Classifier system for normality pre-diagnosis from MRI brain images in cerebral pathology studies

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***Abstract*—This research work presents the modeling and development of a Classifier System applied as a support tool to pre-diagnoses of normality/abnormality in brain pathology studies from TC or MRI digital images of a human brain. The proposed model is composed of three phases: images pre-processing, features extraction basis on Gabor Filtering and a classifier using Support Vector Machine with various kernel. This system has been tested on real MRI brain images obtaining a classification rate of 95% using RBF kernel.**

***Index Terms*—Support vector machine; classifier; medical imaging; features extraction; pre-diagnoses, normality and abnormality**

I. Introduction

Medical images are everyday used in clinical routine to establish a diagnosis, choose or claim a therapeutic action. These images mainly come from the tomography (x-rays) or scanner, MRI or ultrasonography. Although these images provide information about the morphology and organs internal function, their objective and quantitative interpretation is still a challenging task. It is a multidisciplinary domain in which medicine, computer science, applied mathematics and physics are associated to build new support tools to diagnosis, planning and treatment monitoring based on automated analysis of medical images.

Medical images are obtained from different modalities and equipments like MRI, CT, ultrasound, PET, etc. For detection of abnormalities like tumor or hemorraghes CT and MRI can be found as more reliable techniques, for these reason this work is focused on a method of detection and classification of abnormalities from CT and MRI brain images.

In imaging diagnosis, the first step is to determine if the image under observation is normal or abnormal, depending on the skills of highly qualified staff radiologist. Nowadays this process is still done manually and depends on the subjectivity of the specialist. Additionally, from a medical viewpoint, due to technological development there are greater processing and storage capabilities. Now have highly sophisticated imaging techniques such as MRI and CT can produce hundreds of images for each exam. Moreover, storage is no longer a problem, but the proper and effective use of large scale medical images databases is still a problem that requires an innovative approach.

A. Previous work

In a previous work, a CBIR system was modeled and implemented [1], this system, called M-CBIR, was able to evaluate four textures and intensity feature's extractors: Gabor Transform, Haralick, Gray Level Histogram and BIC, from a database contains 772 studies realized in several patients. Figure 1 shows the M-CBIR scheme.

The M-CBIR outcomes from the database show the Gabor filter as the best feature extractor. Thus, Gabor Filter will be used for the proposed work as the feature extractor.

This work is organized as follows, Section 2 presents a brief literature review about classifier models applied in medical images, Section 3 describes the proposal system detailing their phases, Section 4 discusses the test and experimental results and Section 5 states some conclusions.

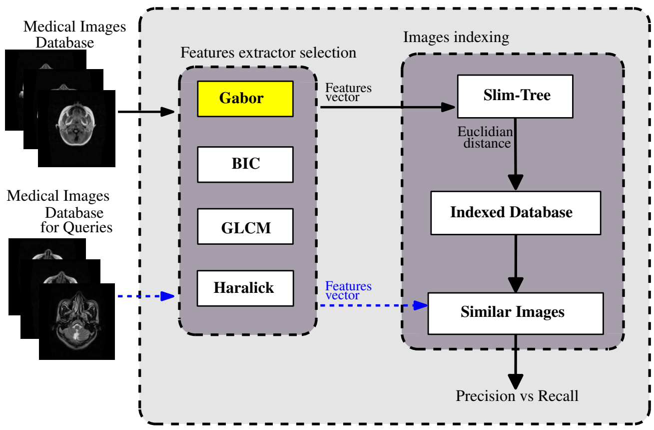


Fig. 1. M-CBIR model scheme [1]

II. Literature Review

In the literature, several works addressing the modeling and implementation of detection and classification systems for abnormalities from brain medical images, both MRI and CT scan can be found. Ray [2] proposes a technique to find and bounding brain abnormalities exploits left-to-right symmetry on brain structure from MRI data, as an initial step to find tumor boundaries. Selvati [3], evaluates Support Vector Machines and Relevance Vector Machine to classify MRI data as normal or abnormal; In this work we determined that the skull stripping and normalization were needed to improve the classification results. Chawla [4] proposes a more complete system to automatic detection and classification of stroke in brain CT images, this system is composed by three main steps: imagen enhancement, detection of mid-line symmetry and classification of abnormal slices.

