PerDMCS: Weighted Fusion of PPG Signal Features for Robust and Efficient Diabetes Mellitus Classification

V. Ramu Reddy[1], Anirban Dutta Choudhury[2], Srinivasan Jayaraman[1], Naveen Kumar Thokala[1], Parijat Deshpande[3] and Venkatesh Kaliaperumal[4]

[1]*TCS Research & Innovation Lab, Bangalore, India*

[2]*TCS Research & Innovation Lab, Kolkata, India*

[3]*TRDDC, Pune, India*

[4]*Institute of Ayurveda and Integrative Medicine, School of Health Sciences, Transdisciplinary University, Bangalore, India*

Keywords: Pervasive Healthcare, Type 2, Diabetes Mellitus, Classification, Heart Rate Variability, Fusion, Photoplethysmogram, Pulse Oximeter, Morphological.

Abstract: Non-invasive detection of Diabetes Mellitus (DM) has attracted a lot of interest in the recent years in pervasive health care. In this paper, we explore features related to heart rate variability (HRV) and signal pattern of the waveform from photoplethysmogram (PPG) signal for classifying DM (Type 2). HRV features includes time-domain (F_1), frequency domain (F_2), non-linear features (F_3) where as waveform features (F_4) are one set of features such as height, width, slope and durations of pulse. The study was carried out on 50 healthy subjects and 50 DM patients. Support Vector Machines (SVM) are used to capture the discriminative information between the above mentioned healthy and DM categories, from the proposed features. The SVM models are developed separately using different sets of features F_1, F_2, F_3,and F_4, respectively. The classification performance of the developed SVM models using time-domain, frequency domain, non-linear and waveform features is observed to be 73%, 78%, 80% and 77%. The performance of the system using combination of all features is 82%. In this work, the performance of the DM classification system by combining the above mentioned feature sets with different percentage of discriminate features from each set is also examined. Furthermore weight based fusion is performed using confidence values obtained from each model to find the optimal set of features from each set with optimal weights for each set. The best performance accuracy of 89% is obtained by scores fusion where combinations of mixture of 90% features from the feature sets F_1 and F_2 and mixture of 100% features from the feature sets F_3 and F_4, with fusion optimal weights of 0.3 and 0.7, respectively.

1 INTRODUCTION

Diabetes is a malfunction of glucose-insulin regulatory system that leads to onset of various complications. It has been recognized as fourth leading cause of death in developed countries (Tabish, 2007). From the recorded data in health centres worldwide it is predicted that it is reaching epidemic proportions in many developing and newly industrialized nations. In terms of diabetic population, the top three countries in the world are China, India and USA (Collaboration et al., 2016). In India it has shot up from 11.9 million in 1980 to 64.5 million in 2014. International Diabetes Federation (IDF), has raised a serious alarm for India by saying that nearly 52% of Indians are not aware that they are suffering from high blood sugar and it is expected to cross 100 million mark by 2030[1]. Risk of cardiovascular disease (CVD) is two or four times greater for diabetic individuals than normal ones and there is a trend in increased risk of cardiac mortality[2] However, till date there is limited medical equipment and awareness of the severity of this disease largely aggravated due to prevalence of bad diet, no physical exercise, abnormal body weight, and use of tobacco. Furthermore, the symptoms of cardiac patients and diabetes patients are similar due

[1]http://ccebdm.org/news.php

[2]www.world-heart-feaderation.org/cardiovascular-disease-risk-factors/diabetes/

Reddy V., Dutta Choudhury A., Jayaraman S., Kumar Thokala N., Deshpande P. and Kaliaperumal V.
PerDMCS: Weighted Fusion of PPG Signal Features for Robust and Efficient Diabetes Mellitus Classification.
DOI: 10.5220/0006297205530560

to change in the arterial stiffness and hence likely to be mis-classified. The symptoms of this disease are high blood sugar include frequent urination, increased thirst, and increased hunger. If left untreated it results in long-term complications include heart disease, stroke, chronic kidney failure, foot ulcers, and damage to the eyes.

