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Citation

SU, Bolan; DINH, Thien Anh; AMBASTHA, A. K.; GONG, Tianxia; SILANDER, Tomi; LU, Shijian; LIM, C. C. Tchoyoson; PANG, Boon Chuan; LEE, Cheng Kiang; Tze-Yun LEONG; and TAN, Chew Lim. Automated Prediction of Glasgow Outcome Scale for Traumatic Brain Injury. (2014). *ICPR 2014: 22nd International Conference on Pattern Recognition Proceedings: 24-28 August 2014, Stockholm, Sweden*. 3245-3250. Research Collection School Of Information Systems.
Available at: https://ink.library.smu.edu.sg/sis_research/2995

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Automated Prediction of Glasgow Outcome Scale for Traumatic Brain Injury

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Abstract—**Clinical features found in brain CT scan images are widely used in traumatic brain injury (TBI) as indicators for Glasgow Outcome Scale (GOS) prediction. However, due to the lack of automated methods to measure and quantify the CT scan image features, the computerized prediction of GOS in TBI has not been well studied. This paper introduces an automated GOS prediction system for traumatic brain CT images. Different from most existing systems that perform the prognosis based on pre-processed data, our system directly works on brain CT scan images based on the image features. Our system can also be extended to large dataset with easy adaptation. For each new image of a CT scan series, our proposed system first makes use of sparse representation model that predicts the GOS of each CT image slice using Gabor features. Logistic regression, which integrates the GOS of each CT scan slice with a pre-trained model, is then applied to estimate the GOS score for the new case which contains multiple CT slices. Evaluation of the system has shown promising results in prediction of GOS of traumatic brain injury cases.**

Index Terms—**Brain CT Scan, Glasgow Outcome Scale, Sparse Representation Classifier, Logistic Regression**

I. INTRODUCTION

Clinical prognosis, which aims to predict the possible outcome of an illness, is usually made by doctors based on the knowledge of association between clinical finding and possible evolvement of an illness. With proper understanding of prognosis, treatment can be applied for the patient in a more sensible way and predictable crisis can be avoided [1]. However, it may not be easy to acquire accurate prognosis due to the limitation of individual doctor's experience. Statistical learning on large population can help to increase the accuracy of prognosis by finding the relationships between important prognostic indicators and their associated outcome. Prognosis can then be made based on the statistics from a large number of existed cases with similar prognostic indicators. In practice, prognosis models have been previously built based on statistical data, such as APACHE II and III [2], [3].

Medical imaging modalities such as CT or MRI have played an important role in improving the quality of clinical diagnosis.

TABLE I
GLASGOW OUTCOME SCALE

1	Dead
2	Vegetative State
3	Severely Disabled
4	Moderately Disabled
5	Good Recovery

Pathological features detected using these modalities are used as important indicators for outcome prediction. With fast developments in medical imaging methods and image processing techniques, more and more radiological data is available for research community in the field of medical imaging. Robust and efficient methods are required for deeper understanding of associations between the medical images and the likely outcome [4], [5].

In this paper, we focus on traumatic brain injury (TBI) [6], which is a major cause of mortality. Glasgow Outcome Scale (GOS) is a widely used five point score to assess the general functioning of the patient with TBI [7]. The GOS denotes the level of recovery that patients have achieved, as illustrated in Table I. Brain CT images are commonly used for clinical prognosis to predict the GOS of TBI. The prognosis is made based on the pathological features extracted from brain CT images.

II. RELATED WORKS

Many studies have been carried out to find the associations between these pathological findings from images and GOS. The relationship between brain midline shift and the recovery from consciousness has been discussed in Ross D.A. et al.'s work [8]. Sucu H.K. et al. further explored the relationship between brain midline shift and the chance of survival [9]. The relationship between hemorrhage location and patient mental status and motor function has been studied by Andrews B.T. et al [10]. Also, the relationship between Marshall CT

classification [11] and patient mortality has been studied by Maas A. I. et al. [12]. However, medical image features used in these studies are either quantitative and manually measured by experts or qualitative. It is time-consuming and expensive to extract quantitative clinical features; hence, existing studies are mostly based on relatively small datasets (less than 100 patients). On the other hand, qualitative feature descriptions may suffer from inconsistency problems and do not provide precise information on the associations between brain CT scan images and possible outcomes. Although there are large amounts of brain imaging data and analysis available in hospitals, quantified feature data is still inadequate. Hence, a robust prognosis model has not been developed.