Diyana [5] also proposes an abnormalities identification using symmetrical features on a CT brain images. Joshi [6] uses Artificial Neural Networks to detect blocks of tumors or lesions in MRI images, histogram equalization, image segmentation, enhancement and morphological operations are used for pre-processing and Gray Level Co-occurrence Matrix (GLCM) is used for feature extraction. Padma [7] compares the Dominant Gray Level Run Length feature extraction with Wavelet based texture feature extraction and Spatial Gray-level Dependent Matrix Method to classify and segment tumor from real brain CT images, by a SVM classifier. The optimal texture features are selected using a Genetic Algorithm. Othman [8] obtains features for MRI images using discrete wavelet transformation and evaluates some Kernels for a SVM classification of MRI images as normal or abnormal, Jayachandran [9] uses a Fuzzy SVM to classify a MRI brain images.

III. The Proposed Classifier

Figure 2 shows the proposed classifier composed by three steps highlighted by blue boxes: the images pre-processing, which enables the received image to the next stage, the feature extractor that convert the image in a vector of numbers to be entered into the classification engine to determine if these numbers correspond to a normal or abnormal image.

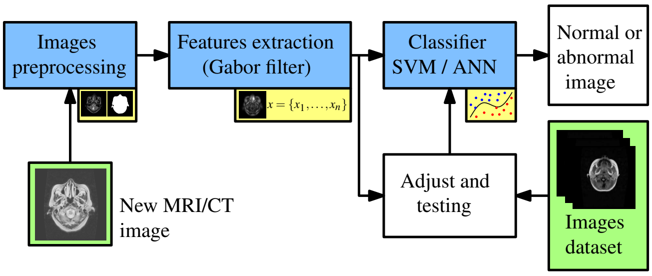


Fig. 2. The three steps of the classifier system: images pre-processing, features extraction and classifier

The following subsections detail each of the steps into proposed classifier model.

A. Pre-processing of medical images

We could say that Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are different in its method of production and have different utilities in images diagnosis. The noise produced by this methods is associated with the use of electrical and external influences which affects the results in the features extraction of the image. These influences are associated with random noise that alter its brightness as consequence of this variability is necessary make a digital image pre-processing step to ensure that the images conforms correctly to an initial pattern, Fig. 3 shows the pre-processing step applied to an image with noisy environment around the regions of interest.

The pre-processing initial step converts the image from RGB to gray scale, then adjust the intensity value of the pixels and finally we binarize the image employing K-means with two channels, resulting in regions of interest like showed in Fig. 3(b), in this way we eliminate the noisy existent in the regions of interest in the image as shown in Fig. 3(a), obtaining a resultant image as shown in Fig. 3(c).

(a) (b) (c)

Fig. 3. Example of a pre-processing step to a digital image. (a) Original Image (b) K-means and morphological filter (c) Resulting Image.

B. Gabor filter as feature extractor

Gabor filter is a two-dimensional Gaussian function modulated with sinusoidal orientations at a particular frequency and direction [10]. This filter is used as basis for a texture extraction from an image [11]. In this work, the method proposed by Manjunath and Ma [12], is used. Expanding the mother wavelet Gabor forms a complete but non-orthogonal basis set. The non-orthogonality implies that there will be redundant information between different resolutions in the output data. This redundancy has been reduced by [12] with the following strategy:

i Lets U_t and U_h denote the high and low frequency of interest.
ii Let S be the total numbers of scales, and K the total number of orientations (or translations) to be computed.
iii The design strategy is to ensure that the half-peak magnitude support of the filter response in the spectrum of frequency of each contact or view as shown in Fig. 4, for $S = 4$ and $K = 6$.

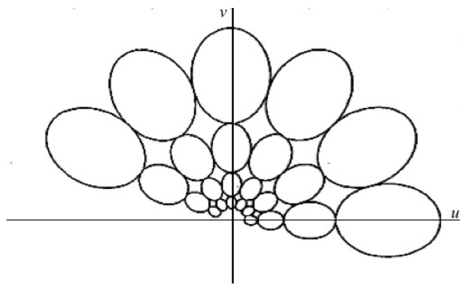


Fig. 4. Spectrum frequency 2D with 4 states and 6 orientations.