These problems are addressed by few existing solutions; such as C-peptide test, fasting plasma glucose test, GAD antibodies test, Hba1c test, oral glucose tolerance test, type-2 diabetes indication test (Association et al., 2015). It should be noted that most of the above-mentioned technique are either invasive or minimal invasive (finger prick) in nature. This study aims to identify the individual's diabetic status by assessing the vascular pulse function and other vital features by using the non-invasive PPG signal. In addendum, continuous monitoring of diabetes patients can aid in assisting the short and long-term complication risks as well. Hence, there is an inherent demand to explore the feasibility for the continuous, non-invasive monitoring and estimation of the type 2 diabetes. In (Schroeder et al., 2005), (Seyd et al., 2012) researchers had explored diabetes detection using HRV features from the time domain, in (Elgendi, 2012) Mohamed has explored PPG features and its applications where as Rohan *et al* has identified HRV and pulse waveform features for identifying coronary artery disease (Banerjee et al., 2016).

Non-invasive, quick, easy, low cost and on time recognizing diabetes with simple method and portable technology for the primary care and community-based clinical settings is the main goal of researchers in this area. The pulse plethysmogram technology has been used in a wide range of commercially available medical devices for measuring oxygen saturation, blood pressure and cardiac output (Allen, 2007). Due to change in glucose level, the amount of blood volume in the finger changes, this variation can be measured by PPG. When a fixed source of infrared radiation is used, the variation of blood volume act as a phototransistor and the receive signal is changed. This is why we use the PPG signal for identifying the diabetic subjects. In this work a low-cost FDA approved pulse oximeter is used to collect vital physiological signal such as PPG signal from finger. Heart rate variability (HRV) features from the time domain along with some useful features related to shape of the pulse (morphological information) are extracted from PPG to discriminate healthy and diabetic subjects. In addition to the above features we have also explored other HRV features extracted from the frequency domain, non-linear and poincare features. Our data-driven approach enables visualization of PPG signals and captures specific features such as heart rate variability (HRV) and features related to shape of the pulse from PPG signal related to change in blood flow which in turn caused due to change arterial stiffness due to diabetes. We have developed pervasive diabetes mellitus classification system (PerDMCS) and has achieved an accuracy of 82%, sesitivity 84% and specificity 90% using above mentioned features. Further weight based fusion technique is proposed for more robust detection of diabetes. Field data shows this method works properly and achieved an improved accuracy of 89% with sensitivity and specificity of 90% and 88%, respectively.

2 DIABETES MELLITUS DATASET

In this study, we have collected data from 50 confirmed diabetic patients and 50 healthy subjects. Diabetic subjects were aged between 34 ± 10 years where as healthy subjects were aged between 41 ± 13. The subjects are selected from IAIMS Research Center located in Bangalore, India. Experimental protocol has been approved by the hospital ethical committee. PPG data were collected from right hand index finger of each subject for 5 minutes using a USB based commercial pulse oximeter (Contec CMS 50D+ [3]) at 60 Hz.

3 PRE-PROCESSING

The collected PPG data is fed as an input to the pre-processing block to obtain accurate RR intervals as an output. This is achieved by following the sequence of steps like baseline removal, peak detection and removal of outliers obtained due to motion artifacts. The signals obtained across each stage are also depicted in Fig. 1, where Fig. 1(a) represents raw PPG signal obtained during data collection and Fig. 1(b) is the corresponding PPG signal obtained after baseline drift removal followed by peak detection. The region where erroneous peak is obtained due to motion artifact is marked with an elliptical region in Fig. 1(b). Subsequently, peaks are calculated to obtain the RR intervals and the outliers of RR intervals are then removed. The steps involved in pre-processing stage are briefly discussed as follows:

- *Baseline Removal:* The baseline removal on the PPG signal is carried out using beads technique (Ning et al., 2014).

[3]http://www.contecmed.com/

- *Peak Detection:* The peak detection is carried out on the baseline removal of PPG signal using peak detection algorithm.
- *Outlier Removal:* After peak detection, RR intervals are computed from peak to peak intervals. The outlier RR intervals resulted due to motion artifacts are removed using the percentage filter. As mentioned in [4] if the percentage change of succeeding RR interval from the preceding RR interval is greater than 20% can be treated as an outlier.

