Risk Quantif cation of Metabolic Syndrome with Quantum Particle Swarm Optimisation

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ABSTRACT

Metabolic syndrome (MetS) is a combination of interrelated risk factors associated with an increased risk of developing type II diabetes Mellitus (T2DM), stroke and cardiovascular diseases (CVD). The economic, social and medical burden coupled with increased morbidity of the aforementioned diseases makes their prevention an active research area. Currently, the traditional method of MetS diagnosis is based on dichotomised definitions provided by various expert health organisations. However, this method is laced with the indetermination of MetS in individuals with borderline risk factor values due to a binary diagnosis and the assumption of equal weighting for all risk factors during diagnosis. The purpose of this paper is to examine the use of the MetS areal similarity degree risk analysis based on weighted radar charts comprising of diagnostic thresholds and risk factor results of an individual. We further enhance this risk quantification method by applying quantum particle swarm optimization to derive the weights. The proposed risk quantification was carried out using a sample of 528 individuals from an examination survey conducted between 2007 and 2014 in Serbia. The results are evaluated with the traditional dichotomised method of MetS diagnosis, in this case the joint interim statement (JIS). The results obtained showed that the proposed risk quantification method outperformed the dichotomised method at diagnosing MetS even in individuals who present risk factor examination values at the threshold borderlines.

Keywords

Metabolic Syndrome; Quantum Particle Swarm Optimisation; Areal Similarity Degree

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Table 1: JIS Defined Thresholds for Five Metabolic Syndrome Risk Factors

Metabolic Syndrome Risk Factors	Thresholds
Fasting Blood Glucose (FBG)	$\geq$ 5.5 mmol/L and/or medication treatment
Waist Circumference (WC)	Male: $\geq$ 94 cm Female: $\geq$ 80 cm
HDL-Cholesterol (HDL-C)	Male: $\leq$ 1.0 mmol/L Female: $\leq$ 1.3 mmol/L and/or medication treatment
Triglyceride (TG)	$\geq$ 1.7 mmol/L
Blood Pressure (BP)	Systolic: $\geq$ 130 mmHg Dystolic: $\geq$ 80 mm Hg and/or medication treatment

1. INTRODUCTION

Metabolic syndrome (MetS) is a combination of metabolic abnormalities, i.e. hyperglycaemia, central obesity, dyslipidemia and hypertension, associated with an increased risk of developing non communicable diseases (NCDs) such as type II diabetes Mellitus (T2DM), stroke and cardiovascular diseases (CVD) [15, 10]. These metabolic abnormalities are characterised by five MetS risk factors (MRFs): elevated blood pressure (BP), decreased HDL-cholesterol (HDL-C), elevated triglyceride (TG), elevated waist circumference (WC), and elevated fasting blood glucose (FBG) [17].

NCDs arising from the presence of MetS are a global burden constituting major health, social, and economic development due to recent changes in dietary habit and lifestyle. They account for about 52 % of the world's mortality rate, majority of which occurs in low- and middle-income countries [13].

Various expert health organisations such as WHO [14], the National Cholesterol Education Program Adult Treatment Panel III (NCEP ATP III) [9], the European Group for the Study of Insulin Resistance (EGIR) [6], the International Diabetes Federation (IDF) [4], have come up with definitions of MetS and have concluded that MetS can be diagnosed by dichotomising its risk factors. In 2009, a new joint interim statement (JIS) was developed in order to consolidate multitude of different pre-existing definitions [3]. Clinical diagnosis of MetS defined by the JIS requires presence of any three out of the five MRFs. Table 1 shows the thresholds for the JIS definition.

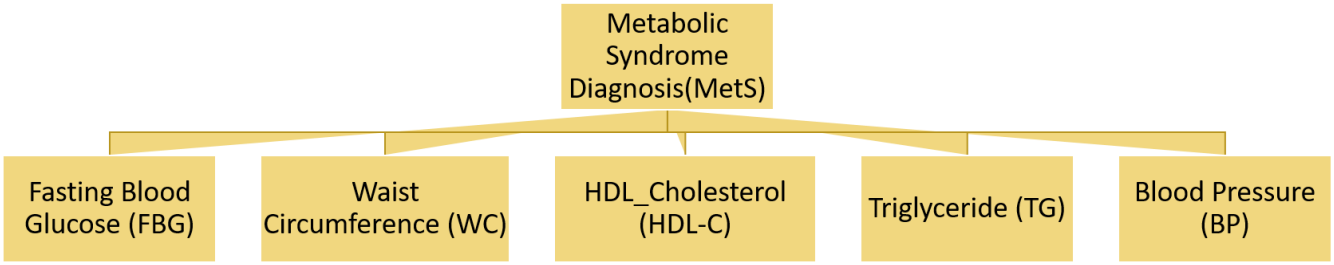


Figure 1: Metabolic syndrome hierarchy structure.

