

Preliminary Experiment Results of Left Ventricular Remodelling Prediction Using Machine Learning Algorithms

D.N.F. Awang Iskandar¹, P.C. Lim¹, A. Said², N.H. Mohd Amin³, A. Khan¹ and H. Ujir¹

¹Faculty of Computer Science and Information Technology,

²Faculty of Medicine and Health Sciences,

Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia.

³Cardiology Department, Sarawak Heart Centre, Jalan Expressway, 94300 Kota Samarahan, Sarawak, Malaysia.
dnfaiz@unimas.my

Abstract—Left ventricular remodelling involves changes in the ventricular size, shape and function where abnormalities eventually lead to heart failure. Early prediction of left ventricular remodelling can help in enhancing clinical decision making in cardiac health management and reducing cardiovascular mortality. Although cardiac magnetic resonance imaging is increasingly being used in clinical assessment of cardiovascular diseases, there is scarce study on predicting the presence of left ventricular remodelling given the derived data from cardiac magnetic resonance images. Four parameters namely left ventricular end diastolic volume, left ventricular end systolic volume, ejection fraction and occurrence/absence of oedema are used for prediction. A preliminary experiment is conducted where multi-layer perceptron and support vector machine are trained with the parameters obtained from cardiac magnetic resonance images in predicting between patients with left ventricular remodelling or normal. The preliminary experimental results indicated that support vector machine model performed better than multi-layer perception.

Index Terms—Machine Learning; Left Ventricular Remodeling; Magnetic Resonance Imaging; Classification.

I. INTRODUCTION

Ischaemic heart disease is the leading cause of death in Malaysian hospital [1]. Unfortunately, in Malaysia, and probably in other developing countries, easy accessibility to specialized coronary care facilities, and interventional coronary laboratories may not be immediately available. Thus, it is imperative that we risk-stratify patients to maximize the use of limited resources available.

Independent prognostic factor affecting the outcome after acute myocardial infarction (AMI) includes extent of the AMI and degree of recovery of the infarcted territory [2, 3]. Left ventricular remodelling (LVR) after AMI depends on clearing of necrotic myocardium, inflammatory cells, residual oedema and haemorrhage, and replacement by scar tissue. This inflammatory healing process is independent of the initial infarct size [4]. Cardiac MRI can be used to observe this infarct healing process and aid in predicting the likely outcome of patients [5, 6]. Existing LVR prediction approaches uses a combination of semi-automated image analysis, statistical analysis or mathematical modelling with shape features or gene expression.

However, beside interventional coronary laboratories may not be immediately available, it is time consuming to perform image quantification and interpretation for the cardiac MRI

images. In addition, there are limited research that focuses on learning patterns from cardiac MRI images and clinical data for LVR prediction. Hence, a machine learning approach is highly desirable in predicting LVR and hopefully mitigates overt heart failure in AMI survivors.

This paper aims to conduct a preliminary experiment in evaluating machine learning algorithms on a small dataset to provide diagnosis of an individual with LVR from a healthy individual. We use multi-layer perceptron (MLP) and support vector machine (SVM) to perform training and learning from the dataset. The experiment results showed that SVM performed better in predicting the pattern of LVR.

II. BACKGROUND STUDIES

Early prediction of LVR after AMI is highly desired to minimize cardiovascular mortality. Advancement in computer technologies has been adapted to assist cardiac experts in data analysis and prediction of LVR. A novel shape analysis using *in vivo* multi-detector computed tomographic (MDCT) images and principal component analysis to distinguish the differences in hearts of patients with ischemic cardiomyopathy from global non-ischemic cardiomyopathy is developed [7]. As MDCT has low temporal resolution, it will overestimate the measurements in LV volume. A mathematical model to predict LVR by thick-wall theory and stretch-induced tissue growth theory is developed [8]. Temporal profiles of LV mass, collagen content change and pressure across LV from aging mice are used as input to the mathematical model which successfully captured the major parameter of LVR. A system-based approach to identify several miRNAs potentially involved in LVR after AMI in [9]. Circulating miRNA expression profiles in patients are obtained using microarrays analysis which requires specific laboratory equipment and tests. Prediction of LVR is assessed by logistic regression models for patient classification.