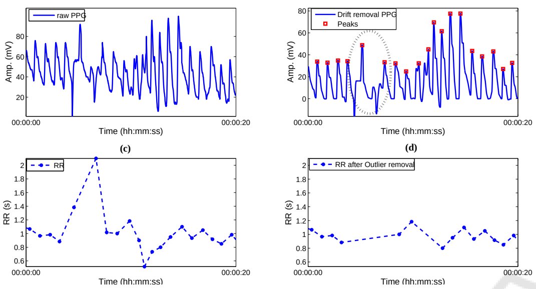


Figure 1: (a) Raw PPG signal, (b) Baseline drift PPG signal (c) RR intervals and (d) RR intervals after Outlier removal.

After preprocessing different features were extracted as shown in Table 1.

4 NUMERICAL RESULTS

In this work, Support Vector Machines (SVM) are explored to discriminate the diabetic and healthy subjects. SVM classification is an example of supervised learning. SVMs are useful due to their wide applicability for classification tasks in many signal processing applications such as emotion recognition (Koolagudi et al., 2010), crowd noise and activity classifications (Reddy et al., 2013) (Reddy and Chattopadhyay, 2014), and physiological signal based CAD detection (Banerjee et al., 2016). A classification task usually involves training and testing data which consist of some data instances. In the training set, each instance contains one target class label and many attributes. The main goal of SVM for classification problem is to produce a model which predicts target class label of data instances in the testing set, given only the attributes. The SVM model was developed as-one against-rest principle by using feature vectors derived from the intended class as positive examples and the feature vectors derived from the other class as negative examples.

Radial Basis Function (RBF) is used in this work. This is because RBF, unlike linear kernel can handle the case where the relationship between the class labels and attributes is non-linear. Another advantage of RBF kernel is its universal approximation properties. Also, it offers good generalization as well as good performance in solving practical problems (Reddy et al., 2014). The basic architecture of diabetes mellitus classification system using SVMs with above mentioned features is shown in Fig. 2.

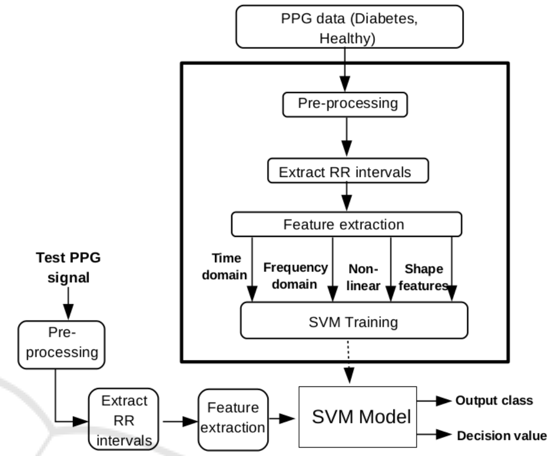


Figure 2: Architecture of Pervasive Diabetes Mellitus Classification System (PerDMCS).

In this study, 100 subjects of data is used out of which 50 subjects are healthy and 50 are diabetic. We have used 5-fold validation technique where 4 folds are used for training and remaining fold is used for testing.

In this work, we first analyzed the capability of individual feature sets F_1, F_2, F_3 and F_4 for discriminating the diabetes and healthy. Five DMCS systems are developed, which are summarized as follows:

1. PerDMCS-1: Pervasive diabetes mellitus classification system using F_1 features.
2. PerDMCS-2: Pervasive diabetes mellitus classification system using F_2 features.
3. PerDMCS-3: Pervasive diabetes mellitus classification system using F_3 features.
4. PerDMCS-4: Pervasive diabetes mellitus classification system using F_4 features.
5. PerDMCS-5: Pervasive diabetes mellitus classification system using combination of all features.

Performance of the pervasive DMCSs using the features discussed earlier, is represented in the form of a consolidated confusion matrix as shown in Table 2. The diagonal elements of the confusion matrix represent the correct classification performance of class. Non-diagonal elements indicate the performance of

[4]http://circ.ahajournals.org/content/93/5/1043

Table 1: List of Features.

