plan behind textile. In boosting, we have a tendency to assign weights to the worth of every doctor's diagnosing, supported the accuracies of previous diagnoses they need created. The ultimate diagnosing is then a mix of the weighted diagnoses.

#### F.A. Test analysis

Neuroimaging with brain MRI for the following: status epilepticus; failure to control seizures, worsening seizures, or changes in seizure manifestations; seizures in children younger than 2 years of age, excluding those with febrile seizures; abnormal neurologic examination; a history of significant development delay, arrest, or regression; or a new-onset focal seizure. For evaluation of hydrocephalus or its complications, brain MRI is a standard imaging modality. For clinical suspicion of a demyelinating disease such as multiple sclerosis in patients presenting with a clinically isolated syndrome, most commonly manifested as unilateral optic neuritis, brainstem syndrome, or partial myelitis, diagnostic criteria for multiple sclerosis have been developed based on the demonstration of central nervous system lesions disseminated in space and disseminated in time on MRI imaging of the brain and, if appropriate, on spinal cord imaging. Requirements for radiographic dissemination in time criteria for multiple sclerosis include either the simultaneous presence of both gadolinium-enhancing (new) and nonenhancing (older) lesions on the same MRI or new T2 weighted lesions on a repeat MRI performed at least 30 days from the initial onset of symptoms. For Parkinson disease and other neurodegenerative conditions, MRI is helpful in differentiating Parkinson disease from atypical Parkinson disease, and can provide additional evidence for the presence of other conditions such as progressive supranuclearpalsy. For precocious puberty, brain MRI is indicated to rule out hypothalamic lesions such as hamartoma. For clinical suspicion of a transient ischemic attack, an expert consensus guideline recommends urgent brain MRI with diffusion-weighting imaging, preferably with 24 hours of symptom onset. For acute ischemic stroke, an expert consensus guideline recommends urgent brain imaging, such as MRI if emergently available and not contraindicated, or CT, prior to initiating any specific therapy, including thrombolytic

medication. An evidence-based national specialty society guideline recommends brain MRI with diffusion-weighted imaging for the diagnosis of ischemic stroke within 12 hours of symptom onset. A prospective study of 356 consecutive patients presenting with clinically suspected stroke concluded that although both brain MRI and CT had comparable accuracy for detection of intracranial hemorrhage, brain MRI had greater sensitivity than CT for the detection of acute ischemic stroke.

## G. Experimental results

The experimental results of the proposed algorithm are shown in this section. The algorithm described in this paper is implemented in MATLAB, version 7.10. We used a personal computer with CPU 2.27 GHz, Core I5 processor and 4 GB of RAM under Windows 7 operating system.

#### Table 1. Comparting Study Algorithms and Dataset

# of images	1	2	3	4		
Classifier	Standard deviation [%]					
ANN	3.89	3.17	2.69	2.04		
RF	3.11	2.38	2.40	2.10		
SVM-RBF	2.82	2.65	2.39	2.05		
SVM-POLY	2.67	2.82	2.49	2.17		
ML	4.03	3.11	2.81	2.82		

Fig. 3. Result dataset and algorithms analysis methods

## H. Melanoma in brain tumor

Melanoma is a form of skin cancer that begins in melanocytes (cells that make the pigment melanin). It may begin in a mole (skin melanoma), but can also begin in other pigmented tissues, such as in the eye or in the intestines. Melanoma can occur on any skin surface. In men, it's often found on the skin on the head, on the neck, or between the shoulders and the hips. In women, it's often found on the skin on the lower legs or between the shoulders and the hips. Melanoma is rare in people with dark skin. When it does develop in people with dark skin, it's usually found under the fingernails, under the toenails, on the palms of the hands, or on the soles of the feet. Melanoma is more likely than other skin cancers to spread to other parts of the body.



Fig. 4. Result of melanoma brain tumor analysis



Fig. 5. Melanoma confusion matrix brain tumor analysis

- **Asymmetry:** The shape of one half does not match the other half.
- **Border that is irregular:** The edges are often ragged, notched, or blurred in outline. The pigment may spread into the surrounding skin.
- Color that is uneven: Shades of black, brown, and tan may be present. Areas of white, gray, red, pink, or blue may also be seen.
- **Diameter:** There is a change in size, usually an increase. Melanomas can be tiny, but most are larger than the size of a pea (larger than 6 millimeters or about 1/4 inch).
- **Evolving:** The mole has changed over the past few weeks or months.

## J. Bagging

Melanomas can vary greatly in how they look. Many show all of the ABCDE features. However, some may show changes or abnormal areas in only one or two of the ABCDE features. In more advanced melanoma, the texture of the mole may change. The skin on the surface may break down and look scraped. It may become hard or lumpy. The surface may ooze or bleed. Sometimes the melanoma is itchy, tender, or painful.

## K. Section analysis

This paper is organized as follows. Section III describes the Implementation. In this section the proposed algorithm E is presented. The methods Classification F as well for categorization and also the Recovery part of the system and significance response will describe in this section G. In section H, experimental results are shown. The results are discussed is section J, while conclusion is mentioned in section IV.

## **IV.** Conclusion

The system proposed a method as a random forest tree for classification of brain tumor. This technique is useful to classify the brain tumor image with more accuracy and less time in training set. Then, by giving an input as an image, they use Bagging and Boosting are improving classifier and predictor accuracy. Then in the last step, before classified image is finding they compare with given training set and test set, find result of the given image and the result is in form of normal or precondition or post condition.

