

Detection of Traumatic Brain Injury Using Visual-Contextual Model in MRI Images

Bhagyashree A. Mathankar¹, Prof.P.V.Chavan²

P.G. Student, Department of Computer Science & Engineering, BDCOE, Sevagram, Wardha, Maharashtra, India¹

Asst. Professor, Department of Computer Science & Engineering, BDCOE, Sevagram, Wardha, Maharashtra, India²

ABSTRACT: Recently, there are various computational methods to detect the traumatic brain injury (TBI) from magnetic resonance imaging (MRI). The detection of brain injury or tumor is very difficult task in early stage in the medical science. There are various soft techniques for the detection of the patch of brain injury on the basis of MRI image content. The proposed method here is a segmentation process of 2D MRI image using various filtering techniques and from the output of this visual-contextual model is obtained, where contextual data contains the textural information like size, volume like labeled data and visual data contains the train features etc. here the output of both the model is combined for proper analysis SVM classifier is used to proper classification to get proper results. MATLAB has been used for the implementation.

KEYWORDS: MRI images; visual-contextual model; Traumatic brain injury (TBI); SVM

I. INTRODUCTION

Traumatic brain injury, often referred to as TBI, is most often an acute event similar to other injuries. That is where the similarity between traumatic brain injury and other injuries ends. One moment the person is normal and the next moment life has abruptly changed. In most other aspects, a traumatic brain injury is very different. Since our brain defines who we are, the consequences of a brain injury can affect all aspects of our lives, including our personality. A brain injury is different from a broken limb or punctured lung. An injury in these areas limit the use of a specific part of your body, but your personality and mental abilities remain unchanged. Most often, these body structures heal and regain their previous function. Brain injuries do not heal like other injuries. Recovery is a functional recovery, based on mechanisms that remain uncertain. No two brain injuries are alike and the consequence of two similar injuries may be very different. Symptoms may appear right away or may not be present for days or weeks after the injury. One of the consequences of brain injury is that the person often does not realize that a brain injury has occurred.

Most people are unaware of the scope of TBI or its overwhelming nature. TBI is a common injury and may be missed initially when the medical team is focused on saving the individual's life. Before medical knowledge and technology advanced to control breathing with respirators and decrease intracranial pressure, which is the pressure in the fluid surrounding the brain, the death rate from traumatic brain injuries was very high. Although the medical technology has advanced significantly, the effects of TBI are significant.

TBI is classified into two categories: mild and severe.

A brain injury can be classified as mild if loss of consciousness and/or confusion and disorientation is shorter than 30 minutes. While MRI and CAT scans are often normal, the individual has cognitive problems such as headache, difficulty thinking, memory problems, attention deficits, mood swings and frustration. These injuries are commonly overlooked. Even though this type of TBI is called "mild", the effect on the family and the injured person can be devastating. Severe brain injury is associated with loss of consciousness for more than 30 minutes and memory loss after the injury or penetrating skull injury longer than 24 hours. The deficits range from impairment of higher level

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017

cognitive functions to comatose states. Survivors may have limited function of arms or legs, abnormal speech or language, loss of thinking ability or emotional problems. The range of injuries and degree of recovery is very variable and varies on an individual basis.

The effects of TBI can be profound. Individuals with severe injuries can be left in long-term unresponsive states. For many people with severe TBI, long-term rehabilitation is often necessary to maximize function and independence. Even with mild TBI, the consequences to a person's life can be dramatic. Change in brain function can have a dramatic impact on family, job, social and community interaction.