The Gabor transform [13] is defined as Eq. 1:

$$W_{m,n}(x,y) = \int I(x_1,y_1) g_{mn}*(x-x_1, y-y_1) d_{x_1} d_{y_1} \quad (1)$$

where:

$*$ denotes the complex conjugate operator;
m, n are integers, where $m = [1, 2, \ldots S]$ and $n = [1, 2, \ldots, K]$;

C. Classifier engine: Support Vector Machine (SVM)

Support Vector Machine [14], [15] are supervised learning models consists in learning algorithms to analyze and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the

other, making it a non-probabilistic binary linear classifier [16]. Thus, 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 on.
Non-linear classification: In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using a function Ψ called *kernel trick* [17] that maps their inputs into high-dimensional feature spaces.
The resulting algorithm is formally similar, except that every dot is replaced by the non-linear kernel function. This allows the algorithm to fit the maximum-margin hyperplane in a transformed feature space. The transformation may be nonlinear and the transformed space high dimensional; thus though the classifier is a hyperplane in the high-dimensional feature space, it may be non-linear in the original input space. Figure 5 illustrate an example of kernel function.

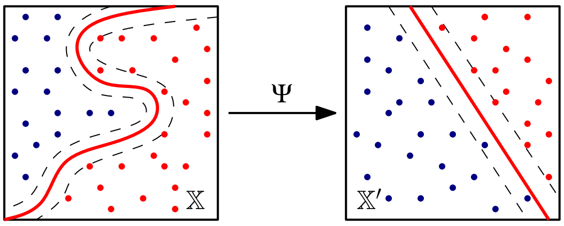


Fig. 5. The kernel Ψ transforms the space $\mathbb{X}$ containing non-linearly separable data into space $\mathbb{X}'$ with linear separable data

Some known kernel functions are:

1) Radial basis function kernel: on two samples $\mathbf{x}$ and $\mathbf{x}'$ represented as feature vectors in some input space is defined as Eq.2:

$$K(\mathbf{x}, \mathbf{x}') = e^{-\frac{||\mathbf{x}-\mathbf{x}'||_2^2}{2\sigma^2}} \tag{2}$$

where $||\mathbf{x} - \mathbf{x}'||_2^2$ is the squared Euclidian distance between the two featured vectors.
The value of RBF decreases with distance and ranges in $]0, 1]$ featuring a similarity measure [18]. The feature space resultant is infinite-dimensional and an expansion for $\sigma = 1$ is as Eq. 3:

$$e^{-\frac{1}{2}||\mathbf{x}-\mathbf{x}'||_2^2} = \sum_{j=0}^{\infty} \frac{(\mathbf{x}^T\mathbf{x}')^j}{j!} e^{-\frac{1}{2}||\mathbf{x}||_2^2} e^{-\frac{1}{2}||\mathbf{x}'||_2^2} \tag{3}$$

2) Polynomial kernel: on two samples $\mathbf{x}$ and $\mathbf{x}'$ is defined as Eq. 4 when the polynom is homogeneous, and by the Eq. 5, when the polynom in in-homogenous:

$$K(\mathbf{x}, \mathbf{x}') = (\mathbf{x}.\mathbf{x}')^d \tag{4}$$

$$K(\mathbf{x}, \mathbf{x}') = (\mathbf{x}.\mathbf{x}' + 1)^d \tag{5}$$

3) Sigmoid kernel: that uses a more related to neural networks function. On two samples $\mathbf{x}$ and $\mathbf{x}'$ the sigmoid kernel is defined by Eq. 6:

$$K(\mathbf{x}, \mathbf{x}') = \tanh\left(a\mathbf{x}^T\mathbf{x}' + r\right) \tag{6}$$

IV. Database and Experiments

A. Database of medical images

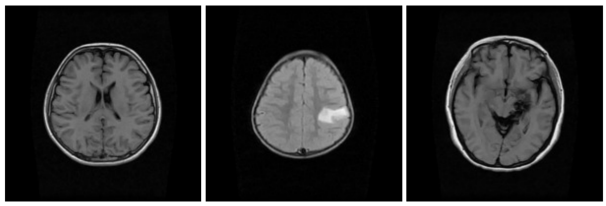
The database used in the experiments was provided by SEDIMED (*Support Service to Medical Diagnose*), a Medical Radiology Company from Arequipa. The SEDIMED's images repository consists on 772 studies realized in several patients.