It is important to automatically quantify clinical features in brain CT images for TBI prognosis research. A number of studies have been conducted on extracting features from the brain CT scan images, such as hematoma detection [13], hematoma classification [14], [15], hematoma region segmentation [16] and midline shift detection [17]. These extracted features such as hematoma and midline shift properties are useful for predicting the possible GOS for TBI [18]. The performance of feature extraction methods is critical and state-of-the-art techniques may not always provide precise clinic features for accurate prognosis. In addition to this, the associations between GOS and hematoma/midline shift properties are qualitatively described and need deeper understanding using statistical and learning techniques. There might also be many unknown associations between the GOS and the original CT scan images, which need to be discovered.

Existing online computer prognosis systems for TBI such as CRASH [19], IMPACT [20] perform the prognosis task using pre-processed data, such as CT classification grades. These systems still require manual interpretation of the original brain CT images by physicians, which is expensive and time-consuming.

In our previous work [21], we found that sparse representation based on Gabor features is a useful way to handle TBI CT images classification for hematoma types. Thus, we propose a new online prognosis system that works directly on brain CT scan images uploaded by users. To the best of our knowledge, this is the first attempt for automatic GOS prediction in TBI. Different from the previous approach [21], which only works on single CT image slices, the proposed system directly associates the original CT scan case and the GOS. We further propose a logistic model that predicts the GOS for the test case by combining the GOS prediction results of each slice in the case. By doing so, the system reduces the effort of human expertise and the dependence on the performance of image processing techniques, and hence is much more robust. Evaluation of the system has shown promising results in prediction of GOS for TBI patients.

III. PROPOSED METHOD

The brain CT scan images are preprocessed beforehand. After this, the prognosis system extracts localized low level features from the preprocessed images using Gabor filter [22].

(a) Original CT scan image   (b) CT scan image after skull removal   (c) CT scan image after normalization
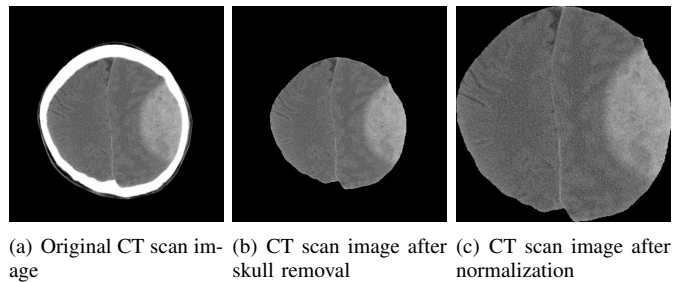
Fig. 2. Preprocessing result of a brain CT scan image.

SRC [23] is then applied to Gabor based features to classify the image slices uploaded by users into certain GOS. Finally, a logistic regression is performed on all the image slices of the testing case. The architecture of our proposed system is illustrated in Figure 1.

Patients with GOS 1 to 3 are considered to have unfavourable results, since they are either deceased or permanently depending on other persons' daily support. On the contrary, patients with GOS 4 and 5 are considered to have favourable results, as they are able to care for themselves independently and resume normal life to some extent. It is common practice to conduct prognosis analysis based on these two outcome categories [24], [25], as providing accurate severe/minor outcome prediction using automatic methods would greatly help the neurologists as well as the patients. Therefore, We classify a TBI case as severe (GOS 1 to 3) or minor (GOS 4 and 5) in addition to classifying it into a specific GOS level to fully provide decision support.

A. Preprocessing and feature extraction

At the preprocessing steps, the cranial structure is first removed from the original image. After that, the intensity and resolution of these images are normalized. The preprocessing results are shown in Figure 2. We then utilize 2-D spatial Gabor filter [26] to extract features at the different locations of the image with different scales and orientations. These features are scale-invariant and preserve information for GOS classification. In our prognosis system, the CT images are downsampled into 21×21. We create a Gabor filter bank with 5 frequencies and 8 orientations. Thus the Gabor feature created for each image is a vector with 17640 dimensions.

