

SUPPORT VECTOR MACHINE BASED FRAMEWORK FOR DEMENTIA CLASSIFICATION

S. K. Aruna^{1*}, S. Chitra², B. Madhusudhanan³

¹Department of Computer Science and Engineering, Paavai Engineering College, Namakkal, TN- 637001, INDIA

^{2,3}Department of Computer Science and Engineering, Er Perumal Manimekalai College of Engineering, TN, INDIA

ABSTRACT

Aims: Dementia is fast rising as a huge public health problem in recent times due to its extreme prevalence rate, huge burdens to patients in terms of health care costs and so on. Identifying alterable risk elements is significant for delaying or even preventing the onset of dementia. Magnetic resonance Imaging (MRI) is an affordable as well as non-radioactive imaging technique which does not have ionizing radiations. It possesses excellent spatial resolution and is commonly accessible within clinical environments. In the current work, image extraction is carried out through usage of Gabor as well as Grey-Level Co-Occurrence Matrix (GLCM). Classification is carried out through classifiers like K-Nearest Neighbor (KNN), Classification and Regression Tree (CART) as well as Support Vector Machines (SVM).

Published on: 18th– August-2016

KEY WORDS

Dementia, Magnetic Resonance Imaging (MRI), K-Nearest Neighbor (KNN), Classification and Regression Tree (CART)

*Corresponding author: Email: arunask.bir@gmail.com

INTRODUCTION

Alzheimer's disease (AD) is the topmost common illness causing dementia amongst the older population. Through at present, there is no cure for the illness research is being carried out for developing novel treatment methods. Because most of these are greatly beneficial to pre-symptomatic patients, earlier detection of the disease is significant and so individuals suffering from Mild Cognitive Impairment (MCI), who are at heightened risk of falling prey to Alzheimer's are of interest here.

In recent times, it is possible to detect traces/biomarkers of AD in individuals who are suffering from Mild Cognitive Impairment through the usage of Magnetic Resonance Imaging (MRI) volumetric study, neurochemical analyses of cerebrospinal fluid, as well as Positron Emission Tomography (PET) scans [1]. This kind of research is costly, requires great technical expertise, invasive as well as available only in select locales. Longitudinal studies measuring the predictive values of neuropsychological tests in the advancement of individuals suffering from mild cognitive impairment to dementia reveal a region under the receiver operating characteristic (ROC) curve of 61-94% but with lesser accuracy as well as sensitivity values. It is significant to enhance values of neuropsychological tests for the prediction of advancement of MCI to dementia amongst patients. This is possible at the clinical level through raising the quantity of patients with longer clinical follow-up. Predictive capability of the tests can be improved by innovative statistical classification as well as data mining methods. Conventional statistical classification techniques for instance, Linear Discriminant Analysis (LDA) or Logistic Regression (LR) are wisely utilized in medical classification issues wherein criteria parameters are dichotomous [2]. Research is also being carried out into improving the accuracy as well as efficacy of data mining with classifiers such as Neural Network (NN), Support Vector Machine (SVM), Classification Tree (CT) as well as Random Forests (RF) utilized for medical predictions as well as classification tasks [3,4].

Dementia is a neurodegenerative illness whose causes are not yet known. AD is a typical kind of dementia wherein there is loss of neurons as well as synapses in the cerebral cortex as well as other sub-cortical areas. Although most individuals affected by dementia are elderly, not all elderly people are suffering from dementia which implies that it is not a natural effect of normal ageing. Dementia may impact anybody but typically it manifests in people above the age of 65. It is also noted that dementia is more prevalent amongst males [5].

In Alzheimer's, automated image classification was utilized in functional imaging as well as cortical thickness metrics for differentiating scans of patients with dementia and healthy patients. Of late, patterns recognition techniques employed to structural MRIs are utilized for distinguishing individuals suffering from mild cognitive impairment from healthy individuals.

MRI is an imaging method which has undergone evolution to become a clinical modality over a period of thirty years. Medical imaging tools assist healthcare professionals in reaching particular diagnoses. Medical image analyses as well as processing possess great importance in healthcare because of their non-invasive treatments as well as clinical studies. It also has a part to play in the identification as well as diagnosis of several illnesses. Imaging assists healthcare professionals in the visualization as well as analysis of images for understanding anomalies in internal structures. Medical images utilize tools such as CTs, MRIs, mammograms for the identification of lesions in the patient [6].

