

# Brain Tumor Diagnosis Based on Lasso Classifier

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**Abstract:** Computed tomography images are widely used in the diagnosis of brain tumour because of its faster processing, avoiding malfunctions and suitability with physician and radiologist. This study proposes a new approach to automated detection of brain tumour. This proposed work consists of various stages in their diagnosis processing such as reprocessing, anisotropic diffusion, feature extraction and classification. The local binary patterns and gray level co-occurrence features, gray level and wavelet features are extracted and these features are trained and classified using LASSO classifier. The achieved results are quantitatively evaluated and compared with various ground truth images. The proposed method gives fast and better segmentation and classification accuracy. We use free-response receiver operating characteristic curves to evaluate detection performance, and compare the proposed algorithm with several existing methods. In our experiments, the proposed framework outperformed all the other methods tested.

**Keywords—** Brain Tumour, Lasso Classifier, Segmentation, image.

## I. INTRODUCTION

The proposed system is divided into five phases (i) image acquisition, (ii) segmentation of tumour region, (iii) image preprocessing, (iv) feature extraction and feature selection and (v) classification and evaluation. The proposed methodology is applied to real datasets representing brain CT images. A computer software system is designed for segmentation and classification of benign and malignant tumour slices in brain computed tomography images. In this study, the authors present a method to select both dominant run length and co occurrence texture features of wavelet approximation tumour region of each slice to be segmented by a support vector machine (SVM). Two-dimensional discrete wavelet decomposition is performed on the tumour image to remove the noise and we can extract the features. This study constructed the SVM and probabilistic neural network (PNN) classifiers and least absolute shrinkage and selection operator (LASSO) classifier with the selected features. The classification accuracy of both classifiers are evaluated using the k fold cross validation method. The segmentation results are also compared with the experienced radiologist ground truth. Quantitative analysis between ground truth and the

segmented tumour is presented in terms of segmentation accuracy and segmentation error. The proposed system provides some newly found texture features have an important contribution in classifying tumour slices efficiently and accurately. The experimental results show that the proposed LASSO classifier is able to achieve high segmentation and classification accuracy effectiveness as measured by sensitivity and specificity.

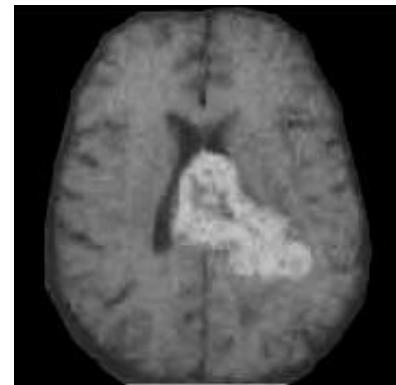


Figure 1: Input Image

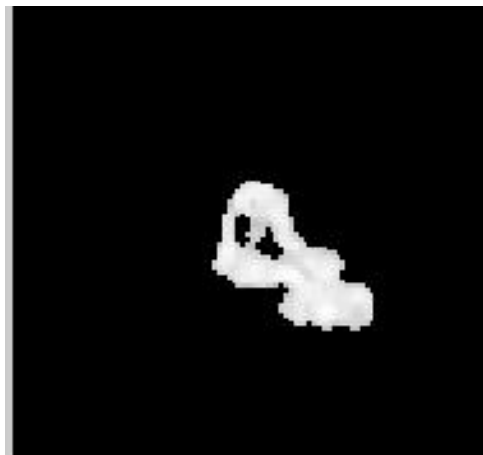


Figure 2: SVM Segment image

## II. THRESHOLDING

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level

(or a threshold value) to turn a gray-scale image into a BINARY image. There is also a balanced histogram thresholding. The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. Recently, methods have been developed for thresholding computed tomography (CT) images. The key idea is that, unlike Otsu's method, the thresholds are derived from the radiographs instead of the (reconstructed) image. For any given segmentation of an image, this scheme yields the number of bits required to encode that image based on the given segmentation. Thus, among all possible segmentations of an image, the goal is to find the segmentation which produces the shortest coding length. This can be achieved by a simple agglomerative clustering method. The distortion in the lossy compression determines the coarseness of the segmentation and its optimal value may differ for each image. This parameter can be estimated heuristically from the contrast of textures in an image. For example, when the textures in an image are similar, such as in camouflage images, stronger sensitivity and thus lower quantization is required.