B. Classification of CT image slices

At this stage, each GOS category is considered as an individual class, and each CT image slice is classified into one of the five GOS classes. We use a sparse representation-based classifier (SRC) [27] for CT image classification. In this method, test data is represented by a linear combination of a small number of training data. The objective function for SRC can be written as:

$$x_{bst} = \arg\min_x ||x||_1$$

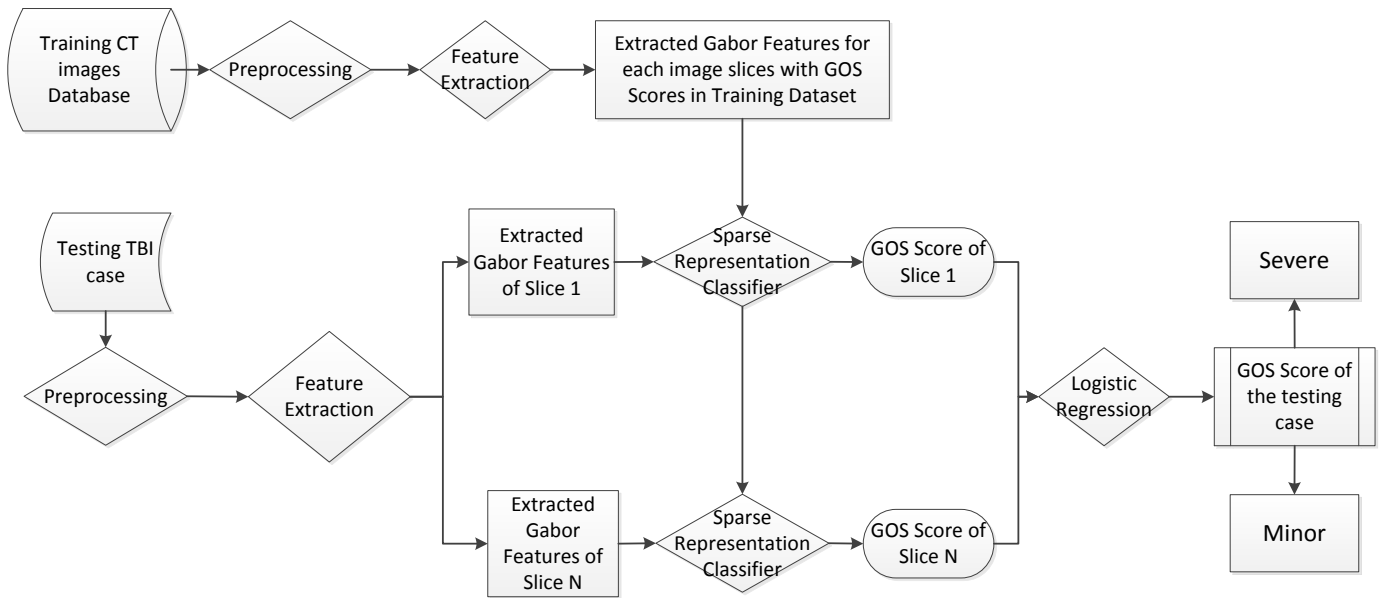$$\text{subject to} ||Ax - y||_2 < \epsilon$$

(1)

Fig. 1. Architecture of our proposed auto-prognosis system.

where A, y, and x denote the train data, test data, and sparse coefficient vector, respectively. $|| * ||_1$ and $|| * ||_2$ denote L1 and L2 norms. x_{bst} is the desired sparse coefficient vector. This optimization problem can be solved efficiently by L1-regularized optimization methods [28]. Based on x_{bst}, the SRC evaluates the contribution of different classes in the reconstruction of the test data y to classify the test data. As each time all the original training data are used to create a new reconstruction model for the new testing data, there is no need to develop a classification rule for all possible testing data before they are encountered.

In our proposed system, the training dataset can be viewed as a set of brain CT scan images, each of which is represented by a Gabor feature vector g_i. So the whole training dataset can be represented by a m by n matrix: $G = [g_1, \ldots, g_n]$, where m denotes the dimension of the feature vector, and n denotes the number of brain CT scan images. Similarly, the testing brain CT scan case can also be represented by a m by k matrix: $C = [c_1, \ldots, c_k]$, where k denotes the number of brain CT scan images in the testing case.

Since the GOS is evaluated at brain CT scan case level, the GOS label is not available for a single image slice. In order to assign a GOS for each image slice in the training dataset, we assume that every image slice of the same CT scan case has the same GOS, which is assigned on that CT scan case. Although this assumption might be naive, it provides a way to interpret the connection between the GOS of the CT scan case and each of its image slices. Furthermore, our proposed system still yields accurate prognosis results on GOS prediction.

For each testing image slice c_i, where $i \in [1, \ldots, k]$, we apply the SRC to reconstruct c_i using the training dataset G and obtain the corresponding sparse coefficient vector π. Then the class specific reconstruction error is calculated for each

GOS by reconstructing c_i only with those training samples with the same GOS and corresponding sparse coefficient vectors. After that, the GOS with the smallest reconstruction error is assigned as the label of c_i, because the testing image slice is better reconstructed by those training images with that GOS, and hence more similar to those training images in that group. The detail of the work flow is illustrated in Algorithm 1.