MRIs refer to scanning devices that utilize magnetic fields as well as computers for capturing images of brains on film. It does not utilize x-rays and yields images from several planes which permit healthcare professionals to view 3D images of the tumor. MRIs identify signals from normal as well as anomalous tissues and ensure clearer image scans of the tumors. It is vastly employed in high quality medical imaging situations, particularly when the brain is involved wherein soft tissue contrasts as well as non-invasive nature of the technique are extremely beneficial. MRIs are typically studied by radiologists and are interpreted visually for identifying anomalous tissues. Brain images are chosen for image references in the current work because brain injuries impact huge areas of the organ. The brain handles the control as well as coordination of movements, behavior as well as homeostatic bodily functions such as heart beat, blood pressure, body temperature and so on. The brain also handles cognition, memories, emotions as well as learning of all kinds.

The classification of brain MRIs as either normal or anomalous is significant in the pruning of healthy individuals and taking into consideration solely those with possible anomalies or tumors. There are only few radiologists and the quantities of MRIs to be examined are numerous, which makes it a very expensive process in labour as well as cost. Hence, there is a need for automatic systems for the analysis as well as classification of the images. Outcomes of human analyses regarding false negatives ought to be very low when handling human life. Double medical image readings result in improved tumors identification.

Classification refers to the assignment of physical entities or events to pre-specified categories. Medical image datasets for image classification or teaching possesses several modality images, obtained from various conditions with differing accuracy of annotations. This holds true for several online resource image scans, like those that access journals online content. Methods that combine visual as well as textual methods for classification show excellent promise in the classification of medical images.

RELATED WORKS

Yasue et al [7] examined 783 patients as well as 2139 healthy controls who took part in a population-based study carried out in Japan. Sinusitis was tested for through usage of MRIs as per the Lund-Mackay scoring system. Sinusitis scores ≥ 4 were sorted as positive while scores ≤ 3 were sorted as negative. The presence of positive sinusitis was 6.3% in individuals with MMSE scores < 24 ($n = 507$), as well as 5.7% in individuals with AD ($n = 280$). The presence of sinusitis was not considerably distinct between healthy individuals as well as those with dementia/AD after modifications for age/sex. The rate of positive sinusitis was greater for males than females in both groups.

Zheng et al [8] presented a summary of existing automatic dementia detection protocols in literature from the perspective of patterns classification. Because mostly these protocols comprise features extraction as well as classification, they offer a review on the three groups of features extraction techniques which are voxel-, vertex- as well as ROI-based ones as well as four groups of classifiers which are the LDA, Bayes classifier, SVM as well as ANN. The performance of the classifiers are contrasted and the comparison reveals that several protocols are capable of distinguishing AD from healthy controls with excellent accuracies although differentiating healthy controls from those suffering from MCI is still a difficult task.

Aruna & Chitra [6] suggested a model for the classification of MRIs for dementia. Dementia is an age-related disorder characterized by deterioration in cognition which is made manifest by the deterioration of cortical as well as sub-cortical structures. The characterization of these morphological alterations assists in the comprehension of development of diseases as well as earlier estimation as well as prevention of the illness. Modeling which is the capturing of the brain's structural variability and which still holds true in the classification as well as interpretation of diseases is a difficult task. Feature extraction is carried out through Gabor filter with 0, 30, 60, 90 orientations as well as GLCM. It is suggested for normalization as well as fusion of features. Independent Component Analysis (ICA) chooses attributes. SVM with various kernels is tested for efficacy in the classification of dementia. The work tests the suggested model through usage of MRIs from the OASIS database for the identification of dementia. Outcomes reveal that the suggested features fusion classifier attains excellent classification accuracy.

METHODOLOGY

MRIs were collected from OASIS and utilized for evaluation of the suggested techniques in the current work. Feature extraction is carried out through usage of Gabor filter with 0, 30, 60, 90 orientations as well as GLCM. Features undergo normalization as well as fusion for obtaining fused features vector. mRMR is used for features selection. Naïve Bayes, Neural Network, Ensemble Neural Network classifiers are utilized for classifying images as dementia or non-dementia on the basis of the chosen attributes.

OASIS data set

OASIS dataset comprises 416 subjects ranging between 18 and 96 years of age which also includes people with early-stage Alzheimer's [9]. 98 right-handed women (aged between 65 and 96) were chosen from the OASIS dataset. 200 subjects with incomplete records were discarded. For the current work, images of 49 normal subjects as well as 49 subjects with very mild to mild Alzheimer's are utilized. OASIS dataset was put together after strict imaging protocols for curbing imaging protocol variants that posed big image standardization problems. Several high-determination auxiliary T1-weighted Magnetization-Prepared Rapid Gradient Echo (MP-RAGE) images were obtained in one imaging session.