Invariably, these MRFs are defined as continuous variables with differing measurement metrics. Let us assume that a middle-aged female presents with fasting blood glucose of 5.4 mmol/L, waist circumference of 78 cm, HDL-Cholesterol of 1.1 mmol/L, Triglyceride of 1.8 mmol/L and blood pressure of 127/78 mm Hg, then according to the dichotomous definition of MetS, she will not be diagnosed as having MetS. The dichotomous definition will recognise only her triglyceride and HDL-cholesterol as having exceeded the recommended threshold. In this regard, studies have shown that dichotomising the continuous variables of the MRFs based on cut-off points potentially leads to misclassification especially when the MRF values are at the borderline of the cut-off points [21]. The dichotomous definition also assumes equal weighting for all the five risk factors during diagnosis despite the different indications that the risk factors represent [22]. Again, if we revisit the MRF values, it can be clearly seen that she was not diagnosed with MetS because only two out of five MRFs were considered in her diagnosis. The dichotomous method excludes any MRF that does not exceed or meet up to the threshold values e.g. HDL-C in this case. For these aforementioned reasons, the dichotomous method incurs information loss in the its diagnosis. It has also been suggested that despite the growing number of research on finding the definition of MetS, an agreement of over a unified definition is yet to be apparent [17]. Thus, it is crucial to evaluate and select efficient MetS risk quantification methods to supplement the traditional binary/dichotomous method of MetS diagnosis.

Therefore, in response to the global burden of NCDs and the MetS diagnosis problems associated with the current MetS definitions, methods for early and accurate diagnosis of MetS are required for the prevention of MetS and its associated diseases. Prevention methods are also necessary to aid in providing solutions for health promotion and dietary habits and lifestyle management.

Statistical and mathematical quantification methods have been proposed to quantify the risk of MetS by including all the MRFs in the diagnoses. However, the statistical approach is mostly applied in the diagnosis of MetS risk in children since the current dichotomous MetS definitions are inconsistent with regards to diagnosing MetS in children [12]. In this paper, we focus the quantification approach which can be applied to both children and adults. One such method is the areal similarity degree (ASD) proposed in [20]. ASD is a quantification method for diagnosis the risk of MetS based on the weighted radar chart. The weight values represent the prevalence of MRF in the population. The radar chart is a visualisation tool used for comparing performances in multiple dimensions simultaneously. It is used to depict medical outcomes and comparative data in multiple relevant outcome dimensions [28]. Despite its ability to visually represent the value of health care outcomes [26], the radar chart is incompetent in the derivation of weights associated with each variable in the outcome. Therefore, ASD adopts the analytic hierarchy process (AHP) [18] in order to calculate the different weights of the MetS risk factors (MRFs) in the radar chart.

AHP is a multi-attribute decision making technique for addressing events of uncertainty and making ranked judgements based on multiple criteria. Ranking in AHP is carried by priority estimation. Priority estimation in AHP is the process of deriving a priority vector or a vector of weights form a pair-wise comparison matrix through the application of various priority estimation methods. This process is important in AHP for determining the weighting for each criterion of the decision making problem. The most widely use priority estimation method is the eigenvector method proposed by Saaty [18]. The weighted least-squares method was proposed by Chu *et al.* [7] while Saaty and Vargas [19] also suggested a least squares method (LSM). An in-depth analysis of AHP priority estimation methods can be found in [24].

In this paper, we propose the adoption of quantum particle swarm optimisation (QPSO) [27] method to estimate the priority vector from the pairwise matrix of each MRFs derived using the AHP. The weights from the priority vectors are then used to quantify the risk of MetS using the ASD and also for visualisation using the radar chart.

2. MATERIALS AND METHODS

2.1 Study Population

The study population has been previously described [23]. Briefly, the study was conducted between 2007 to 2014. It included 528 males (n=182) and (n=346) female aged 7 to 77 years recruited from the Clinic of Endocrinology, Diabetes and Metabolism Disorders, Clinical Center of Serbia, Belgrade. The characteristics of the study population, as stratified by gender are presented in Table 2.