To increase the processing speed, we propose to use the local SRC technique [29], which uses a subset of the training data instead of the whole training dataset to apply the SRC. The subset is chosen by selecting the N most similar data samples from the original training dataset based on Euclidean Distance. This mechanism also relieves the imbalance of our brain CT scan dataset.

C. GOS prediction of testing brain CT scan case

The GOS for every image slice of the testing brain CT scan case has been obtained in previous section. We still need to predict the GOS for the testing case C, given the GOS vector of each image slice $L_C = [l_{c_1}, \ldots, l_{c_k}]$. A simple and straightforward method would be majority voting, which is to choose the most frequently GOS in L_C as the representative GOS for the brain CT scan case. However, majority voting does not take the relationship between GOS into account. For example, a testing case with a GOS vector ¡1, 1, 2, 5, 5¿ should be likely to have a GOS 1 than 5. Furthermore, majority voting just considers the GOS distribution of the single testing case.

In our proposed system, we choose logistic regression [30] to predict the GOS for the testing brain CT scan case. Logistic regression is widely used in different classification problems. This method tries to fit the possible outcome and input variables with some regression analysis. It could avoid the over-fitting problem when the number of features is more

Algorithm 1 GOS prediction for testing brain CT images

Require: A matrix $G = [g_1, \ldots, g_n]$ of training samples and corresponding GOS labels.

A testing brain CT scan case $C = [c_1, \ldots, c_k]$.

Ensure: A label vector $L_C = [l_{c_1}, \ldots, l_{c_k}]$ corresponding to the testing CT scan image case.

1: Scale each column of G and the test sample C to have unit L2-norm.
2: **for** each testing CT image slice $c_i, i \in [1, \ldots, k]$: **do**
3:     Find a sparse coefficient vector π of length N to reconstruction c_i using the training samples G by solving the L1-norm minimization problem defined in Equation 1, where G, c_i, π refer to A, y, x, respectively.
4:     **for** each unique GOS label $p = 1, \ldots, P$: **do**
5:         Construct a vector π^p that only contains values whose corresponding labels are GOS p.
6:         Construct a matrix G^p that only contains features whose corresponding labels are GOS p.
7:         7. Evaluate the class specific reconstruction error:

$$r_p(c_i) = ||G^p \pi^p - c_i||_2$$

8:     **end for**
9:     Choose the GOS with the minimum reconstruction error and assign it as the label l_{c_i} of the testing CT image slice c_i.
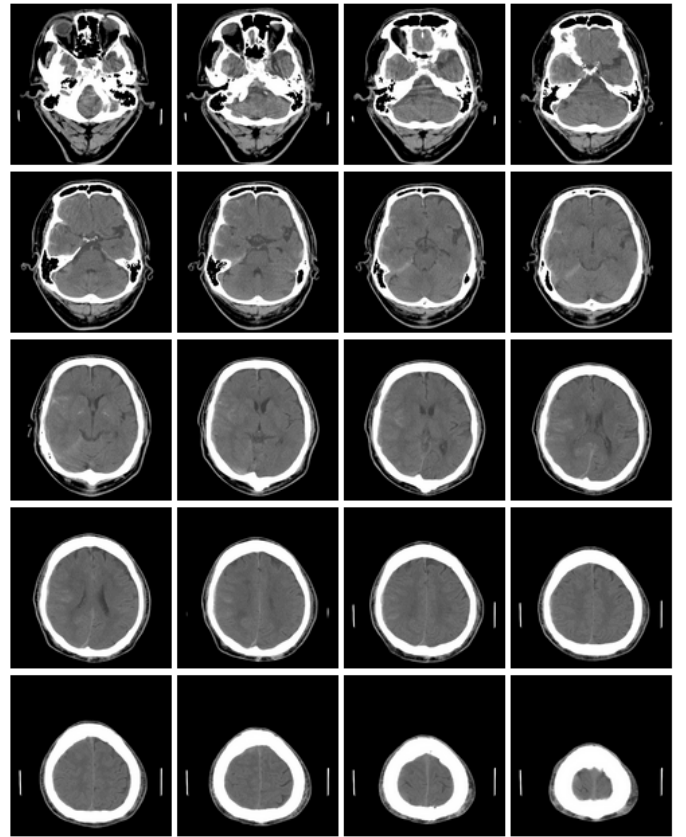10: **end for**