Feature Extraction

Statistical Parameter Mapping (SPM12) is utilized for segmentation of brain images into Grey as well as White Matter. Textural features are chosen through Gabor as well as GLCM. Gabor filters are transform functions associated with Fourier transforms that may be utilized for conveying spatial data additional to frequency characteristics of signals. It is generally employed as band-pass filters in signal processing wherein it is utilized for the determination of sinusoidal frequencies as well as phase content of local sections of time-varying input signals and has been proven to be helpful in the case of image compressions. Amongst other helpful characteristics, Gabor filter has been discovered to perform minimization of conjoint time-frequency information resolutions of signals in a better manner. 1D Gabor filter is featured as a collection of cosine/sine (even/odd) waves with Gaussian windows,

$$g_e(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}} \text{Cos}(2\pi w_o x) \quad (1)$$

$$g_o(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}} \text{Sin}(2\pi w_o x) \quad (2)$$

Wherein refers to focus (frequency wherein filters yield most significant reactions) as well as σ refers to distribution of Gaussian windows.

The strength of Gabor filters responses depend on the filters' congruence with local signals; wherein the filters' sensitivities is defined through tuning of variables which are orientation, phase as well as frequency [10]. Because Gabor filters are not orthogonal [11], optimum set of variables for the design of Gabor filter jets which will identify favored range of object features with minimal redundancy is determined. Assume $g(x, y, \theta, \phi)$ is a function that characterizes Gabor filters run at root with θ as spatial frequency while ϕ refers to orientation. Gabor filters are represented as (3):

$$g(x, y, \theta, \phi) = \exp\left(-\frac{x^2 + y^2}{\sigma^2}\right) \exp(2\pi\theta i(x \cos \phi + y \sin \phi)) \quad (3)$$

It was revealed that σ , standard deviations of Gaussian kernels rely on θ measured.

Two-dimensional Gabor functions comprise sinusoidal plane waves of frequency as well as orientation, altered by two dimensional Gaussian envelopes. Canonical Gabor filters in space are given by (4):

$$h(x, y) = \exp \left\{ -\frac{1}{2} \left[\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right] \right\} \cos(2\pi\mu_0 x + \phi) \quad (4)$$

Wherein μ_0 as well as ϕ refer to frequency as well as period of sinusoidal plane waves along the z-axis (that is, the 0° orientation), refer to space constants of Gaussian envelopes along x-axis as well as y-axis, separately. Gabor filters with self-assertive introductions may be obtained through unbending revolutions of x-y coordinates model [12].

When investigating statistical textures, texture attributes are computed on statistical conveyance of pixel intensities at locations relative to others in pixels associating with image matrices. Contingent upon pixels or spots in combinations, there is first-order, second-order or higher-request statistics. GLCM based features extraction is second-order statistics which studies images as textures. A basic method for description of intensities, but not regarding the relative position of pixels with regard to one another in that particular texture is suggested. Utilizing a statistical method like co-occurrence matrix will assist in the provision of valuable data regarding about the relative position of neighboring pixels in a particular image. GLCM (similarly grey tone spatial reliance matrix) refers to frequency tabulation of how often a combination of pixel luminance quality in images. Apart from horizontal heading (0°), GLCM may be shaped for bearing of 45°, 90° and 135°. The feature vectors of Gabor and GLCM are normalized and fused to obtaining a combined features vector.

Feature Selection

A filter-based features extraction framework known as minimum-Redundancy Maximum-Relevance (mRMR) that attempts to choose the important attributes with target class labels as well as decrease redundancy among chosen attributes all the while, the protocol utilizes Mutual Information $I(X, Y)$ that assesses the degree of similitude between two discrete arbitrary parameters X as well as Y [14]:

$$I(X, Y) = \sum_{x \in X} \sum_{y \in Y} p(x, y) \log \left(\frac{p(x, y)}{p_1(x)p_2(y)} \right) \quad (5)$$

Wherein $p(x, y)$ refers to the joint probability distribution capability of X as well as Y, while $p_1(x)$ as well as $p_2(y)$ refer to the minor probability distribution elements of X as well as Y separately.