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image.

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique. The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. The desired edges are the boundaries between such objects or spatial-taxons. Spatial-taxons are information granules, consisting of a crisp pixel region, stationed at abstraction levels within hierarchical nested scene architecture. They are similar to the Gestalt psychological designation of figure-ground, but are extended to include foreground, object groups, objects and salient object parts. Edge detection methods can be applied to the

spatial-taxon region, in the same manner they would be applied to a silhouette. This method is particularly useful when the disconnected edge is part of an illusory contour. Segmentation methods can also be applied to edges obtained from edge detectors. Lindeberg and Li developed an integrated method that segments edges into straight and curved edge segments for parts-based object recognition, based on a minimum description length (MDL) criterion that was optimized by a split-and-merge-like method with candidate breakpoints obtained from complementary junction cues to obtain more likely points at which to consider partitions into different segments.

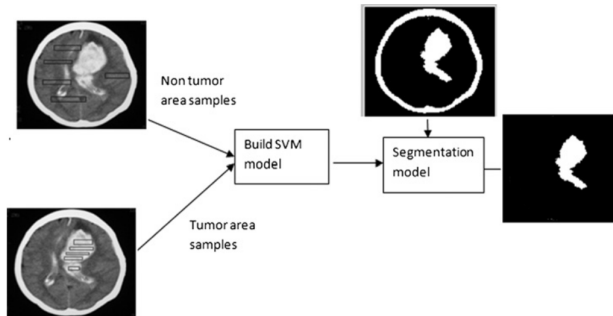
### **III. IMAGE SEGMENTATION FUNDAMENTALS**

There have been numerous research works in this area, out of which a few have now reached a state where they can be applied either with interactive manual intervention (usually with application to medical imaging) or fully automatically. The following is a brief overview of some of the main research ideas that current approaches are based upon. The nesting structure that Witkin described is, however, specific for one-dimensional signals and does not trivially transfer to higher-dimensional images. Nevertheless, this general idea has inspired several other authors to investigate coarse-to-fine schemes for image segmentation. Koenderink proposed to study how iso-intensity contours evolve over scales and this approach was investigated in more detail by Lifshitz and Pizer. Unfortunately, however, the intensity of image features changes over scales, which implies that it is hard to trace coarse-scale image features to finer scales using iso-intensity information.

### **IV. SUPPORT VECTOR MACHINE**

A Support Vector Machine (SVM) is a new and popular classifier which has self-learning features. SVMs were introduced by Vapnik (1998). SVM has been proved as one of the most accurate classifier with high efficiency. The SVM classifying technique, even though requires a very long training time, it is dimensionality independent and also feature space independent. SVM is a feed forward network with a single layer of non-linear units and the classifying results of SVM are highly accurate. Its architecture has a good generalization of performance and aims at the implementation of structural risk minimization as explained in Vapnik Chervonenkis (VC) dimension theory. SVM works on the principle of minimizing the bound on the errors made by the