Research employing machine learning algorithms to learn from data is gaining popularity for the past years. Learning algorithms are broadly categorized into supervised learning and unsupervised learning [10]. Supervised learning algorithms are commonly used in classification task while unsupervised learning algorithms are mainly used for finding some patterns within a set of data. Various reviews on supervised [11, 12] or unsupervised [13, 14] machine learning algorithms are widely available.

Among others, artificial neural network (ANN) is a computational approach that is inspired by the brain processes information which composed of a large number of neurons. ANNs have remarkable ability in deriving meaning from imprecise data or to extract patterns that are too complex to be noticed by humans or other computer techniques, which is highly desired in medical diagnosis [15]. Reviews on ANN in medical diagnosis can be found in various literatures [16, 17, 18].

The MLP is the most commonly used for medical diagnosis. Structure of an MLP consists of a single input layer, one or multiple hidden layer and an output layer. The number of hidden layer and hidden neuron in each hidden layer depends on the complexity of the problem addressed. The optimal structure and values must be determined experimental and evaluated based on domain knowledge. In [19], a MLP-based decision support system is developed to assists in the clinical decision of five heart diseases. The system is evaluated with cross-validation, holdout and bootstrapping techniques where the system achieved >90% accuracy in recognizing all five heart diseases. In comparing the ability to predict myocardial infarction (MI), MLP trained with genetic algorithm outperformed Radial Basis Function (RBF) in predicting MI in patients on the basis of electrocardiogram (ECG) findings and clinical data [20], while SVM is superior to ANN in diagnosing patients with acute coronary syndrome [21, 22]. Variant of ANNs are actively used in building model by learning from small but good quality examples which fits the issue address in this paper.

III. DATA COLLECTION

Dataset used for experiments in this paper are subsampled of two databases – Sarawak Heart Centre (SHC) [23] and Sunnybrook cardiac data (SCD) [24]. The SCD is a public access database that consisted of cine-MRI images of 45 patients. SCD database is initially used in an automatic myocardium segmentation challenge in 2009 while the SHC database is from ongoing studies [23]. The SHC database consist of cardiac MRI images collected after myocardial infarction in five sessions (admission date, 2 weeks after, 1 month, 3 months and 6 months after) on a Philips Achieva 1.5-T system. Next, ventricular volume analysis was performed offline (Phillips Extended MR Workspace release 2.6.3.5) by one experienced observer who was blinded to the clinical data of the patient before the accumulated data are stored as the Sarawak Big Heart Data. Details of the cardiac MRI acquisition and image analysis for the SHC database followed the standard procedure as in [25].

IV. EXPERIMENTAL METHOD

This paper aims to achieve the goal of building a predictive model to classify a healthy individual from a patient with LVR. Figure 1 outlines the three phases involved to accomplish for LVR prediction model using the machine learning approach.

A. Dataset

Dataset for experiments is created by subsampling from SHC [23] and SCD [24]. An automatic contour segmentation system [26] is utilized for the derivation of volumetric parameters such as LVEDV (ml), LVESV (ml) and LVEF

(%) on CMRI of 10 patients from [23] and 9 patients from the normal group in [24]. The fourth parameter represents presence or absence of oedema which is encoded into numerical format as ANN only accepts numerical data as input. Dataset for experiment consists of two classes where individuals with LVEF>55% are considered to be normal based on [27]. In contrast, individuals with lower LVEF are at high risk of LVR.