Information theoretic positioning criterion mulls over nonlinear links between features as well as targets. Evaluation of features is carried out in an autonomous manner and features redundancy is not capable of being managed. For investigating mRMR systems as well as or handling the issue of redundancy, choosing of perfect features for classification is carried out. For features set S comprising n_0 attributes $\{x_i\}$, ($i = 1 \dots n_0$). The topmost priority is the identification of attributes so that common data characteristics between individual attributes as well as target class are to be amplified. Assume $D(S, y)$ is the mean of common data between individual attribute as well as target y . It is mathematically given by:

$$\max D(S, y) = \frac{1}{|S|} \sum_{x_i \in S} I(x_i, y) \quad (6)$$

Although two attributes might possess solid separability on the target class, it is not desirable to include them just in case they have exceptional correlation. The notion of minimal redundancy is the choosing of attributes which have common maximum divergence. Assume $R(S, y)$ is the mean of the common data between sets of features in S. It mathematically given by:

$$\min R(S) = \frac{1}{|S|^2} \sum_{x_i, x_j \in S} I(x_i, x_j) \quad (7)$$

The foundation bringing together the two equations given above is known as mRMR. mRMR features set is obtained through the boosting of $D(S, y)$ as well as minimization of $R(S)$ simultaneously that needs combining the two metrics into one model capacity (one criterion function).

Classifiers

K Nearest Neighbor (KNN)

KNN refers to a supervised patterns recognition method that carries out segmentations through comparison of novel data to set of labeled samples in training sets. KNN classifiers are easier to utilize relative to others and this ensures that the procedure is more rapid. Hence, the primary benefit is that training models may be created more rapidly.

Classification and Regression Tree (CART)

CART [15] refers to an alternate method wherein data space is split into small sections wherein parameter interactions are clear. CART is a non-parametric, machine-learning technique which splits values of all predictor parameters in a recursive manner into two sets such that values of outcome parameters are homogeneous in all sets. All predictor parameters are regarded as potential splits, including all grouped values of numerical predictors. Optimal splits are those with greatest decrease in impurity indices that measure level of misclassification at a particular node.

Support Vector Machine (SVM) Classification

Support Vector Machines refer to supervised, multivariate classification techniques, which imply that they possess training sets for learning about the differences between groups to be sorted. The technique was earlier employed to neuroimaging data. The data required for this technique is not required to fulfill presumptions of Random Field Theory, ensuring further smoothening not necessary [16]. Within the context of machine learning, individual MRIs are considered as points situated in high-dimensional space.

The space utilized for classification of image data is of greater dimensions, the total quantity of dimensions is defined by the number of voxels in all MRIs. Practically, linear kernel matrices are generated from normalized grey matter segmented scans. For this purpose, all MRIs undergo pair-wise multiplication with the others. All elements in the kernel matrices are thereby dot products of two images. Kernel matrices are also understood as similitude metric amongst subjects on a characterized set. Voxels are efficiently treated as coordinates of higher dimensional spaces and the position is defined by the intensity values at all voxels. The images do not span the entire higher-dimensional space and instead, they cluster in sub-spaces comprising images which are alike. This is the reason why image normalization into standard spaces is a significant pre-processing stage. Excellent normalization tightens clustering as well as reduces dimensionality.

The usage of SVMs for image classification is an instance of linear discrimination. In basic models, they are binary classifiers which imply that space is divided into which MRIs are sorted into two classes through identification of separating hyper planes. In simple two dimensional spaces, boundaries are denoted by lines but are known as hyper planes in higher dimensional spaces. Fisher's LDA or linear perceptron is capable of identifying linear discriminant hyper planes. But the reason or usage of SVMs is the fact that they utilize the principle of 'structural risk minimization' that focuses on the discovery of hyper planes which make maximum the distance between training classes.

Support Vector Machine (SVM) refers to a machine learning derived classifier that map vectors of predictors into high dimensional planes through linear or nonlinear kernel functions. In binary classification issues, the two groups, for instance $\{-1\}$ as well as $\{+1\}$, are made separate in higher-dimension hyperplanes according to the structural risk minimization principle. The aim is the discovery of linear separating hyper planes

$$w'\phi(x) + b = 0$$

Generated from vector x of predictors mapped into high dimensional features space by non-linear features function ϕ , vector w of weights as well as a bias offset b , which sorts all observations y_i into one of the two $\{-1; +1\}$. Classification function is given by:

$$f(x) = \text{Sign}(w'\phi(x) + b)$$

Because in binary classification issues there are infinite separation hyper planes, the aim is the discovery of optimal linear planes that group best. For finding optimal planes farthest from $\{-1\}$ as well as $\{+1\}$ groups, one method is the maximization of distances or margins of separation from the supporting planes, correspondingly $w'\phi(x) + b \geq +1$ for $\{+1\}$ as well as $w'\phi(x) + b \leq -1$ for $\{-1\}$. The support planes are pushed apart till they turn into a small set of observations or training patterns which respect the limits mentioned and therefore are known as support vectors. Figure 2 shows this notion. Classification goals may be attained through the maximization of distances or margins of separation r between the two planes $w'\phi(x) + b = +1$ and $w'x + b = -1$ specified by $r = 2 / \|w\|$. This is the same as the minimization of the cost function

$$C(w) = \frac{\|w\|^2}{2} + c \sum_{i=1}^n \xi_i = \frac{1}{2} w'w + c \sum_{i=1}^n \xi_i$$