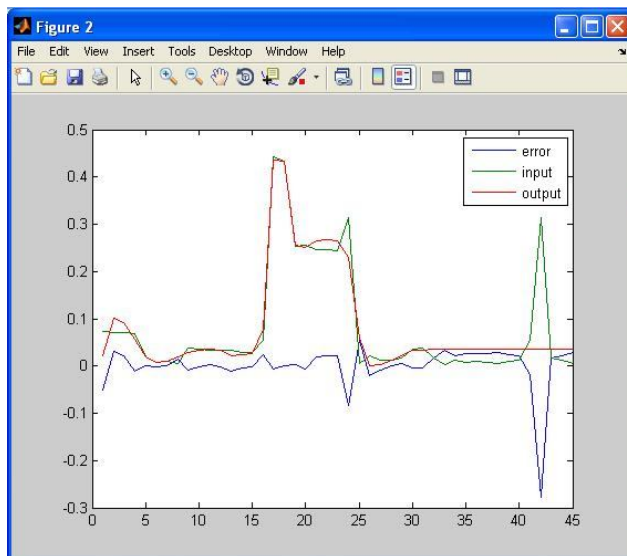
learning machine over the test dataset which were not used during training. It does not minimize the objective function of the training datasets. Hence, the SVM is able to perform perfectly over the images that do not belong to training datasets by concentrating and learning of difficult datasets during its training process. Such difficult to classify datasets in training are called support vectors.computational complexity.



**Fig. 3 Segmentation process using SVM classifier**

SVM has the following advantages: 1) It is designed to use limited samples to obtain optimum solution for practical problem; 2) It can ensure to find the global rather than local optimum solution. 3) The generalization ability of SVM is very good with relatively less computational complexity.

Probabilistic neural network classifier can be used for classification problems based on Bayesian classification and classical estimators for probability density function. It uses the exponential activation function instead of the sigmoidal activation function.



**Figure 4: Input, output and Error Signals**

Pulse-coupled neural networks (PCNNs) are neural models proposed by modeling a cat’s visual cortex and developed for high-performance biomimetic image processing. In 1989, Eckhorn introduced a neural model to emulate the mechanism of a cat’s visual cortex. The Eckhorn model provided a simple and effective tool for studying the visual cortex of small mammals, and was soon recognized as having significant application potential in image processing. In 1994, the Eckhorn model was adapted to be an image processing algorithm by Johnson, who termed this algorithm Pulse-Coupled Neural Network. Over the past decade, PCNNs have been utilized for a variety of image processing applications, including: image segmentation, feature generation, face extraction, motion detection, region growing, noise reduction, and so on. A PCNN is a two-dimensional neural network. Each neuron in the network corresponds to one pixel in an input image, receiving its corresponding pixel’s color information (e.g. intensity) as an external stimulus. Each neuron also connects with its neighboring neurons, receiving local stimuli from them. The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. Through iterative computation, PCNN neurons produce temporal series of pulse outputs. The temporal series of pulse outputs contain information of input images and can be utilized for various image processing applications, such as image segmentation and feature generation. Compared with conventional image processing means, PCNNs have several significant merits, including robustness against noise, independence of geometric variations in input patterns, capability of bridging minor intensity variations in input patterns, etc.

## V. LASSO

The sparse model character of 1-norm penalty term of Least Absolute Shrinkage and Selection Operator (LASSO) can be applied to automatic feature selection. Since 1-norm SVM is also designed with 1-norm (LASSO) penalty term, this study labels it as LASSO for classification. This paper introduces the smooth technique into 1-norm SVM and calls it smooth LASSO for classification (SLASSO) to provide simultaneous classification and feature selection. In the experiments, we compare SLASSO with other approaches of “wrapper” and “filter” models for feature selection. Results showed that SLASSO has slightly better accuracy than other approaches with the desirable ability of feature suppression.

This paper focuses on the feature selection problem in the support vector machine for binary classification. Feature suppression is very important in the development of new techniques in bioinformatics that utilize gene microarrays for prognostic classification, drug discovery, and other tasks. Many studies use 2-norm SVM for solving the classification problems. However, 2-norm SVM classifier can not automatically select input features. 1- norm SVM can automatically discard irrelevant features by estimating corresponding variables by zero. Thus, 1-norm SVM is both a wrapper method [13] and an automatic relevance

determination (ARD) model. When there are many noise features in training set, 1-norm SVM has significant advantages over 2-norm SVM. Methods for simultaneous classification and feature selection have grown popularly.