All subjects were asked to report their age, gender, and morbidity (diabetes, hypertension, hyperlipidemia, angina pectoris, myocardial infarction, peripheral vascular disease) history of their family members. Physical examination was carried out to collect MRF measurements such as body weight, height, waist circumference, systolic and diastolic blood pressure. After 12 hours of fasting, other MRF measurements such as Cholesterol, HDL-C, and Triglyceride were measured using spectrophotometric method and the Friedwald formula

Table 2: Characteristics of study sample

	Male		Female	
Number of Subjects, n (%)	182 (34.47)		346 (65.53)	
Age, years	11.67±18.55		24.41±22.15	
0-17 (child)	31 (17.0)		42 (12.1)	
18-39 (young)	86 (47.3)		152 (43.9)	
40-64 (middle-aged)	60 (33.0)		136 (39.3)	
65 and above (old)	5 (2.7)		16 (4.6)	
Fasting Glucose (mmol/L)	5.05±0.90	Mn 3 Mx 13	4.97±0.99	Mn 0 Mx 16
Waist Circumference (cm)	108.71±15.14	Mn 73 Mx 150	99.318±18.30	Mn 0 Mx 160
HDL-Cholesterol (mmol/L)	1.08±0.22	Mn 0 Mx 2	1.31±0.35	Mn 1 Mx 4
Triglyceride (mmol/L)	2.04±1.24	Mn 0.6 Mx 75	1.70±0.88	Mn 1 Mx 6
Systolic Blood Pressure (mm Hg)	128.82±16.03	Mn 90 Mx 190	125.68±18.79	Mn 0 Mx 130
Diastolic Blood Pressure (mm Hg)	84.08±10.19	Mn 60 Mx 140	81.48±12.82	Mn 0 Mx 130

Note: Values are means±SD or n(%); Mn, Minimum; Mx, Maximum

was used to compute the LDL-C. Fasting blood glucose was measured following the WHO guidelines [5]. In this paper, we have categorised all subjects into two groups by gender and a further sub-categorisation by age: young (from 18 to 39 years old), middle-aged (from 40 to 64 years old), and old (more than 65 years old), respectively. Our age stratification is not far off from that of Al-Zaarani *et al.* [2] where age group is classified as younger (18 to 34 years old), middle-aged (35 to 59 years old), and older (60 to 90 years old) adults . However, we removed all subject of child age (below 18 years) because the dichotomous MetS is not appropriated for defining MetS in children [1]. The JIS [3] definition, which is the latest health expert MetS definition, was used to determine presence of MetS in subjects. The JIS defines MetS as having any three or more of the following components:

- Waist circumference (WC $\geq$ 90 cm for men and $\geq$ 80 cm for women);
- Elevated triglyceride (TG $\geq$ 150 mg/dl or being under treatment);
- Low, high-density lipoprotein cholesterol (HDL-C $<$ 40 mg/dl for men and $<$ 50 mg/dl for women or being under treatment);
- Elevated blood pressure systolic blood pressure (SBP $\geq$ 130 mmHg, or diastolic blood pressure DBP $\geq$ 85 mmHg or receiving anti-hypertensive medications);
- Elevated fasting plasma glucose (FPG $\geq$100 mg/dl or treatment for hyperglycaemia).

People who are taking medication the treatment of hypertension, T2DM, are hyperglycaemia will be automatically diagnose as having MetS without taking into consideration the other MRFs.

2.2 Proposed Metabolic Syndrome Risk Quantif cation Method

Our proposed method takes in measurement values of all the MRF measurement values and computes an ASD value between 0 and 1. The steps involved in the MetS risk quantification method proposed in this paper shown in Figure 2 will be described as follows.

2.2.1 Data Preprocessing

MetS risk factors (MRFs) as can be seen in Table 2 have different measurement metrics. Therefore, data from the population study for each MRF in each subgroup is normalised to scale the variables to an input range between 0 and 1. Let each MRF variable be a_i and let the maximum and minimum value of the data be $a_{i_{min}}$ and $a_{i_{max}}$. Then the normalised variable $a_{i_{new}}$ is calculated as follows:

$$a_{i_{new}} = \frac{a_i - a_{i_{min}}}{a_{i_{max}} - a_{i_{min}}}. \quad (1)$$

2.2.2 Generating the Pairwise Matrix

As mentioned in Section 1, the AHP is adopted to generate the pairwise matrix for priority estimation using QPSO. This procedure is necessary in order to accommodate the varying effect of each MRF on the MetS risk quantification. AHP allows the MetS risk factors to be represented in a hierarchical structure which enables a stable pairwise matrix generation. All MRFs are on the same AHP hierarchy level as depicted in Figure 1.