Subject to linear inequality limits

$$\gamma_i(w'\phi(x_i) + b) \geq 1 - \xi_i \text{ and } \xi_i \geq 0$$

wherein $c > 0$ is penalty variable which balances classification errors versus the complexity of the framework that is

monitored by margins of separation while ξ_i is known as the slack-parameter. The parameter is the penalty of misclassified observations which control how far on the wrong side of hyper planes points may lie when training data is not capable of being classified without errors, i.e. when objects are not capable of linear separation and soft separating non-linear margins are needed.

As features space may be infinite, non-linear mapping by features function ϕ is calculated through special non-linear semi-positive definite K functions known as kernels. Hence, the above minimization is typically resolved by dual formulation issue:

$$\min \frac{1}{2} \sum \gamma_i \gamma_j \alpha_i \alpha_j K(x_i, x_j) - \sum_{i=1}^n \alpha_i$$

Subject to linear limits

$$\sum_{i=1}^n \gamma_i \alpha_i = 0 \text{ and } 0 \leq \alpha_i \leq C$$

Wherein α_i ($i = 1, \dots, n$) represent non-negative Lagrange multipliers while $K(\cdot)$ represents kernel functions. In classification issues (c-SVM) the typical kernel functions are linear kernel $K(x_i, x_j) = x_i x_j$ or Gaussian $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$ wherein γ refers to kernel variable. The usage of kernel functions possesses the benefit of operating in the initial input parameters wherein solutions of classification problems are weighted sum of kernels tested at support vectors [18].

RESULTS

In proposed method for experiments, 280 normal MRI image and 140 images with dementia are used. In this section, the classification accuracy, Sensitivity for Normal, Sensitivity for abnormal, Specificity for Normal and Specificity for abnormal are evaluated in table 1. Figure 1 to 5 shows the same.

Table 1 Summary of Results

	KNN	CART	SVM
Classification Accuracy	84.69	85.71	89.8
Sensitivity for Normal	0.8571	0.9184	0.9184
Sensitivity for abnormal	0.8367	0.7959	0.8776
Specificity for Normal	0.8367	0.7959	0.8776
Specificity for abnormal	0.8571	0.9184	0.9184

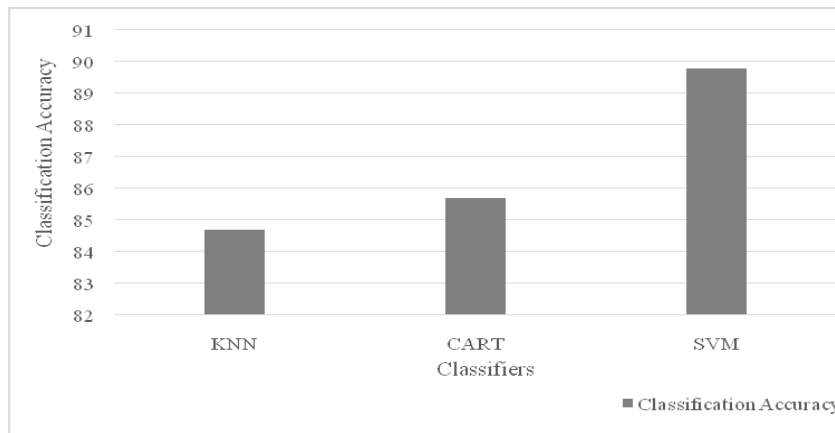


Fig. 1: Classification Accuracy

From the table 1 and figure 1, it can be observed that the classification accuracy for normal image of SVM performs better by 5.81% than KNN and by 4.66% than CART.