However, it was not possible to find a complete set of abnormalities from the total studies database, because most of these studies were not specifically brain studies. The effective input dataset consists on 187 images used for the classification, each image file consists of 512×512 pixels with MR images. Table I shows the set of images for each subset and its orientation (Sagital, Axial and Coronal).

TABLE I
Quantity of images from test set

Type	Normal	Abnormal	Total
Axial	80	64	144
Sagital	11	08	19
Coronal	15	09	24

In addition, Figure 6 shows a sample set of images used, with one normal image and two abnormal images in these order.



(a) (b) (c)

Fig. 6. Samples of dataset: (a) is a normal image and (b),(c) are abnormal images contains some pathology.

B. System for testing

To perform experiments, the medical images system classification according to the workflow shown in Figure 7 was implemented. The workflow first extract features of the set of images to use for pre-diagnostic, features are then indexed by a metric structure Slim-Tree using the Canberra distance metric. Note that in [1] showed that the combination of Canberra and Slim-Tree allowed to obtain better results for the CBIR. The SVM was tested with different kernels as linear and RBF, with this last proving more effective for the separation of sets, then the set of vectors is entered to the engine classification through training.

As a final step, it enables real-time queries since the feature extraction takes place once per queried image, then a kind of classification is given, and a set of similar images is retrieved and displayed to the user. The purpose is to provide the greatest possible amount of information under requirements demanded by the radiologist to make a diagnosis.

C. Experiments and Results

Based upon data set detailed in Table I, the following experiments were performed:

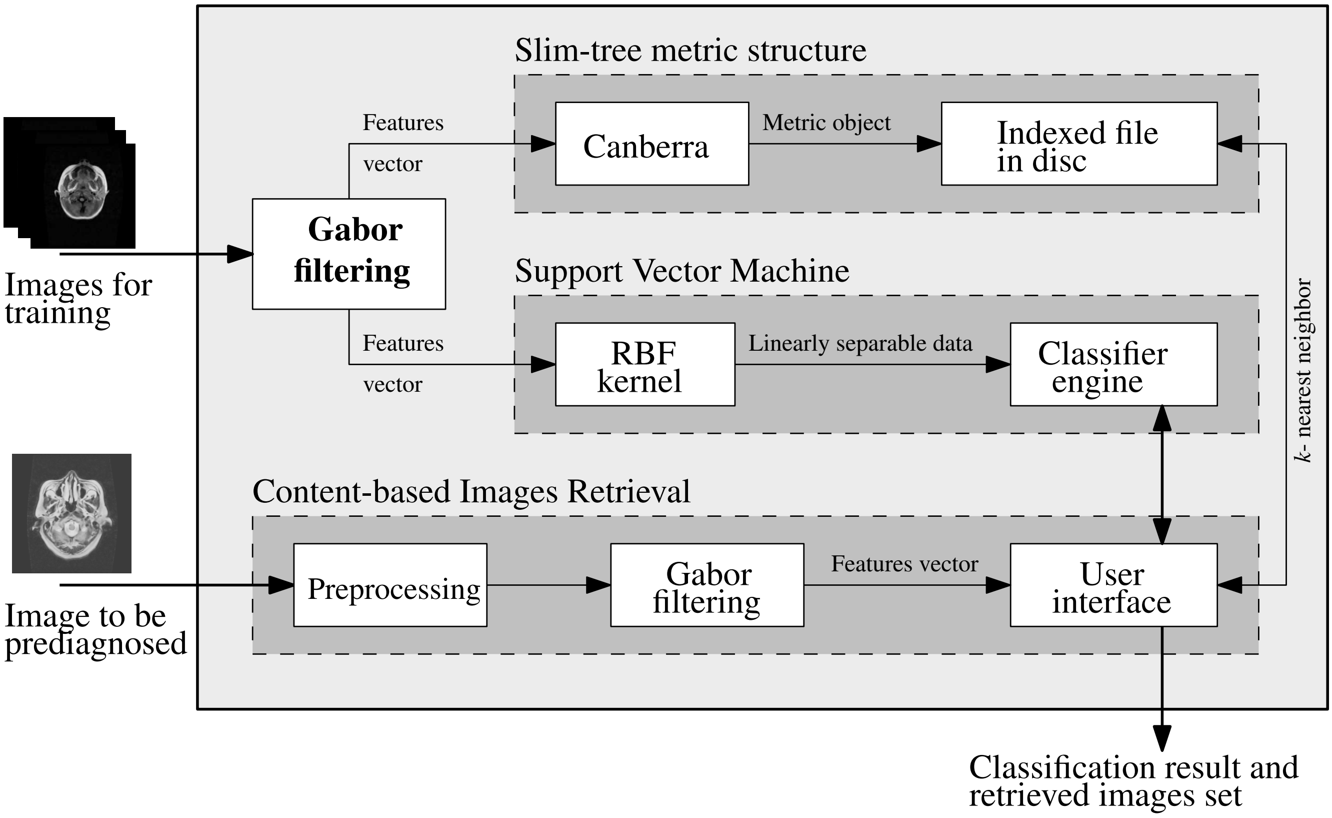


Fig. 7. Workflow used for experiments of the proposed classifier system

1) Classifying the entire set of images: In order to evaluate the quality of the classification of the data sets, three types of kernel SVM classifier were used for testing. As Table II shows, RBF achieved a total of 176 correct and 11 incorrect images, these are the best results, a total of 94.12% of classification rate is achieved, making project objectives accomplish.

TABLE II
CLASSIFICATION ERROR FOR EACH KERNEL

Kernel	Correct	Error	Correct(%)
Linear SVM	136	51	72.73
RBF	176	11	94.12
Sigmoidal	107	80	57.21
Polinomial	160	27	85.56

After obtaining results for SVM kernels, the next step was to evaluate these outcomes by a confusion matrix, as seen in Table III. In this table, total errors of 7.32% for abnormal class and 4.76% for the Normal class are observed. Thus, for the set of images, the error relates to between 5-6 images of the 81 being considered.

TABLE III
CONFUSION MATRIX FOR THE WHOLE IMAGES SET

	Abnormal	Normal	Error (%)
Abnormal	76	5	6.17
Normal	6	100	5.66
Error(%)	7.32	4.76	5.88

2) Clasiffying sagital, axial and coronal images: In addition, an evaluation by image type (Sagittal, Axial, Coronal) classification is performed allowing to obtain the confusion matrices shown in Tables IV, V and VI respectively. Should be note, in sagittal images, errors of 0% for abnormal class versus 9.09% for normal class. In general for other classifiers, 10% minor errors are noticeable, making these classifiers also acceptable.

TABLE IV
CONFUSION MATRIX FOR SAGITTAL IMAGES

	Abnormal	Normal	Error C(%)
Abnormal	8	0	0.00
Normal	1	10	9.09

TABLE V
CONFUSION MATRIX FOR CORONAL IMAGES

	Abnormal	Normal	Error C(%)
Abnormal	8	1	11.11
Normal	1	14	6.66

TABLE VI
CONFUSION MATRIX FOR AXIAL IMAGES

	Abnormal	Normal	Error C(%)
Anormal	60	4	6.25
Normal	4	76	5.00

V. CONCLUSION AND ANALYSIS

In this paper an algorithm for brain MRI data classification into normal and abnormal is proposed and implemented using SVM and some kernel functions to adjust the points into features space to be a linearly separable. It is observed that images pre-processing and normalization of features enhances the classification accuracy and also in this work the obtained outcomes for the classification from MRI data are promising and applicable for a pre-diagnosis automated system, however we believe that an increase in the set of test data would provide more representative results for pre-diagnosis, as a future work we will develop a tool for pre-diagnoses with an relevance feedback module for better results.