Name	Description	DM Range *mean* ± *std*	Non DM Range *mean* ± *std*
	Time Domain Features (F_1)		
meanNN	mean values of NN intervals (ms)	787 ± 133	735 ± 111
medianNN	median values of NN intervals (ms)	787 ± 134	735 ± 114
SDNN	standard deviation of NN intervals (ms)	26.58 ± 14.13	41.85 ± 18.45
RMSSD	root mean square of successive NN differences (ms)	27.89 ± 15.27	34.81 ± 16.75
NN50	total # of of successive NN intervals differing by $\geq$ 50 ms	4.52 ± 6.9	9.14 ± 9.62
pNN50	percentage of successive NN intervals differing by $\geq$ 50 ms	0.07 ± 0.1	0.12 ± 0.13
HRVti	Ratio of number of all NN intervals to maximum number	3.39 ± 1.32	4.89 ± 1.71
	Frequency domain Features (F_2) (Welch, 1967)(Billman, 2007)		
aVLF	raw area of VLF (0-0.04 Hz) band (ms^2)	100 ± 42	294 ± 97
aLF	raw area of LF (0.04-0.15 Hz) band (ms^2)	134 ± 25	351 ± 39
aHF	raw area of HF (0.15-0.5 Hz)band (ms^2)	143 ± 29	284 ± 92
aTotal	total raw area of VLF, LF and HF bands	892 ± 116	2062 ± 177
LFHF	ratio of LF and HF areas	1.49 ± 1.79	2.1 ± 1.83
nLF	normalized LF area w.r.t to LF+HF	0.15 ± 0.08	0.2 ± 0.08
nHF	normalized HF area w.r.t to LF+HF	0.15 ± 0.08	0.14 ± 0.07
%VLF	relative VLF area w.r.t to total area	12.04 ± 7.34	12.59 ± 7.89
% LF	relative LF area w.r.t to total area	13.15 ± 7.08	18.03 ± 7.6
% HF	relative HF area w.r.t to total area	13.79 ± 7.99	12.66 ± 7.01
peakVLF	freq. of highest power in VLF band	0.02 ± 0.02	0.02 ± 0.02
peakLF	freq. of highest power in LF band	0.02 ± 0.03	0.03 ± 0.03
peakHF	freq. of highest power in HF band	0.14 ± 0.08	0.09 ± 0.08
	Non-linear Features (F_3)		
pSD1	Poincaré SD i.e., standard deviation of points perpendicular to the axis of line-of-identity	19.86 ± 10.89	24.77 ± 11.93
pSD2	Poincaré SD i.e., standard deviation of points along the axis of line-of-identity	31.43 ± 17.66	53.31 ± 24.19
sampEN	sample entropy estimates	1.57 ± 0.45 1.4 ± 0.42 1.33 ± 0.42	2.04 ± 0.48 1.73 ± 0.46 1.66 ± 0.5
alpha	detrended fluctuation analysis i.e., slope of log-log plot of integrated RR vs window size	0.4 ± 0.31 0.84 ± 0.26 0.81 ± 0.28 0.43 ± 0.29 0.89 ± 0.7 0.34 ± 0.88	0.5 ± 0.31 0.98 ± 0.23 1.04 ± 0.27 0.44 ± 0.3 0.85 ± 0.68 0.65 ± 0.86
	Waveform Features (F_3)		
meanFS	mean value of falling slopes	0.03 ± 0.01	0.03 ± 0.01
meanRS	mean value of rising slopes	0.07 ± 0.02	0.09 ± 0.02
meanPWp75 meanPWp50 meanPWp25	mean value of pulse widths at 75% mean value of pulse widths at 50% mean value of pulse widths at 25%	0.18 ± 0.02 0.29 ± 0.04 0.46 ± 0.06	0.15 ± 0.03 0.27 ± 0.06 0.45 ± 0.07
meanCT	mean value of crest times	0.21 ± 0.03	0.17 ± 0.03
meanDT	mean values of diastolic times	0.58 ± 0.11	0.56 ± 0.1
meanPH	mean values of pulse heights	50.46 ± 9.5	52.91 ± 7.65
meanPI	mean values of pulse intervals	0.79 ± 0.13	0.73 ± 0.11

misclassification. Columns 3-4 indicate the performance of the PerDMCS systems. Other performance measurements like true positive, false positive, true negative, false negative, precision, recall, sensitivity , specificity and overall model accuracy are presented in Table 3.