TBI is the leading cause of mortality and morbidity in the world for individuals under the age of 45. Traumatic brain injuries are classified in penetrating or closed, and the pathophysiological processes differ for each. Primary injury is the mechanical damage occurring at the moment of impact, and secondary injuries are the non-mechanical aspects that result, including altered cerebral blood flow and metabolism, excitotoxicity, edema (swelling), and inflammatory processes. The extensive tearing of nerve tissue throughout the brain obtains these additional injuries since neurotransmitters are released, resulting in disturbance of the brain's normal communication and chemical processes. Permanent brain damage, coma, or death is possible. As per the clinical studies and those using experimental models of TBI, manual quantitative analysis has been used to evaluate TBI in MRI. These manual studies are used to identify the location and size of a lesion from MRI with correlative histology and assessment of long term neurological effects. However, manual detection of lesions in TBI is very difficult and often requiring 1) hours per scan is required for manual region-of-interest analysis, 2) a trained operator to improve the analysis, 3) large data sets for statistically sound analysis but, and 4) multi-modal it becomes resource intensive and multi-modal inputs as mild or subtle alterations on MR images are often difficult to identify (low contrast). In the present study, the ability of computer vision and learning techniques to assess subtle alterations on quantitative T2 maps after induction of TBI. Currently, neurological injuries are evaluated using the Glasgow Coma Scale (GCS) ,it evaluates a patient consciousness level through his/her ability to respond to motor, verbal and visual stimuli.

However, manual detection of lesions in TBI is very difficult and often requiring hours per scan is required for manual region-of-interest analysis, a trained operator to improve the analysis, large data sets for statistically sound analysis but, and multi-modal it becomes resource intensive and multi-modal inputs as mild or subtle alterations on MR images are often difficult to identify (low contrast). In the present study, the ability of computer vision and learning techniques to assess subtle alterations on quantitative T2 maps after induction of TBI. Currently, neurological injuries are evaluated using the Glasgow Coma Scale (GCS) ,it evaluates a patient consciousness level through his/her ability to respond to motor, verbal and visual stimuli. The manual detection of brain injury is very hard and challenging task, so by using various soft techniques we can create solutions for problems in the medical science.

In the proposed system, we used two models i.e. contextual model and visual model. These two models are used in SVM classification to detect the injury in the given MRI image. Contextual data is knowledge based i.e. in the proposed system some images have their .plq files and according to database those images have the injury and otherwise no injury so according to this labelled data gives the contextual model. Visual data is texture feature based i.e. in the proposed system, train features gives the visual model.

In this way SVM classifier is applied to get the final output of availability of injury or not in an MRI image.

II. RELATED WORK

Anthony Bianchi [1] proposed advance approach to detect mTBI lesion from MRI and improve the performance of visual and contextual modeling. The contextual model estimates the progression of the disease using subject information, such as the time since injury and the knowledge about the location of mTBI. The visual model utilizes texture features in MRI along with a probabilistic support vector machine to maximize the discrimination in unimodal MR images. These two models are fused to obtain a final estimate of the locations of the mTBI lesion.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017

N.Zhange [2] proposed SVM classification followed by region growing. It gives prior segmentation knowledge and features.

Renske de Boer [3] proposed the k-nearest neighbor for initial tissue segmentation. Gray matter is reclassified to lesion or non-lesion using the FLAIR channel, an automatic lesion segmentation method that uses only three-dimensional fluid-attenuation inversion recovery (FLAIR) images. It evaluates the method against the manual segmentation performed by an experienced neuroradiologist and compares the results with other unimodal segmentation approaches.

F.Krugel [4] proposed texture based segmentation for lesion. It utilizes high dimensional texture features. The co-occurrence features with PCA and the distance to cluster centers is used to make a probability map of injury.

M.L.Seghier [5] proposed tissue classification with an iteratively learned abnormal class. Tissue segmentation with an extra class is followed by outlier detection in the gray/white matter classes.

Carolina [6] proposed various context based object categorization model which contains semantic, spatial and scale context. In this work it addresses the problem of incorporating different types of contextual information for robust object categorization in computer vision.

Yu Sun [7] proposed symmetry integrated injury detection for brain MRI and asymmetric detection by kurtosis and skewness of symmetry affinity matrix.

O.Marques [8] proposed the roadmap to enhance current image analysis technologies by incorporating information from outside the target object, including scene analysis as well as metadata.

M. Kafai [9] proposed a stochastic multi-class vehicle classification system which classifies a vehicle (given its direct rear-side view) into one of four classes Sedan, Pickup truck, SUV/Minivan, and unknown. A feature set of tail light and vehicle dimensions is extracted which feeds a feature selection algorithm to define a low-dimensional feature vector. The feature vector is then processed by a Hybrid Dynamic Bayesian Network (HDBN) to classify each vehicle.