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REFERENCES

[1] H. Chuctaya, C. Portugal, C. Beltran, J. Gutierrez, C. Lopez, and Y. Tupac, "M-CBIR: A medical content-based image retrieval system using metric data-structures," in *Computer Science Society (SCCC), 2011 30th International Conference of the Chilean*, Nov 2011, pp. 135–141.

[2] N. Ray, B. Saha, and M. Graham Brown, "Locating brain tumors from mr imagery using symmetry," in *Signals, Systems and Computers, 2007. ACSSC 2007. Conference Record of the Forty-First Asilomar Conference on*, Nov 2007, pp. 224–228.

[3] D. Selvathi, R. Ram Prakash, and S. Thamarai Selvi, "Performance evaluation of kernel based techniques for brain mri data classification," in *Conference on Computational Intelligence and Multimedia Applications, 2007. International Conference on*, vol. 2, Dec 2007, pp. 456–460.

[4] M. Chawla, S. Sharma, J. Sivaswamy, and L. T. Kishore, "A method for automatic detection and classification of stroke from brain ct images," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, Sept 2009, pp. 3581–3584.

[5] W. Diyana, W. Zaki, and C. Kong, "Identifying abnormalities in computed tomography brain images using symmetrical features," in *Electrical Engineering and Informatics, 2009. ICEEI '09. International Conference on*, vol. 01, Aug 2009, pp. 88–92.

[6] D. Joshi, N. K. Rana, and V. M. Misra, "Classification of brain cancer using artificial neural network," in *Electronic Computer Technology (ICECT), 2010 International Conference on*, May 2010, pp. 112–116.

[7] A.Padma and R.Sukanesh, "Automatic classification and segmentation of brain tumor in ct images using optimal dominant gray level run length texture features," *International Journal of Advanced Computer Science and Applications*, vol. 2, no. 10, pp. 53–59, 2011.

[8] M. Othman, N. Abdullah, and N. Kamal, "Mri brain classification using support vector machine," in *Modeling, Simulation and Applied Optimization (ICMSAO), 2011 4th International Conference on*, April 2011, pp. 1–4.

[9] A. Jayachandran and R. Dhanasekaran, "Brain tumor detection and classification of mr images using texture features and fuzzy svm classifier," *Research Journal of Applied Sciences, Engineering and Technology*, vol. 6, no. 12, pp. 2264–2269, Jul. 2013.

[10] D. Gabor, "Theory of communication," *Electrical Engineers - Part I: General, Journal of the Institution of*, vol. 94, no. 73, pp. 58–, January 1947.

[11] I. Fogel and D. Sagi, "Gabor filters as texture discriminator," *Biological Cybernetics*, vol. 61, no. 2, pp. 103–113, jun 1989. [Online]. Available: http://dx.doi.org/10.1007/BF00204594

[12] B. Manjunath and W. Ma, "Texture features for browsing and retrieval of image data," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 18, no. 8, pp. 837–842, Aug 1996.

[13] W. Wan Ahmad and M. Fauzi, "Comparison of different feature extraction techniques in content-based image retrieval for ct brain images," in *Multimedia Signal Processing, 2008 IEEE 10th Workshop on*, Oct 2008, pp. 503–508.

[14] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," in *Proceedings of the Fifth Annual Workshop on Computational Learning Theory*, ser. COLT'92. New York, NY, USA: ACM, 1992, pp. 144–152. [Online]. Available: http://doi.acm.org/10.1145/130385.130401

[15] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995. [Online]. Available: http://dx.doi.org/10.1007/BF00994018

[16] V. Vapnik and A. Lerner, "Pattern Recognition using Generalized Portrait Method," *Automation and Remote Control*, vol. 24, 1963.

[17] M. A. Aizerman, E. A. Braverman, and L. Rozonoer, "Theoretical foundations of the potential function method in pattern recognition learning." in *Automation and Remote Control,*, ser. Automation and Remote Control,, no. 25, 1964, pp. 821–837.

[18] K. Tsuda and B. Schölkopf, *A primer on kernel methods*. MIT Press, 2004, pp. 35–70.