Analysis: From Tables 2 and 3, it is observed that feature sets F_1, F_2, F_3, and F_4 have discriminatory information related to diabetes. It is also observed that the diabetes is well discriminated compared to healthier subjects using shape related features i.e., F_4 , whereas using non-linear information i.e. F_3, classification of healthier shows better performance compared to diabetes. From this we can hypothesize that both F_3 and F_4 are complementary in nature, and if integrated can lead into better classification. Though combination of all features (i.e. PerDMCS-5) yields the best model accuracy, one can observe that PerDMCS-3 outperforms PerDMCS-5 in some of the performance measurements (True Positive, True Negative, Precision and Specificity). This is due to the inclusion of unimportant features from F_1 and F_2. Results indicate that there is a scope of minute features selection from individual feature sets. Hence for improving performance of the entire system, different fusion technologies are explored.

5 WEIGHTED FUSION: PROPOSED METHOD

5.1 Features Fusion

In this study, the fusion at feature level is performed by concatenation of the different percentage of discriminative features from each set i.e., F_1 to F_4. The concatenation process of features is carried out as follows.

1. The features are ranked using correlation of features and labels (Hall, 2000).
2. Different percentage of features are selected from ranked features. In this work, we have explored top 50% features to 100% with increments of 10% i.e., 6 variations such as 50%, 60% 70%, 80%, 90% and 100% most discriminative features.
3. Finally we have concatenated different percentage of features from each set to build the PerDMCS model.

Different technologies of features level fusion are employed e.g. different percentages from each domain separately (One vs One vs One vs One), different percentage from the combinations of two feature sets and different percentages from each of the rest (Two vs One vs One) etc. The comparisons of different feature level fusions are presented in 3.

Table 2: Performance of pervasive diabetes mellitus classification systems developed using different features. The entries in the table indicate the subjects of classification. Act: Actual, Pred: Predicted.

PerDMCS	Act. / Pred.	Diabetic	Healthy
PerDMCS 1	Diabetic	**34**	11
	Healthy	16	**39**
PerDMCS 2	Diabetic	**37**	9
	Healthy	13	**41**
PerDMCS 3	Diabetic	**38**	8
	Healthy	12	**42**
PerDMCS 4	Diabetic	**40**	13
	Healthy	10	**37**
PerDMCS 5	Diabetic	**42**	10
	Healthy	8	**40**

As shown in 3(a), 24 (out of 1296) feature combinations result in accuracy of 83%. In Fig. 3(b), it can be observed that the model accuracy is improved slightly i.e., 2% for some different feature combinations compared to combination of all individual features as shown in Table 3. Here, 8 feature combinations results in high accuracy of 84% and which is 1% improvement compared to the earlier combination. The best model accuracy remains similar 84% (for the combination of 50% features from F_3 and 90% features from (F_2 + F_4) as shown in Fig. 3(c)). In Fig. 3(d), the best model accuracy is 83% for the combination of 50% features from (F_1 + F_4) and 80% features from (F_2 + F_3). However, the average accuracy is slightly less than the best combinations of *Two vs One vs One* and *Two vs One* fusions. Fig. 3(e) shows that the maximum accuracy achieved in this fusion approach is 81% and it marks a clear degradation in performance compared to the combinations mentioned above. Here, among all 144 combinations, 8 feature combinations results in 81% accuracy.

5.2 Scores Fusion

Score level fusion is performed by summing the weighted confidence scores (evidences) derived from the different PerDMCSs. The weighing rule for combining the confidence scores of individual modalities is as follows:

$$C = \frac{1}{m}\sum_{i=1}^{m} w_i c_i \tag{1}$$

Table 3: Objective parameters of different PerDMCSs.