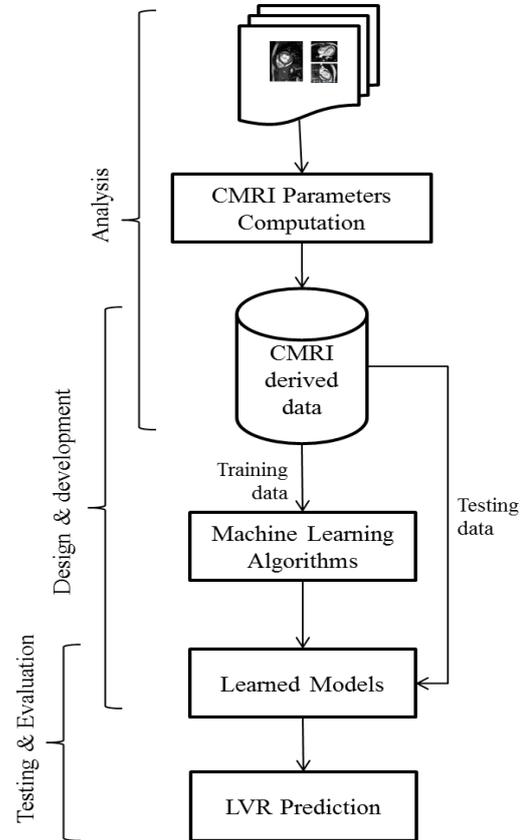


Figure 1: Outline of LVR prediction using machine learning approach

B. Experiment Design

As LVR prediction is a classification task, supervised learning algorithms are selected to construct predictive model from the dataset. The LVR prediction was performed by MLP and SVM using MATLAB [28].

The MLP used in this paper is a standard feed-forward network containing a single input-, hidden- and output-layer as illustrated in Figure 2. Each neuron in a layer is connected with each neuron in the next layer through a weight. The i -th neuron in a hidden layer processes the input data x_j by computing the weighted sum of inputs and including the bias term,

$$z_i^{(l)} = \sum W_{ij}^{(l)} x_j + b_i^{(l)} \quad (1)$$

where $W_{ij}^{(l)}$ denote the weight associated with the connection between j -th input neuron in layer l and i -th hidden neuron in layer $l+1$, $b_i^{(l)}$ is the bias associated with i -th neuron in layer $l+1$. Equation (2) defines the computation of output vector $z_i^{(l)}$ in layer l using the output $z_i^{(l-1)}$ of the previous layer,

$$Z_i^{(l)} = f(W_{ij}^{(l)}Z_i^{(l-1)} + b_i^{(l)}) \quad (2)$$

where the activation function f commonly used is sigmoid or tangent. Activation functions in the hidden-layer are computed before the top layer outputs are used for making prediction. The optimal number of hidden neurons that would result in a predictive model with maximal sensitivity and specificity is obtained through experiments. The optimal number of hidden neurons is determined using series of experiments with different number of hidden neurons ($n_h=2, \dots, 20$). For each n_h , 100 models were constructed and the results is the average of the 100 MLP models.

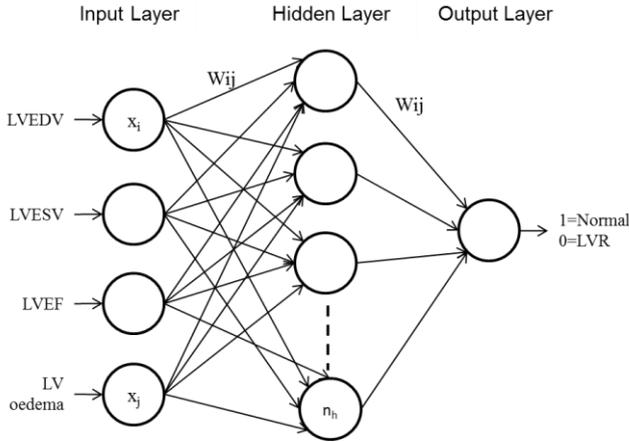


Figure 2: MLP architecture

A SVM is a learning model used for classification by finding a hyperplane that can separate data into two classes with following equation,