J. C. Platt [10] proposed Platt's probabilistic outputs for Support Vector Machines has been popular for applications that require posterior class probabilities.

R.Perko[11] proposed a framework for visual context-aware object detection. Methods for extracting visual contextual information from still images are proposed, which are then used to calculate a prior for object detection.

K. A. Tong [12] proposed CT remains the first-line imaging procedure in the acute evaluation of head injury; magnetic resonance (MR) imaging is becoming increasingly important for more detailed analysis of the degree and type of traumatic brain injury (TBI), as well as for predicting clinical outcome.

L.F.Costa [13] gives an integrated and conceptual introduction to this dynamic field and its myriad applications. Beginning with the basic mathematical concepts, it deals with shape analysis, from image capture to pattern classification, and presents many of the most advanced and powerful techniques used in practice.

I. Kharatishvili [14] compared MRI markers measured at acute post-injury phase to indicators of injury severity in the ability to predict the extent of histologically determined post-traumatic tissue damage.

A.Obenaus [15] evaluated temporal and regional changes after mild fluid percussion (FPI) and controlled cortical impact (CCI) injury using T2-weighted-imaging (T2WI) and diffusion-weighted imaging (DWI) MRI over 7 days. Region of interest analysis of brain areas distant to the injury site was undertaken.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017

Seung-Hyun Lee [16] proposed a modular Bayesian network system to extract context information by cooperative inference of multiple modules, which guarantees reliable inference compared to a monolithic Bayesian network without losing its strength like the easy management of knowledge and scalability.

T.Morris [17] gives the causes of traumatic brain injury and effects such as short term and long term symptoms and detailed information of traumatic brain injury.

N. C. Colgan [18] proposed in vivo sequelae of traumatic brain injury (TBI) following lower and higher levels of impact to the frontal lobe using quantitative MRI analysis and a mechanical model of penetrating impact injury levels, with greater significance for higher impacts.

R.C.Cantu [19] gives the information about second impact syndrome, it also gives the causes and its effects on the brain which are in extreme cases may cause death.

S. K. Divvala [20] proposed an empirical evaluation of the role of context in a contemporary, challenging object detection task .In this work, it presents our analysis on a standard dataset, using top-performing local appearance detectors as baseline. It evaluates several different sources of context and ways to utilize it.

II. PROPOSED METHODOLOGY

The proposed method gives as the following flow diagram .

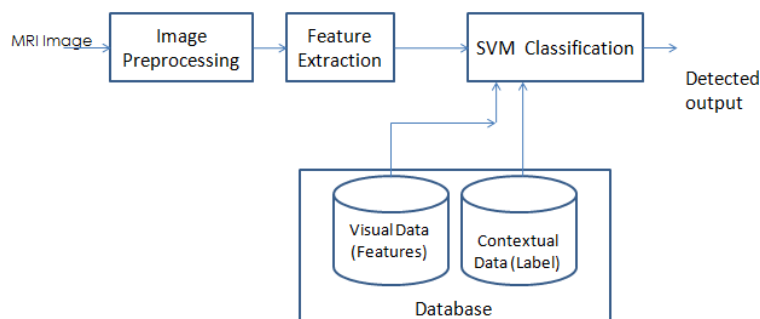


Fig. System Flow Diagram

The above system flow diagram gives the work flow of the proposed system. The input MRI image is resized and cropped because these images are gathered from various sources, so to maintain standard size and to remove the unwanted part of the of input images. After that Gaussian Filter is applied to enhance the image. Then feature extraction is done in which it gives diagonal, horizontal and vertical coefficients. Then SVM classification is applied using Visual and Contextual image model to get the proper results.

The dataset contains around 500 images. From those we have train labelled data and training features set for further processing.

(A)Image Preprocessing

It is most useful method in the image processing for applying further methods to get the proper results.