Performance Measurements	PerDMCS-1	PerDMCS-2	PerDMCS-3	PerDMCS-4	PerDMCS-5
True Positive	34	37	38	40	**42**
False Positive	11	9	**8**	13	10
False Negative	16	13	12	10	**8**
True Negative	39	41	**42**	37	40
Precision	0.76	0.80	**0.83**	0.75	0.81
Sensitivity	0.68	0.74	0.76	0.80	**0.84**
Specificity	0.78	0.82	**0.84**	0.74	0.80
Model Accuracy	0.73	0.78	0.80	0.77	**0.82**

where C is the weighted confidence score, w_i and c_i are weight and confidence score of the i^{th} modality, and m indicates number of modalities used for combining the scores. In this work, we have combined different modalities as described in section VI-A, such as two modalities (Two vs One, Two vs Two and Three vs One), three modalities (Two vs One vs One) and four modalities (One vs One vs One vs One).

In our study, for two modality systems one of the weights (w_i) is varied in steps of 0.1 from 0 to 1, and the other weight is determined using the formula: w_j = 1- w_i such that total weight $w_i + w_j$ = 1. Hence, we get 11 combinations of weighing factors. Similarly, for three modality systems two of the weights (w_i and w_j) are varied in steps of 0.1 from 0 to 1 and the other weight is determined using the formula: w_k = 1- w_i-w_j such that total weight $w_i + w_j + w_k$ = 1 and $w_k \geq 0$. Hence, we get 60 combinations of weighting factors. For four modality systems three of the weights (w_i, w_j and w_k) are varied in steps of 0.1 from 0 to 1 and the other weight is determined using the formula: w_l = 1- w_i-w_j -w_k such that total weight $w_i + w_j + w_k + w_l$ = 1 and $w_l \geq 0$. The classification performance of the combined system for various combinations of the weighting factors are as follows.

5.2.1 One vs One vs One vs One

It is observed that out of 313632 fusion of score combinations only 12 instances found to produce highest accuracy of 85%. The accuracy of fusion based models at score level is performed slightly better than the models obtained by simple feature level combinations.

5.2.2 Two vs One vs One

It is observed that out of 77760 fusion of score combinations only 3 instances found to produce highest accuracy of 85%. The accuracy of fusion based models at score level is performed slightly better than the models obtained by simple feature level combinations.

5.2.3 Two vs One

It is observed that out of 4752 fusion of score combinations only 20 instances found to produce highest accuracy of 84%. The accuracy of fusion based models at score level is not improved compared to the accuracy obtained by simple feature level combinations.

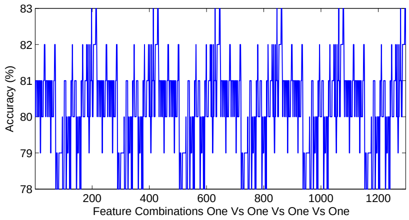
5.2.4 Two vs Two

It is observed that out of 1188 fusion of score combinations only 2 instances found to produce highest accuracy of 89%. The accuracy of fusion based models at score level is performed better than the models obtained by simple feature level combinations.

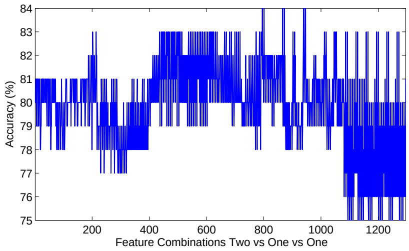
5.2.5 Three vs One

It is observed that out of 1584 fusion of score combinations only 14 instances found to produce highest accuracy of 82%. The accuracy of fusion based models at score level is performed slightly better i.e.1% than the models obtained by simple feature level combinations. However, still the accuracy is very low compared to other feature level and score level fusion models.