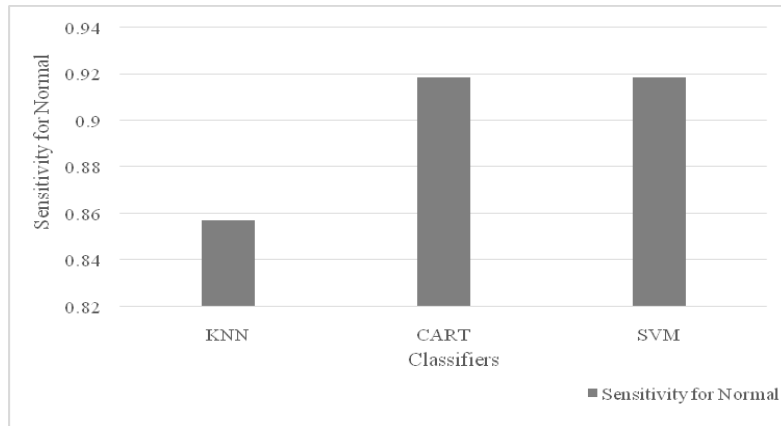


Fig. 2: Sensitivity for Normal

From the table 1 and figure 2, it can be observed that the sensitivity of SVM and CART performs in equal way. Both performs better by 6.91% than KNN.

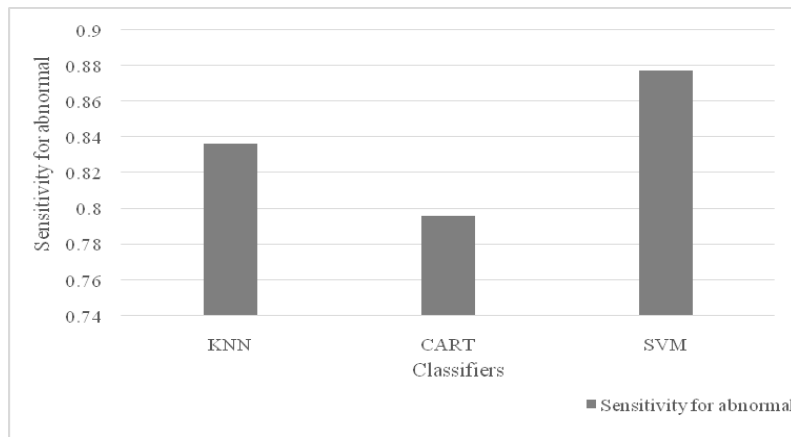


Fig. 3: Sensitivity for abnormal

From the table 1 and figure 3, it can be observed that the sensitivity for abnormal image of SVM performs better by 4.77% than KNN and by 9.8% than CART.

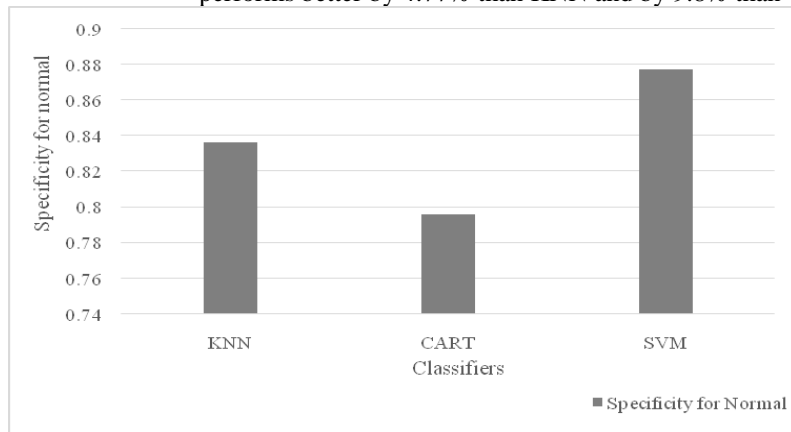


Fig. 4: Specificity for Normal

From the table 1 and figure 3, it can be observed that the specificity for normal image of SVM performs better by 4.77% than KNN and by 9.8% than CART.

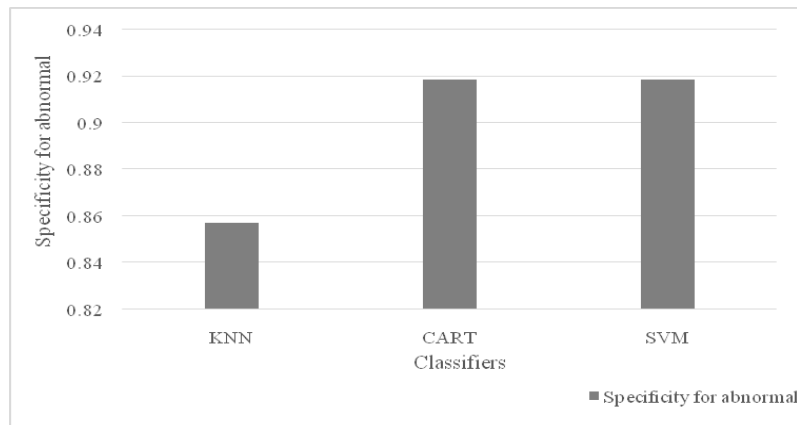


Fig. 5: Specificity for abnormal

From the table 1 and figure 3, it can be observed that the specificity for abnormal image of SVM and CART performs in equal way. Both performs better by 6.91% than KNN.