1.Resize and Cropping

There are various sources of input images so it is not in standard format hence resize the image in standard format. Cropping is the removal of unwanted areas from a photographic or illustrated image. One of the most basic photo manipulation processes, it is performed in order to remove an unwanted subject or irrelevant detail from a photo, change its aspect ratio, or to improve the overall composition. A horizontal and vertical projection gives cropped image.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017

2. Image Enhancement

Image enhancement is achieved using Gaussian filter. In image processing, a Gaussian blur (also known as Gaussian smoothing) is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. Mathematically, applying a Gaussian blur to an image is the same as convolving the image with a Gaussian function. This is also known as a two-dimensional Weierstrass transform. By contrast, convolving by a circle (i.e., a circular box blur) would more accurately reproduce the bokeh effect. Since the Fourier transform of a Gaussian is another Gaussian, applying a Gaussian blur has the effect of reducing the image's high-frequency components; a Gaussian blur is thus a low pass filter.

(B) Feature Extraction

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction.

In this Discrete Wavelet transform is used for the feature extraction. In this Haar wavelet is used, In mathematics, the Haar wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. It is very easy and fast computation. Hence to reduce complexity we used Haar transform.

To get the features of images, we decomposed the wavelet.

(C) Classification

In machine learning, support vector machines (SVMs, also support vector networks^[1]) are supervised learning models with associated learning algorithms that analyse data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

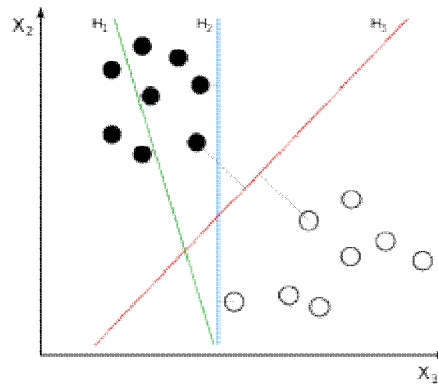
When data are not labeled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The clustering algorithm which provides an improvement to the support vector machines is called support vector clustering and is used in industrial applications either when data are not labeled or when only some data are labeled as a preprocessing for a classification pass.

Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a new data point will be in. In the case of support vector machines, a data point is viewed as a p-dimensional vector (a list of numbers), and we want to know whether we can separate such points with a (p-1)-dimensional hyperplane. This is called a linear classifier. There are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum-margin hyperplane and the linear classifier it defines is known as a maximum margin classifier; or equivalently, the perception of optimal stability.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017

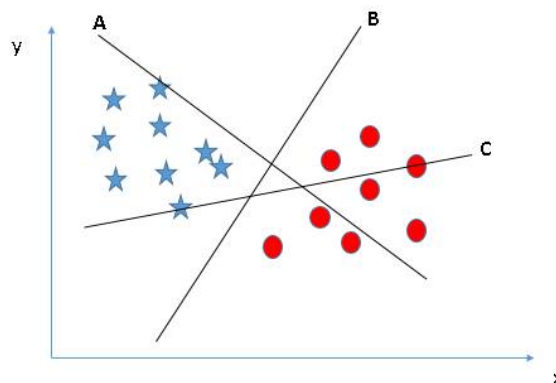


Figure

H_1 -does not separate the classes. H_2 does, but only with a small margin. H_3 -separates them with the maximum margin.

It is worked as follows.

- **Identify the right hyper-plane (Scenario-1):** Here, we have three hyper-planes (A, B and C). Now, identify the right hyper-plane to classify star and circle.



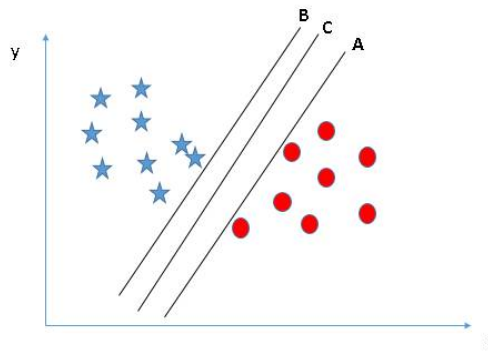
You need to remember a thumb rule to identify the right hyper-plane: “Select the hyper-plane which segregates the two classes better”. In this scenario, hyper-plane “B” has excellently performed this job.

- **Identify the right hyper-plane (Scenario-2):** Here, we have three hyper-planes (A, B and C) and all are segregating the classes well. Now, How can we identify the right hyper-plane?