Fig. 4. A brain CT scan case with 20 slices.

than the number of training examples. The logistic regression function is defined as follows:

$$p(O = i|V, \theta_i) = \frac{1}{1 + e^{-\theta_i^T V}}$$

$$O_{bst} = \arg\max_i(p(O = i|V, \theta_i)) \qquad (2)$$

where O and V denote the possible outcome and the input variable, respectively. θ_i denotes the trained logistic regression model for GOS i. The final classification result O_{bst} is assigned to the label with maximum probability. The outcome O of our logistic regression model is the five level GOS. The input variable is a five dimension vector that denotes the possibility of each GOS in a brain CT scan case, which is defined as follows:

$$V = [v_1, \cdots, v_5]$$

$$v_i = \frac{N_i}{N} \qquad (3)$$

where v_i refers to the possibility of GOS i, N_i and N denote the number of slices with predicted GOS i, and the number of slices in the test case, respectively.

We then construct the training data for the logistic regression model by cross-validating the scan-based training dataset. For each case C in the training dataset, we use the remaining training cases to reconstruct each image slice c_i based on local SRC. As a result, these image slices will be assigned a GOS.

By combining predictions of these slices, we can construct the input variable V for logistic regression using Equation 3, which is illustrated in Figure 3.

In total, we can build N corresponding input variables and outcome tuples $[V_i, O_i]$ for the logistic regression model given a brain CT scan image training dataset with N samples. These tuples are then used to solve the logistic regression model. Finally, the testing brain CT scan case is assigned a GOS based on the GOS of its image slices using the trained logistic regression model.

IV. EXPERIMENTS AND DISCUSSION

Data used for evaluation of our proposed method is taken from the database of the Neuroradiology Department in a tertiary referral hospital specializing in neurological diseases in Singapore.

In this work, we focus on prediction of GOS, so cases without abnormalities were removed from the dataset beforehand. In total, the data set consists of the CT scan cases for 147 patients with TBI. Each case is in the form of a volumetric stack consisting of 10 to 30 slices and is manually labeled with a GOS by radiologists. Figure 4 shows a sample brain CT scan case. Each slice is an 8-bit gray-scale image with size 512×512. We further manually remove slices that are without hematoma. However, the dataset is quite imbalanced; most of the brain CT scan cases are labeled with GOS 1 or 5. Due
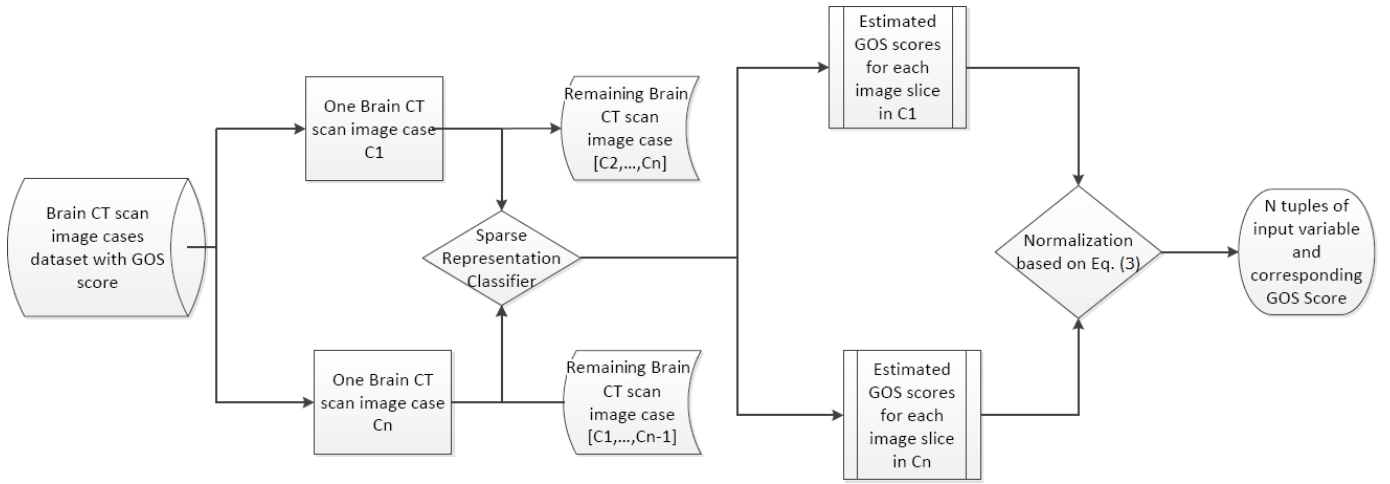
Fig. 3. The workflow of construction training data for logistic regression model

to the lack of CT scan case samples of GOS 2, we combine GOS 1 and 2.