DISCUSSION

AD is the most common cause of age-related dementia. Because of the rising proportion of older people in western societies, the presence of dementia is anticipated to double in the coming thirty years. MRI images collected from OASIS are used to identify dementia. Feature extraction through usage of Gabor filter with 0, 30, 60, 90 orientations as well as GLCM. For experiments, classifiers such as KNN, CART and SVM for obtaining performance measures such as Classification accuracy, sensitivity and specificity for normal and abnormal images. Results show that the classification accuracy for normal image of SVM performs better by 5.81% than KNN and by 4.66% than CART.

The lab coat can get contaminated by microorganisms due to improper handling practices. They get easily contaminated because patients continuously shed infectious microorganisms in the hospital environment, and the health care providers are in constant contact with these patients. *Staphylococci* are the pathogens belonging to the group of Enterobacter bacteria, which cause several infections to humans. They are facultative anaerobic gram-negative cocci mainly found in the skin and mucosa and are of three types *Staphylococcus aureus*, *Staphylococcus epidermidis* and *Staphylococcus haemolyticus* [7]. Health care professionals are most susceptible to colonization, and the main form of transmission is through temporarily colonized hands. Importantly, treatment of infections caused by *S. aureus* has become difficult because of their higher resistance to various drugs [8].

S aureus is part of the normal human microbial flora and it is found in the nasal passages, throat, gastrointestinal tract and skin. It is considered as one of the most important pathogenic bacteria, causing series of infections [9, 10] leading to the formation of abscesses. It causes infections such as furuncles, folliculitis, scalded skin syndrome, meningitis, and pneumonia. Coagulase-negative *Staphylococci* (CONS) which is a skin commensal has recently got attention as a potential pathogen, specifically for nosocomial infections [11-13]. CONS are a major cause of nosocomial infection and septicemia, especially in cases of immune-compromised patients [12].

This study evaluated the type of microbial flora present on the lab coats of the clinicians working in the Dept of Endodontics and their antibiotic sensitivity. Three sites were chosen i.e chest, pocket, cuff for determining the type of microbial flora. Microbial contamination was thought to be highest as these sites most commonly comes in contact with the patients [14,15]. This study showed that the numbers of gram positive cocci was the same as that of other studies and maximum of them were potentially pathogenic [15,16]. This is consistent with other studies that showed contamination of lab coats ranging from 23% to 95% [17]. They possess a risk of cross contamination if the host is immune compromised. *Micrococci* may act as an opportunistic pathogen in patients with compromised immune systems and they most commonly cause blood stream infection. Gram negative *Bacilli* were also isolated, but these were significantly lesser in number and they may be potentially infectious, as was reported by Zachary and Grabsch. They have shown that bacterial survival rate is of longer period of time on

hospital fabrics [18,19]. Chacko et al have shown that on lab coat fabrics made up of either cotton polyester or polyester material, bacteria can survive between 10-98 days [20]. Hence the lab coats should be washed daily or at least once in 3 days [20]. Of the two predetermined sites selected for examination on the lab coat, the mouth of the dominant pocket was more contaminated than the chest and cuffs of the sleeve. This is similar to the study of Nelly and contrary to that of Uneke and Ijeocoma which indicated that cuff has more bacterial load than the pocket [21, 22]. Pocket is the highly contaminated area because it frequently comes in contact with the hands of the health care professionals harboring bacterial contaminants.

Antibiotic sensitivity testing showed resistant species of microorganisms on the lab coats against Amoxicillin, Penicillin G, Gentamycin, and Cotrimoxazole. Antibiotic sensitivity results showed the organisms which were sensitive to most common antibiotics on 1st day got resistant on 3rd day [Figure-4]. Of the *S. aureus* isolated, 10% were MRSA. The MRSA has emerged as significant bacteria in hospital acquired infections. According to the Centre for Disease Control and Prevention, more than 60% of all hospital infections are caused by MRSA in United States. Because of frequent dermal contact, lab coats can harbor these resistant bacteria. In orders to prevent cross infection, guidelines should be followed for handling and washing procedures of lab coats.

This is a uni-centric study, done to create awareness among our dental colleagues. This study reflects center-specific microbial contamination in a dental operator. To reach to a more generalized conclusion, the study requires a multi-centric evaluation with a larger sample size.