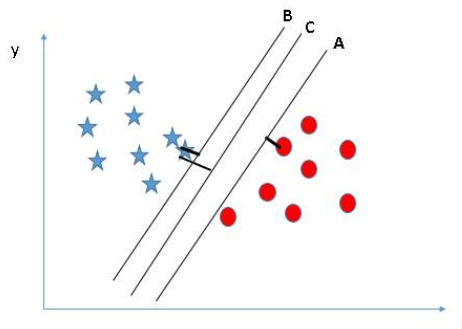
International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017

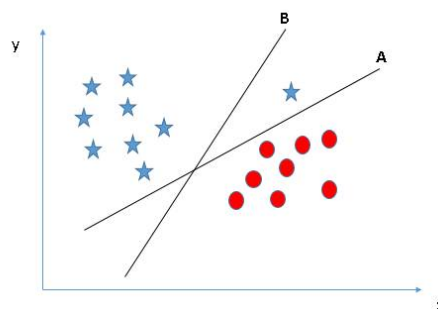


Here, maximizing the distances between nearest data point (either class) and hyper-plane will help us to decide the right hyper-plane. This distance is called as Margin. Let's look at the below snapshot:



Above, you can see that the margin for hyper-plane C is high as compared to both A and B. Hence, we name the right hyper-plane as C. Another lightning reason for selecting the hyper-plane with higher margin is robustness. If we select a hyper-plane having low margin then there is high chance of miss-classification.

- **Identify the right hyper-plane (Scenario-3):** Hint: Use the rules as discussed in previous section to identify the right hyper-plane

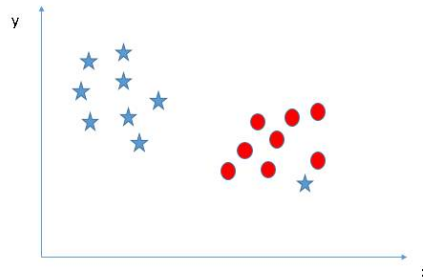


- **Classify two classes (Scenario-4):** Below, it is unable to segregate the two classes using a straight line, as one of star lies in the territory of other(circle) class as an outlier

International Journal of Innovative Research in Science, Engineering and Technology

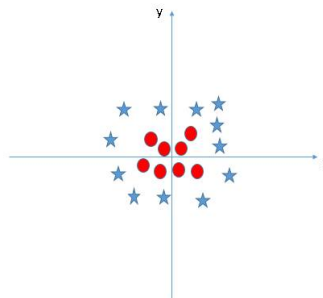
(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017

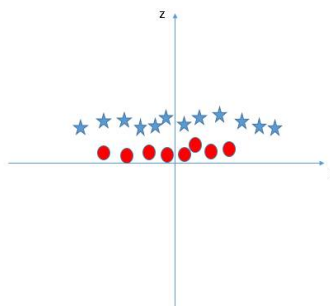


As it is already mentioned, one star at other end is like an outlier for star class. SVM has a feature to ignore outliers and find the hyper-plane that has maximum margin. Hence, we can say, SVM is robust to outliers.

- **Find the hyper-plane to segregate to classes (Scenario-5):** In the scenario below, we can't have linear hyper-plane between the two classes, so how does SVM classify these two classes? Till now, we have only looked at the linear-hyperplane.



SVM can solve this problem.Easily! It solves this problem by introducing additional feature. Here, we will add a new feature $z=x^2+y^2$. Now, let's plot the data points on axis x and z:



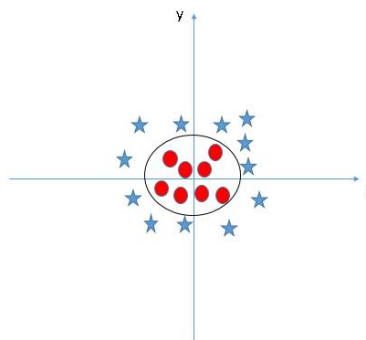
- In above plot, points to consider are:
 - All values for z would be positive always because z is the squared sum of both x and y
 - In the original plot, red circles appear close to the origin of x and y axes, leading to lower value of z and star relatively away from the origin result to higher value of z.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017

In SVM, it is easy to have a linear hyper-plane between these two classes. But, another burning question which arises is, should we need to add this feature manually to have a hyper-plane. No, SVM has a technique called the **kernel trick**. These are functions which takes low dimensional input space and transform it to a higher dimensional space i.e. it converts not separable problem to separable problem, these functions are called kernels. It is mostly useful in non-linear separation problem. Simply put, it does some extremely complex data transformations, then find out the process to separate the data based on the labels or outputs you've defined.