$$c = \sum_i \alpha_i k(s_i, x) + b \quad (3)$$

where s_i denotes support vectors, α_i denotes weights, b denotes bias and k denotes the kernel function. If $c \geq 0$, then x is classified as member of first group, otherwise it is classified as member of the second group. There are many hyperplanes that can classify data (circle) as represented by solid lines labelled as h_1 , h_2 and h_3 in Figure 3. The best hyperplane is h_2 which has the largest margin between the two classes. The support vectors are the data points closest to the hyperplane represented by red circles in Figure 3. This paper aim to conduct two-class learning, hence, SVM with linear kernel is used to find the best hyperplane. The holdout method is used for SVM evaluation where dataset is randomly divided into disjointed training and testing sets of equal sizes. Training set is used to build SVM before evaluated with the testing set. The holdout evaluation is iterated 100 times and the results are average of the iterations.

C. Performance evaluation

Models performances are evaluated using standard measurements of sensitivity, specificity and accuracy using confusion matrix in Table 1 [29]. Data in test set is used as input to the model learned for class prediction before comparing the actual class label (normal, patient with LVR) with predicted class label (predicted-normal, predicted-LVR).

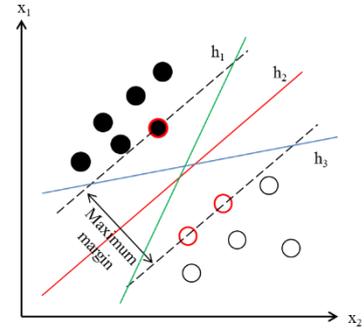


Figure 3: SVM

 Table 1
Confusion matrix

	Predicted-LVR	Predicted-Normal
Patient with LVR	True Negative (TN)	False Positive (FP)
Normal	False Negative (FN)	True Positive (TP)

Sensitivity measures the proportion of a healthy individual who is correctly identified as normal (TP) to total number of normal (TP+FN). Specificity measures the proportion of patients correctly identified as patient with LVR (TN) to total number of patient with LVR (TN+FP). Sensitivity and specificity is respectively defined as:

$$S_1 = \frac{TP}{TP + FN} \quad (4)$$

$$S_2 = \frac{TN}{TN + FP} \quad (5)$$

Accuracy is defined as the total number of correct predictions in patient with and without LVR (TP+TN) to the total number of patients (TP+FP+FN+TN). Higher sensitivity and specificity is desired in the medical field as it indicates better classifier.

V. RESULTS

All experiments were performed on a 1.6GHz Core i7 CPU processor with 8GB of RAM, Windows 7 operating system with MATLAB installed.

Misdiagnosing the occurrence of LVR may lead to death as appropriate treatment and management is not provided timely. Performance of MLP and SVM model in predicting LVR in patients post AMI is reported and discussed. The performance measurements reported are the average of 100 MLP models and 100 iterations of SVM.

Table 2 reported the average performance of MLP models constructed using various numbers of hidden neurons. For each number of hidden neuron, the model is repeatedly trained using randomly split training, validation and test data. The MLP model with ten hidden neurons yields the highest accuracy of 75.00% with 71.00% sensitivity and 71.02% specificity for the training phase. In the testing phase, MLP model with five hidden neurons obtained the highest accuracy of 78.33% with 72.17% specificity and a surprisingly low 45.00% sensitivity.

Yet, all the MLP models using various numbers of hidden neurons reported performance of less than 80% in both training and testing phases. The poor performance may due to the limited information used for model construction. One of the issues is the amount of data available and choosing an optimal number of hidden neurons. MLP modelling required

dataset to be divided into training, validation and testing set with 70/15/15 percentage split ratio, hence, the limited data in training set causes models built to generalize poorly to the testing data (unknown and new to the model constructed). The number of hidden neurons is determined using series of experiments and the poor testing results suggested overfitting. This phenomenon is due to choosing too many hidden neurons. Other issue includes the determination of suitable weights and bias values to avoid being trapped in a local minimum. As each time an MLP model is constructed and trained, initial weights and bias values are randomly assigned which led to different solution. Therefore, 100 models are constructed and trained on the same problem.