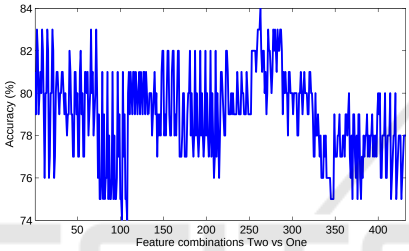
From the results it is found that the fusion of scores performed better than the models simple feature level fusion. Among all the models the highest accuracy is obtained for score level fusion of Two vs Two combinations. The best accuracy is observed to be 89% for the feature combinations of mixture of 90% features from the feature sets F_1 and F_2 and mixture of 100% features from the feature sets F_3 and F_4, with optimal weights of 0.3 and 0.7, respectively. Similarly, another best combination is observed to be for the feature combinations of mixture of 100% features from the feature sets F_1 and F_2 and mixture of



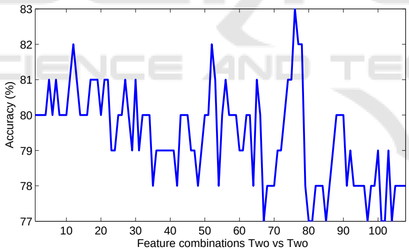
(a) One vs One vs One vs One



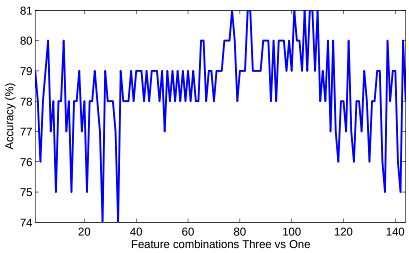
(b) Two vs One vs One



(c) Two vs One

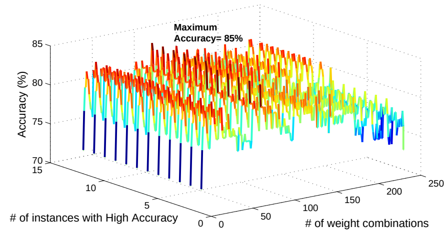


(d) Two vs Two

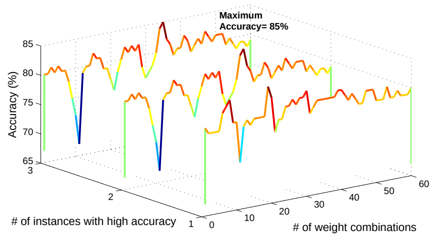


(e) Three vs One

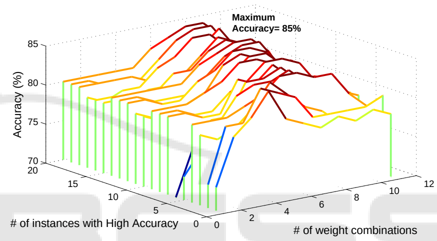
Figure 3: Accuracy of Feature Fusions.



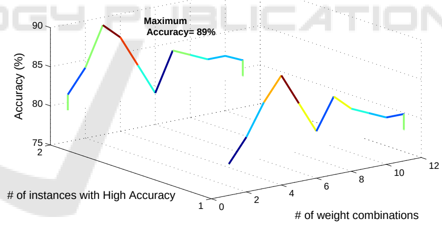
(a) One vs One vs One vs One



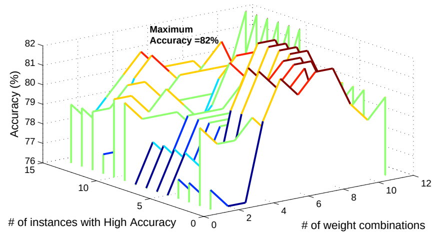
(b) Two vs One vs One



(c) Two vs One



(d) Two vs Two



(e) Three vs One

Figure 4: Accuracy of Score Fusion.

100% features from the feature sets F_3 and F_4, with optimal weights of 0.2 and 0.8, respectively.

It is noted that the best combination in feature level fusion at Two vs Two level showed the best accuracy of 83% for the combination of mixture of 50% features from the feature sets F_1 and F_4 and mixture of 80% features from the feature sets F_2 and F_3. However, in score level fusion it is not improved. In score level fusion it picked the different set of feature combinations and the performance of the system improved from 83% at feature level to 89% at score level. It can be seen that the best feature combination observed in score level fusion exhibits 81% accuracy in feature level fusion from the Fig. 3(d) with equal weights i.e. 0.5 and 0.5 (6th combination across # of weight combination). This indicates that fusion is able to combine the complementary nature of evidence obtained from different sets of features. The performance measures for the best combination is observed to be same and given in Table 4. From the results, it is observed that the score based fusion based PerDMCS system is outperformed compared to individual system performances (Table 2).