When we look at the hyper-plane in original input space it looks like a circle:

Some of you may have selected the hyper-plane **B** as it has higher margin compared to **A**. But, here is the catch; SVM selects the hyper-plane which classifies the classes accurately prior to maximizing margin. Here, hyper-plane B has a classification error and A has classified all correctly. Therefore, the right hyper-plane is A.

III. EXPERIMENTAL RESULTS

Following figures gives the step by step results after applying the proposed method.

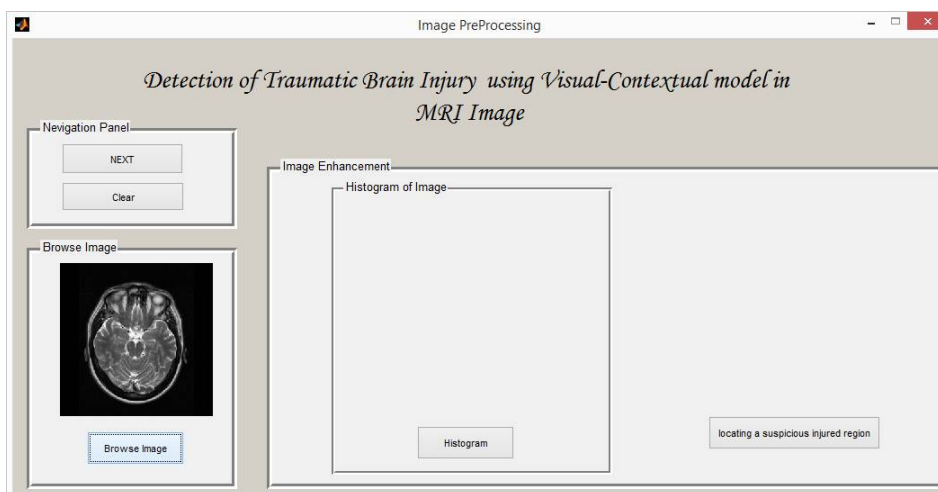


Fig (A) GUI of Proposed System with browse image

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017

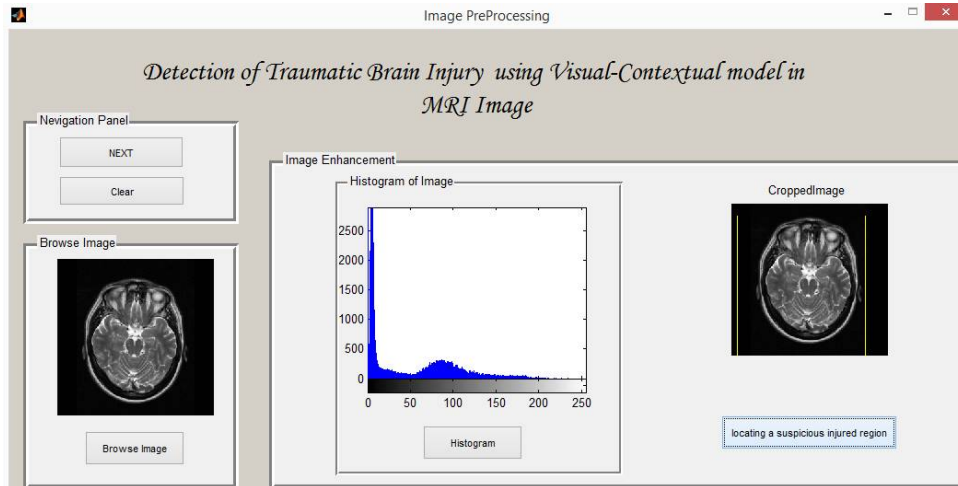
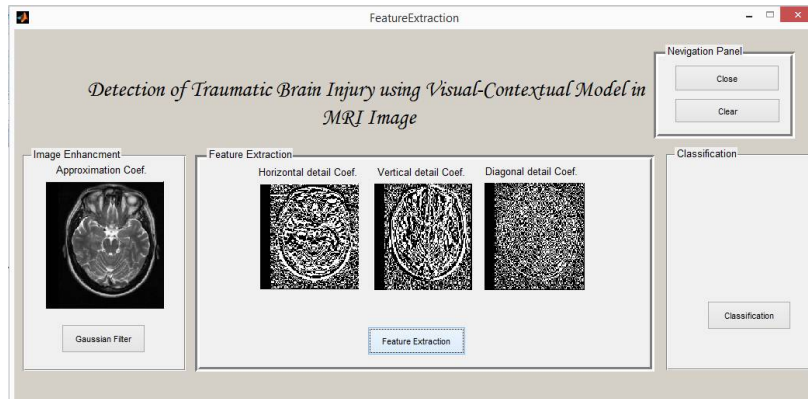
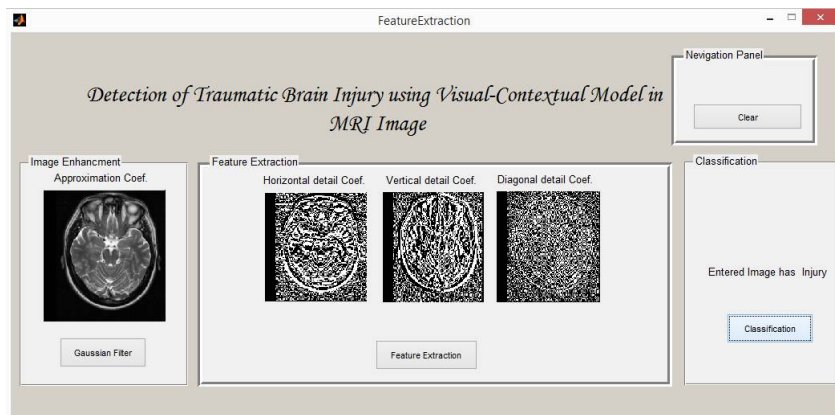


Fig (B):GUI for Image Preprocessing with Gaussian Filter



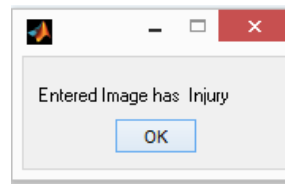
Fig(C): GUI for Feature Extraction



International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 6, Special Issue 11, May 2017



Fig(D): GUI of Final Result

IV. CONCLUSION

This approach gives the fusion of visual and contextual model which reduce the time and complexity for evaluation of model. The SVM classifier gives more accuracy with the help of training labeled data and train features which leads to the qualitative and quantitative results. It reduces the burden on the manual detection by the train observer. Traditional methods are more complex and time consuming.

As the number of patients are increased due to road accidents, military blasts etc. It is very necessary to get the fast diagnosis and treatment. Brain injury is very dangerous and it requires fast treatment. So, from the MRI images to detect the injury some computational methods are applied to get the result easily. Here in the proposed methodology SVM classification is used. This method gives more effective and proper results.