Table 3 reported the average performance of SVM using different parameter combination. Any parameter combination with oedema yields 100% accuracy, sensitivity and specificity which may due to the overclouding by the binary encoding. SVM model with LVEDV, LVESV and LVEF achieved the best performance with 94.40% accuracy, 97.50% sensitivity and 74.20% specificity among other parameter combination in the training phase. For the testing phase, the combination of LVEDV and LVEF obtained best performance with 88.22% accuracy and 81.00% specificity

and sensitivity of 97.25%.

Figure 4 and 5 compared the average best performance of SVM and MLP with ten and five hidden neurons in the training and testing phase respectively. It is obvious that SVM model achieved better performance than MLP model in the training phase where accuracy and sensitivity obtained is approximately more than 90% except a lower specificity. Similarly, SVM achieved better performance than MLP in the testing phase. The higher performance measurements for SVM may due to the balance data (approximately equal number of individuals from each class) were used for training, hence, less prone to overfitting as occurred in MLP.

For SVM, dataset was divided into two sets using the holdout technique. The advantage of using holdout technique for classifier evaluation is the simplicity and less computation time needed. The weakness of holdout technique is the possibility of high variance as the evaluation depends heavily on how the data is divided into training and testing set. In this paper, this weakness is addressed by repeatedly train SVM with 100 iterations using the holdout method. The accuracies reported are the average of the repeated accuracies.

Table 2
Average sensitivity, specificity and accuracy values for MLP using various numbers of hidden neurons

Phase	Hidden neuron											
	$n_h = 5$			$n_h = 10$			$n_h = 15$			$n_h = 20$		
	S_1 (%)	S_2 (%)	Accuracy (%)	S_1 (%)	S_2 (%)	Accuracy (%)	S_1 (%)	S_2 (%)	Accuracy (%)	S_1 (%)	S_2 (%)	Accuracy (%)
Training	79.00	68.04	73.08	71.00	71.02	75.00	73.00	71.64	74.77	79.00	70.10	74.00
Testing	45.00	72.17	78.33	49.00	68.50	74.33	56.00	69.50	75.67	52.00	68.33	76.33

Table 3
Average sensitivity, specificity and accuracy values for SVM using various parameters combination

Phase	Combination											
	LVEDV, LVESV			LVEDV, LVEF			LVESV, LVEF			LVEDV, LVESV, LVEF		
	S_1 (%)	S_2 (%)	Accuracy (%)	S_1 (%)	S_2 (%)	Accuracy (%)	S_1 (%)	S_2 (%)	Accuracy (%)	S_1 (%)	S_2 (%)	Accuracy (%)
Training	92.80	85.40	89.10	98.80	87.80	93.30	98.40	79.80	89.10	99.60	89.20	94.40
Testing	87.00	75.00	80.33	97.25	81.00	88.22	96.00	67.40	80.11	97.50	74.20	84.56

Table 4
Performance comparison in literature

Work	Brief description	S_1	S_2	Accuracy
[19]	352 patients (clinical data),			
	• MLP – cross validation	-	-	91.5%
	• MLP – holdout	-	-	92.0%
	• MLP – bootstrapping	-	-	91.1%
[20]	935 patients (ECG or clinical data),			
	• ECG data, RBF – cross validation	88.65%	84.26%	87.45%
	• ECG data, MLP – cross validation	75.15%	87.27%	81.35%
	• Clinical data, RBF – cross validation	94.33%	98.58%	96.45%
	• Clinical data, MLP – cross validation	81.75%	91.15%	86.46%
[21]	351 patients (clinical, laboratory & genetic data),			
	• ANN – cross validation	78.00%	70.00%	70.00%
	• SVM – cross validation	91.00%	99.00%	98.00%
[22]	228 patients (clinical, laboratory & ECG data),			
	• SVM – cross validation	98.22%	100.00%	99.13%
	• ANN – cross validation	-	-	90.10%
	• Naïve Bayes – cross validation	-	-	88.75%
	• Logistic Regression – cross validation	-	-	91.26%
Our	19 patients (imaging data),			
	• MLP – holdout	51.05%	68.27%	75.00%
	• SVM – holdout	95.55%	79.52%	86.64%