## Acknowledgment

This paper is made possible through the help and support from everyone, including: My wife M.Suganya and Daughter S.S.Inakshi and My sir S.SyedNazimuddeen, and in essence, all sentient beings. I sincerely thank to N.Periyasamy and P.Chinnaponnu brother P.Nallusamy, family, and friends, who provide the advice and financial support. The product of this paper would not be possible without all of them.

### **V.REFERENCES**

- Arthur H. Fierman, Foreword: Pediatric Sarcomas, Leukemias, and Brain Tumors, *Current Problems in Pediatric and Adolescent Health Care*, Volume 46, Issue 7, July 2016, Pages 211-212.
- Charles W. Huang, Ming-Xiong Huang, Zhengwei Ji, Ashley Robb Swan, Anne Marie Angeles, Tao Song, Jeffrey W. Huang, Roland R. Lee, High-resolution MEG source imaging approach to accurately localize Broca's area inpatients with brain tumor or epilepsy, *Clinical Neurophysiology*, Volume 127, Issue 5, May 2016, Pages 2308-2316.
- Mantzavinos, D., M.G. Papadomanolaki, Y.G. Saridakis, A.G. Sifalakis, Fokas transform method for a brain tumor invasion model with heterogeneous diffusion in 1 + 1 dimensions, *Applied Numerical Mathematics*, Volume 104, June 2016, Pages 47-61.
- Dominik Sturm, Brent A. Orr, Umut H. Toprak, Volker Hovestadt, David T.W. Jones, David Capper, Martin Sill, Ivo Buchhalter, Paul A. Northcott, Irina Leis, Marina Ryzhova, Christian Koelsche, Elke Pfaff, Sariah J. Allen, Gnanaprakash Balasubramanian, Barbara C. Worst, Kristian W. Pajtler, Sebastian Brabetz, Pascal D. Johann, Felix Sahm, JüriReimand, New Brain Tumor Entities Emerge from Molecular Classification of CNS-PNETsCell, Volume 164, Issue 5, 25 February 2016, Pages 1060-1072.

- EliseeIlunga-Mbuyamba, Jorge Mario Cruz-Duarte, Juan Gabriel Avina-Cervantes, Carlos Rodrigo Correa-Cely, Dirk Lindner, Claire Chalopin, Active contours driven by Cuckoo Search strategy for brain tumour images segmentation, Expert Systems with Applications, Volume 56, 1 September 2016, Pages 59-68.
- Heba M. Abdou, Mokhtar I. Yousef, Desouki A. El Mekkawy, Ahmed S. Al-Shami, Prophylactic neuroprotective efficiency of co-administration of Ginkgo biloba and Trifolium pretense against sodium arsenite-induced neurotoxicity and dementia in different regions of brain and spinal cord of rats, *Food and Chemical Toxicology*, Volume 94, August 2016, Pages 112-127.
- Marieke Anna de Ruiter, JaapOosterlaan, Antoinette Yvonne Narda Schouten-van Meeteren, Heleen Maurice-Stam, Dannis Gilbert van Vuurden, Corrie Gidding, Laura Rachel Beek, Bernd Granzen, Huib N. Caron, Martha Alexandra Grootenhuis, Neuro feedback ineffective in paediatric brain tumour survivors: Results of a double-blind randomised placebo-controlled trial, *European Journal of Cancer*, Volume 64, September 2016, Pages 62-73.
- Senthil P. Image Mining Brain Tumor Detection using Tad Plane Volume Rendering from MRI (Ibita). *Journal of Computer Science*, 2016; 2(Vo.1 Issue. 1, June- 2016, pages. 1-13).
- Senthil P. Enhanced of Image Mining Techniques the Classification Brain Tumor Accuracy (Encephalon). International Journal of Computer Science and Mobile Compution, 2016; 5(Issue 5):pages-110.
- Senthil P. Image Mining Effect Using Gaussian Smooth In Brain Tumor Increasing The Segmenting Accuracy (I-Meningioma). *Journal of Computer – JoC*, 2016 Jul 26; 2(Vol.1 Issue. 2, July- 2016):pages-63.
- Senthil P. Image Mining Base Level Set Segmentation Stages To Provide An Accurate Brain Tumor Detection. *International Journal of Engineering Science and Computing*, July 2016. 2016 Jul 28;6(Volume 6 Issue No. 7):Page-8295.
- Senthil P. Image Mining in Fuzzy Model Approaches Based Random walker algorithm Brain Tumor Analysis (Meningioma Analysis). *International Journal of Computer Science & Engineering Technology (IJCSET)*, 2016 Aug 1;7(Vol. 7 No. 07 Jul 2016):Pages-303.
- Mohammad Havaei, Axel Davy, David Warde-Farley, Antoine Biard, Aaron Courville, Yoshua Bengio, Chris Pal, Pierre-Marc Jodoin, Hugo Larochelle, Brain tumor segmentation with Deep Neural Networks, *Medical Image Analysis*, Volume 35, January 2017, Pages 18-31.
- Wenhua Ma, Na Li, Yonghui An, Changpeng Zhou, Changwen Bo, Guangyu Zhang, Effects of Temozolomide and Radiotherapy on Brain Metastatic Tumor: A Systematic Review and Meta-Analysis, *World Neurosurgery*, Volume 92, August 2016, Pages 197-205.
- YazanAbuodeh, Kamran A. Ahmed, Arash O. Naghavi, Puja S. Venkat, SiripornSarangkasiri, Peter A.S. Johnstone, Arnold B. Etame, Hsiang-Hsuan Michael Yu, Postoperative Stereotactic Radiosurgery Using 5-Gy × 5 Sessions in the Management of Brain Metastases, World Ne'surgery, Volume 90, June 2016, Pages 58-65.