CONCLUSION

The present study highlights the fact that the lab coats may act as a vector for transmission of cross infection. In order to prevent transmission of cross infection, a strict protocol should be set in order to prevent cross contamination between doctor and patient. Efforts should be made to limit the use of coats outside the working area and they should be laundered every day. Wearing of plastic aprons or altering lab coat material to plastic-laminated clothing or closely woven waterproof cotton can reduce the bacterial transfer rate and cross-contamination

CONFLICT OF INTEREST

The authors declare no conflict of interests.

ACKNOWLEDGEMENT

None

FINANCIAL DISCLOSURE

None.

REFERENCES

- [1] Dubois B, Feldman HH, Jacova C, Dekosky ST, Barberger-Gateau P, Cummings J, Delocourte A, Galasko D, Gauthier S, Jicha G, et al: Research criteria for the diagnosis of Alzheimer's disease: revising the NINCDS-ADRDA criteria. *Lancet Neurology* 2007, 6:734-746.
- [2] Pohar M, Blas M, Turk S: Comparison of Logistic Regression and Linear Discriminant Analysis: A Simulation Study. *Metodološki zvezki* 2004, 1:143-161.
- [3] Peter CA: A comparison of regression trees, logistic regression, generalized additive models, and multivariate adaptive regression splines for predicting AMI mortality. *Statistics in Medicine* 2007, 26:2937-2957.
- [4] Zollner FG, Emblem KE, Schad LR: Support vector machines in DSC-based glioma imaging: Suggestions for optimal characterization. *Magn Reson Med* 2010.
- [5] Chen, Y., & Pham, T. D. (2013). Development of a brain MRI-based hidden Markov model for dementia recognition. *Biomedical engineering online*, 12(Suppl 1), S2..
- [6] Aruna, S. K., & Chitra, S. (2016). Machine Learning Approach for Identifying Dementia from MRI Images. *World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering*, 9(3), 881-888.
- [7] Yasue, M., Sugiura, S., Uchida, Y., Otake, H., Teranishi, M., Sakurai, T., ... & Nakashima, T. (2015). Prevalence of Sinusitis Detected by Magnetic Resonance Imaging in Subjects with Dementia or Alzheimer's Disease. *Current Alzheimer Research*, 12(10), 1006-1011.
- [8] Zheng, C., Xia, Y., Pan, Y., & Chen, J. Automated identification of dementia using medical imaging: a survey from a pattern classification perspective. *Brain Informatics*, 1-11.
- [9] <http://www.bio-edicine.org/Biology>
- [10] Li, C.T.; Wei, C.H; Wei, C.H.; Li, C. (2005); A Content-based Approach to Medical Image Database Retrieval, Database Modeling for Industrial Data Management: Emerging Technologies and Applications 10(6): 681-685.

- [11] Wei, C.H.; Chang-Tsun, L.; Roland, W. (2009); A Content-based Approach to Medical Image Database Retrieval, Database Technologies: Concepts, Methodologies, Tools, and Applications: 1062-1083.
- [12] Gulgezen, G., Cataltepe, Z., & Yu, L. (2009). Stable and Accurate Feature Selection. Springer
- [13] R. C. Gonzalez, R. E. Woods, Digital Image Processing, 3rd Ed. Prentice Hall, 2008.
- [14] Zhuo, Z. (2012). Automatic Glaucoma Diagnosis with mRMR-based Feature Selection. Journal of Biometrics & Biostatistics.
- [15] Koroukian, S. M., Schiltz, N., Warner, D. F., Sun, J., Bakaki, P. M., Smyth, K. A., ... & Given, C. W. (2016). Combinations of Chronic Conditions, Functional Limitations, and Geriatric Syndromes that Predict Health Outcomes. *Journal of general internal medicine*, 1-8.
- [16] Klöppel, S., Stonnington, C. M., Chu, C., Draganski, B., Scahill, R. I., Rohrer, J. D., ... & Frackowiak, R. S. (2008). Automatic classification of MR scans in Alzheimer's disease. *Brain*, 131(3), 681-689.
- [17] Data mining methods in the prediction of Dementia: A real-data comparison of the accuracy, sensitivity and specificity of linear discriminant analysis, logistic regression, neural networks, support vector machines, classification trees and random forests
- [18] Ivanciuc O: Applications of Support Vector Machines in Chemistry. In Reviews in Computational Chemistry. Volume 23. Edited by: Lipkowitz KB, Cundari TR. Weinheim: John Wiley 2007:291-400.

**DISCLAIMER: This published version is uncorrected proof, plagiarisms and references are not checked by IIOABJ, the article is published as provided by author and checked/reviewed by guest editor.