Table 4: Performance of best pervasive diabetes mellitus classification systems developed using fusion technique. The entries in the table indicate the subjects of classification.

Predicted \ Actual	Diabetic	Healthy
Diabetic	**45**	6
Healthy	5	**44**

6 SUMMARY

In this work, HRV features related to time domain, frequency domain and non-linear and shape (morphological) related features extracted from PPG signal are used to discriminate between diabetic and healthy. SVMs are used as classification models for developing different PerDMCS systems. The performance of the PerDMCS systems developed by individual features are improved by exploring fusion techniques, by combining different percentage of discriminate features from different combinations of feature sets and scores of the individual systems and different combination systems as well. An improvement in classification performance of the system is observed at score level fusion with average classification performance of 89%. This is attributed to the complementary nature of evidence present in the features.

ACKNOWLEDGEMENTS

We are immensely grateful to the subjects for spending their valuable time and providing the data for this study. We are thankful to IAIMS Research Center. Further, we express our gratitude towards Dr. Arpan Pal and Dr. Balamurali P. for their guidance and support.

REFERENCES

Allen, J. (2007). Photoplethysmography and its application in clinical physiological measurement. *Physiological measurement*, 28(3):R1.

Association, A. D. et al. (2015). 2. classification and diagnosis of diabetes. *Diabetes care*, 38(Supplement 1):S8–S16.

Banerjee, R., Vempada, R., Mandana, K., Choudhury, A. D., and Pal, A. (2016). Identifying coronary artery disease from photoplethysmogram. In *Int. Joint Conf. on Pervasive and Ubiquitous Computing: Adjunct*, pages 1084–1088. ACM.

Billman, G. E. (2007). The lf/hf ratio does not accurately measure cardiac sympatho-vagal balance. *Heart Rate Variability: Clinical Applications and Interaction between HRV and Heart Rate*, page 54.

Collaboration, N. R. F. et al. (2016). Worldwide trends in diabetes since 1980: a pooled analysis of 751 population-based studies with 4· 4 million participants. *The Lancet*, 387(10027):1513–1530.

Elgendi, M. (2012). On the analysis of fingertip photoplethysmogram signals. *Current cardiology reviews*, 8(1):14–25.

Hall, M. A. (2000). Correlation-based feature selection of discrete and numeric class machine learning.

Koolagudi, S. G., Reddy, V. R., and Rao, K. S. (2010). Emotion recognition from speech signal using epoch parameters. In *Proc. of SPCOM*, pages 1–5, India.

Ning, X., Selesnick, I. W., and Duval, L. (2014). Chromatogram baseline estimation and denoising using sparsity (beads). *Chemometrics and Intelligent Laboratory Systems*, 139:156–167.

Reddy, V. R., Chakravarty, K., and Aniruddha, S. (2014). Person identification in natural static postures using kinect. In *ECCV*, pages 793–808. Springer.

Reddy, V. R. and Chattopadhyay, T. (2014). Human activity recognition from kinect captured data using stick model. In *HCI. Adv. Interaction Modalities and Techniques*, pages 305–315. Springer.

Reddy, V. R., Sinha, A., and Seshadri, G. (2013). Fusion of spectral and time domain features for crowd noise classification system. In *Intelligent Systems Design and Applications*, pages 1–6. IEEE.

Schroeder, E. B., Chambless, L. E., Liao, D., Prineas, R. J., Evans, G. W., Rosamond, W. D., and Heiss, G. (2005). Diabetes, glucose, insulin, and heart rate variability the atherosclerosis risk in communities (aric) study. *Diabetes care*, 28(3):668–674.

Seyd, A., Joseph, P. K., and Jacob, J. (2012). Automated diagnosis of diabetes using heart rate variability signals. *Journal of medical systems*, 36(3):1935–1941.

Tabish, S. A. (2007). Is diabetes becoming the biggest epidemic of the twenty-first century? *International Journal of health sciences*, 1(2):V.

Welch, P. D. (1967). The use of fast fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. *IEEE Transactions on audio and electroacoustics*, 15(2):70–73.