The whole brain CT scan image dataset is randomly sampled into five-fold sub-datasets for cross validation. This is to evaluate the performance of our classifiers. We compared the performance of our proposed method with the SVM classifier. SVM classifier is treated as a baseline method and is directly trained using the Gabor feature. The GOS is first divided into 4 classes, by treating GOS level 1 and 2 as one class. We further compare the performance of using majority voting and logistic regression when classifying the testing cases into 2 classes: Severe with GOS of 1 to 3, and Minor with GOS of 4 and 5.

Table II shows the accuracy of GOS prediction using different methods. The experimental results show that our proposed method outperforms the SVM classifier in both 2 GOS classification and 4 GOS classification. That is because the GOS of the image slices in the training dataset are labeled based on their corresponding cases, which might be inaccurate. The SVM classifier when directly applied on these labels may fail to distinguish the data from different classes. On the other hand, our proposed method that makes use of local SRC [27] tries to reconstruction the testing image slices with similar slices in training data. This non-parameterized mechanism helps to suppress the noise within the training dataset.

Furthermore, the performance of SVM classifier varies for different folds, which is due to the imbalance of data between different folds and within a fold. The GOS distribution of each fold is non-uniform. Some GOS levels, such as 1 and 5, appear more frequently than the other GOS within a fold. So the classifier tends to assign the testing image slice into class 1 or 5. The local SRC [29] is proposed to handle such problem by selecting a subset of the data as the new training dataset. The variation of performance of our proposed technique on the five folds is much smaller compared with the SVM classifier.

Comprehensive human evaluation might be important for the performance of our proposed prognosis system for GOS

prediction. In our initial evaluation with physicians, the prediction accuracy is promising from their perspective. In practice, the GOS is determined not only based on the patient's CT scan images, but also relied on the medical profile of the patient (age, health record, etc.). Our proposed system provides an initial prognosis result based only on CT scan images.

V. CONCLUSION

In this paper, we propose a sparse representation based prognosis model for GOS prediction. The proposed method makes use of the sparse representation and logistic regression methods to directly build the association between the brain CT scan image case and the GOS. The prognosis system first applies the sparse representation classifier (SRC) using Gabor feature to predict the GOS of each image slice of the testing CT scan case. A logistic regression model is then trained to predict the GOS of the testing CT scan case based the estimated GOS of its image slices. Experimental results have shown promising performance of our proposed prognosis system.

One advantage of our proposed model is the direct association between the CT scan images with the prognosis outcome. This model enables statistical research on large TBI datasets. The proposed system could be useful to physicians and researchers dealing with prognosis information. Furthermore, the proposed prognosis model can be easily generalized to other prognosis problems.

On the other hand, our proposed model is a non-parameterized method, which will take longer time to compute when the size of the training dataset increases. Parallel computation technique can be a clue for this problem. In addition to this, our dataset suffers from imbalance data problem. Most of the CT scan cases have GOS 1 or 5, which makes us difficult to model the cases with GOS of 2 to 4.

In future, we would like to include some hematoma properties (size, location, etc.) and midline shift feature into our prognosis model. These features will provide more information

TABLE II
GOS PREDICTION ACCURACY OF DIFFERENT METHODS

Methods	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
SVM Classifier for 4 GOS	0.41	0.63	0.37	0.52	0.45
SVM Classifier for 2 GOS using majority voting	0.62	0.73	0.47	0.66	0.52
SVM Classifier for 2 GOS using logistic regression	0.66	0.73	0.43	0.66	0.48
Proposed method for 4 GOS	0.66	0.67	0.67	0.59	0.66
Proposed method for 2 GOS using majority voting	0.55	0.67	0.7	0.62	0.62
Proposed method for 2 GOS using logistic regression	**0.83**	**0.83**	**0.73**	**0.7**	**0.76**

for GOS prediction. It may improve the prognosis accuracy by building association between the hematoma and midline properties and GOS. However, better hematoma segmentation and midline shift detection techniques will have to be employed. Furthermore, it will also help to improve the GOS prediction accuracy by incorporating with the demographic information of the cases in our system. Besides we will explore a better model to describe the relationship between the GOS of a CT scan case and its individual image slices.

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