REFERENCES

1. A. Bianchi, B. Bhanu, V. Donovan, "Visual and contextual modeling for the detection of repeated mild traumatic brain injury". Publish in IEEE Transactions on Medical Imaging, vol. 33, no. 1, pp.1-12, January 2014.
2. R. de Boer, H. A. Vrooman, F. Van Der Lijn, M. W. Vernooij, M.A. Ikram, A. Van Der Lugt, M. M. B. Breteler, and W. J. Niessen, "White matter lesion extension to automatic brain tissue segmentation on MRI". publishes in NeuroImage, vol.45, no.4, pp.1151-1161, May 2009.
3. N. Zhang, S. Ruan, S. Lebonvallet, Q. Liao, and Y. Zhu, "Kernel feature selection to fuse multi-spectral MRI images for brain tumor segmentation". publish in Comput. Vis. Image Understand., vol. 115, no. 2, pp.256-269, Feb. 2011.
4. F. Kruggel, J. S. Paul, and H.-J. Gertz, "Texture-based segmentation of diffuse lesions of the brain's white matter" publishes in NeuroImage, vol. 39, no. 3, pp. 987-996, Feb. 2008.
5. M. L. Seghier, A. Ramalackhansingh, J. Crinion, A. P. Leff, and C. J. Price, "Lesion identification using unified segmentation normalization models and fuzzy clustering" publish in NeuroImage, vol. 41, no. 4, pp. 1253-1266, Jul. 2008.
6. A. Rabinovich, A. Vedaldi, C. Galleguillos, E. Wiewiora, and S. Belongie, "Objects in context" publish in IEEE Int. Conf. Comput. Vis, Riode Janeiro, Brazil, 2007, pp. 1-8.
7. Y. Sun, B. Bhanu, and S. Bhanu, "Automatic symmetry-integrated brain injury detection in MRI sequences", in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., Jun. 2009, pp. 79-86
8. O. Marques, E. Barenholtz, and V. Charvillat, "Context modeling in computer vision: Techniques, implications, and applications, Multimedia" Tools Appl., vol. 51, no. 1, pp. 303339, Jan. 2011.
9. M. Kafai and B. Bhanu, "Dynamic Bayesian networks for vehicle classification in video", IEEE Trans. Ind. Informat., vol. 8, no. 1, Pp.100-109, Feb. 2012.
10. J. C. Platt, "Probabilistic outputs for support vector machines and comparison to regularized likelihood methods", in Advances in Large Margin Classifiers. Cambridge, MA: MIT Press, 2000, pp. 61-74.
11. R. Perko and A. Leonardis, "A framework for visual-context-aware object detection in still images", Comput. Vis. Image Understand, vol.114, no. 6, pp. 700-711, Jun. 2010.
12. K. A. Tong, "New MRI techniques for imaging Of head trauma: DWI MRS, SWI", Appl. Radiol, vol. 32, no. 7, pp. 29-34, Jul. 2003.
13. L. F. Costa and R. M. Cesar, "Shape Analysis and Classification: Theory and Practice", Boca Raton, FL: CRC, 2001.
14. I. Kharatishvili, A. Sierra, R. J. Imonen, O. H. J. Grhn, and A. Pitknen, "Quantitative T2 mapping as a potential marker for the initial assessment of the severity of damage after traumatic brain injury in rat," Exp. Neurol., vol. 217, no. 1, pp. 154-164, May 2009.
15. A. Obenaus, M. Robbins, G. Blanco, N. R. Galloway, E. Snissarenko, E. Gillard, S. Lee, and M. Currs-Collazo, "Multi-modal magnetic resonance imaging alterations in two rat models of mild neurotrauma", Neurotrauma, vol. 24, no. 7, pp. 11471160, Jul. 2007.
16. Seung-Hyun Lee, Kyon-Mo Yang, Sung -Bae Cho, "Integrated modular Bayesian networks with selective inference for context-aware decision making", Neurocomputing 163, vol. 3840, pp 3846, August 2014.
17. T. Morris, "Traumatic brain injury, in Handbook of Medical Neuropsychology." L. Armstrong and L. Morrow, Eds. New York: Springer, 2010, ch. 2, pp. 1732.
18. N. C. Colgan, M. M. Cronin, O. L. Gobbo, S.M. OMara, W. T. O'Connor, and M. D. Gilchrist, "Quantitative MRI analysis of brain volume changes due to controlled cortical impact" Neurotrauma, vol.27, no. 7, pp. 12651274, July 2010.
19. R. C. Cantu, "Second-impact syndrome", Clin. Sports Med., vol. 17, no.1, pp. 3744, 1998.
20. S. K. Divvala, D. Hoiem, J. H. Hays, A.A. Efros, and M. Hebert, "An empirical study of context in object detection", in Proc. IEEE Cong. Comput. Vis. Pattern Recognit., Miami, FL, 2009, pp. 12711278.