## VI. RESULTS

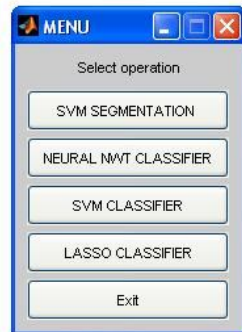
To analyze the performance of the proposed algorithm to detect the tumors, the images obtained using the proposed methodology is compared with its corresponding ground truth images. The proposed technique is analyzed with the following quality parameters to study its performance:

$$\text{SENSITIVITY} = \text{TP}/(\text{TP} + \text{FN}) * 100$$

$$\text{SPECIFICITY} = \text{TN}/(\text{TN} + \text{FP}) * 100$$

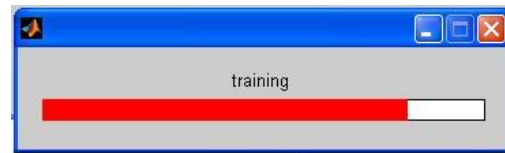
$$\text{ACCURACY} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

Where TN is the number of benign cases truly classified as negative, TP is the number of malignant cases truly classified as positive, FN, malignant cases falsely classified as negative and FP, benign cases falsely classified as positive. Sensitivity is the ability of the method to identify malignant cases. Specificity is the ability of the method to identify benign cases. Accuracy is the proportion of correctly diagnosed cases from the total number of cases.

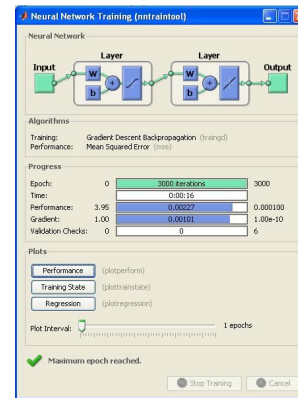


**Figure 5: Main Menu**

When it encounters a problem with large numbers of features, this study applies the Sherman-Morrison-Woodbury identity to decrease the training time. In the classification testing of LASSO, this study compares SLASSO with other approaches of “wrapper” and “filter” models for feature selection. Results showed that LASSO has slightly better accuracy than other approaches and performs well in feature suppression.

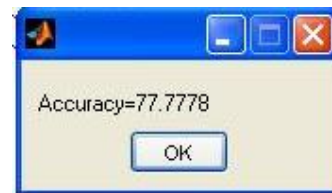


**Figure 6: Calculating Efficiency**

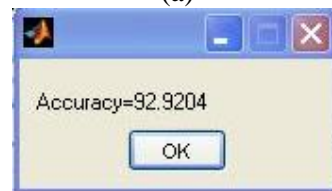


**Figure 7: Proposed Neural Network**

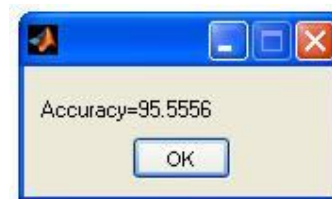
The simulation and experimental studies demonstrate the effectiveness of the proposed concept.



(a)



(b)



(c)

**Figure 8: Efficiencies for different Classifiers (a) Neural Network Classifier (b) SVM Classifier (c) Lasso Classifier**

## VII. CONCLUSION

In this research, a new approach for the segmentation and classification of brain tumor is proposed. It helps the physician and radiologist for brain tumor detection and diagnosis for tumor surgery. The local binary patterns and gray level co-occurrence features are extracted from brain images with benign and brain images with malignant and normal brain images. These extracted features are trained using LASSO classifier in training mode. The same features are extracted from test brain image and classified with trained patterns using LASSO classifier in classification mode. This proposed computer aided automation system for brain tumor segmentation and classification achieve sensitivity, specificity, accuracy.

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