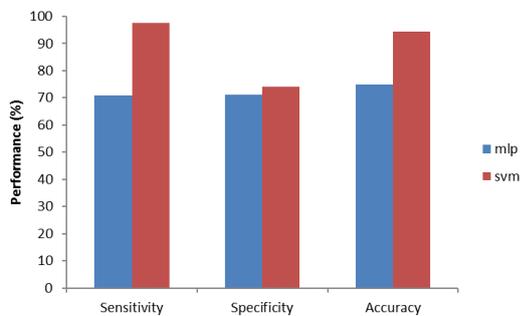


Figure 4: Comparison of best performance in training phase for MLP (10 hidden neurons) and SVM (LVEDV, LVESV and LVEF)

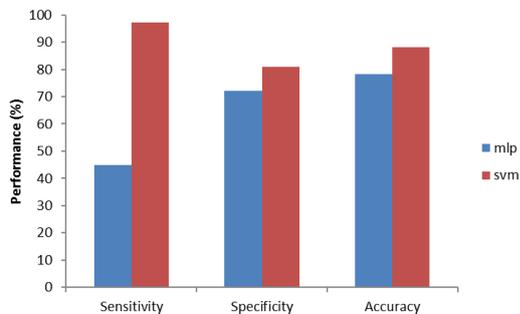


Figure 5: Comparison of best performance in testing phase for MLP (5 hidden neurons) and SVM (LVEDV and LVEF)

Review of the algorithms in other studies is shown in Table 4. Note should be taken that no benchmark for performance comparison is done due to the used of different datasets in the literature reported. A decision support systems to diagnose five types of heart diseases with MLP [19] found that approximately the same average accuracy (91.1% to 92%) is achieved regardless of the assessment methods used. It is found in study [20] that MLP (96.45%, 86.46%) achieved higher accuracy compared to RBF (87.45%, 81.35%) in predicting AMI using either ECG or clinical data. Another study [21] compared model of ANN and SVM in the ability to identify low or high risk of death in patients with acute coronary syndrome. Again, SVM (98.00% accuracy, 91.00% sensitivity and 99.00% specificity) achieved better performance than ANN model (70.00% accuracy, 78.00% sensitivity and 70.00% specificity) with three top-ranking variables. In [22], four machine learning methods (SVM, ANN, Naïve Bayes and Logistic Regression) are used to make decision of hospitalisation or discharge of patients with chest pain. It is reported that SVM achieved highest accuracy of 99.13% among the four methods. In our preliminary experiments, results confirmed with literature that SVM is superior than other MLP classifiers where SVM achieved higher performance in predicting patient who are normal at 86.64% accuracy than 75.00% accuracy by MLP. However, the performance is still lower than those reported in [21] and [22] but acceptable as less variables are used. A lower MLP performance is achieved as compare to [19] and [20] but marginally different with result reported in [22].

The limitations in this paper were that only 19 patients are used. This limited number of patients causes poor performance in MLP where overfitting occurred. Experiments with a larger sample sizes and inclusion of more parameters are needed and will be reported in the near future as data collection is still on going.

No conclusive decision was made on model selection for the prediction of LVR in a patient or normal individual. Although the experimental results suggested that SVM performed better than MLP, it is believed that there are more parameters that influence the prediction output than the four used in this paper.

VI. CONCLUSION

The ability to predict early LVR would be a breakthrough in the field of cardiology, but to date there is no reliable method for this. This paper compared the ability of MLP and SVM to correctly predict LVR in two groups of patients on the basis of four cardiac MRI parameters. SVM performed better than MLP in terms of accuracy, sensitivity and specificity. Although the performance of MLP is comparatively lower, the reported experiments results provide proof that ANN may be useful in medical diagnosis where appropriate parameters are chosen and when medical decision is highly subjective. Future experiments where SVM and MLP will be train with more cardiac MRI parameters and inclusion of clinical data obtains from a larger pool of patients will be reported elsewhere.

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