2.2.3 Priority Estimation from Pairwise Matrix using QPSO

The QPSO is a simple evolutionary algorithm which relatively inexpensive in terms of speed and memory consumption [8]. Genetic operators like crossover and mutation are absent in QPSO and particles update themselves with the internal velocity [25]. Hence, the computational effort required by QPSO to meet the optimal result is relatively less than other evolutionary algorithms such as the genetic algorithm [11]. Moreover, only one parameter is required for update in the QPSO.

Let $A = (a_{ij})_{n\times n}$ be a pairwise comparison matrix with $a_{ij} = 1/a_{ii} = 1$ and $a_{ij>0}$ for $i, j = 1, \ldots, n$ and $W = (w_1, \ldots, w_n)^T$ be a priority vector with $\sum_{i=1}^{n} = 1$ and $w_i \geq 0$ for $i = 1, \ldots, n$. Therefore, if $a_{ij} = a_{ik}a_{kj}$ holds for any $k = 1, \ldots, n$, then $A = (a_{ij})_{n\times n}$ is said to be a consistent pairwise comparison matrix; otherwise it is inconsistent [18]. The perfectly consistent comparison matrix of MRFs for each subgroup is showed in an example as follows:

$$A = \begin{array}{c} \begin{matrix} \text{FBG} & \text{WC} & \text{HDL}-\text{C} & \text{TG} & \text{BP} \end{matrix} \\ \begin{bmatrix} 1 & 0.3096 & 0.1713 & 0.4569 & 0.2638 \\ 3.2296 & 1 & 0.5532 & 1.4757 & 0.8520 \\ 5.8376 & 1.8076 & 1 & 2.6674 & 1.5401 \\ 2.1885 & 0.6776 & 0.3749 & 1 & 0.5774 \\ 3.7905 & 1.1737 & 0.6493 & 1.7320 & 1 \end{bmatrix} \end{array}$$

To obtain the weights of the matrix above, we use the QPSO as mentioned in Section 1. The pairwise matrix is fed into the QPSO algorithm and the following steps will ensue:

1. Initialise algorithm parameters (population size, particle dimension, maximum number of iterations MAXGEN), population initialisation, initialisation of particles history, and global history optimal value.
2. Evaluate fitness value for each individual.
3. Update the optimum population in history if the particle's fitness is better than the particle history itself, with the current value of the replacement; otherwise, the history optimal particles remain unchanged.

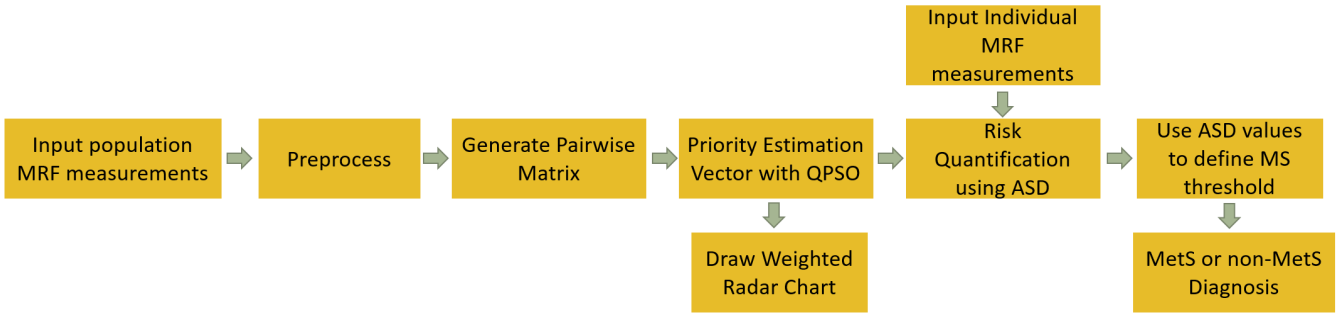


Figure 2: Flowchart of metabolic syndrome risk quantification with ASD and QPSO.

4. Update the history global optimum particle in a population which is the best fitness value of all the particles in the population.
5. Update particles by using quantum behaved particle swarm optimisation algorithm formula for all the particles in space.
6. If the algorithm reaches the maximum number of iterations, then output the optimal solution, and the algorithm terminates; otherwise, continue to implement the Step 2.

The resulting priority vector from the pairwise matrix above is given below:

$$W = \begin{matrix} w_{\text{FBG}} & w_{\text{WC}} & w_{\text{HDL-C}} & w_{\text{TG}} & w_{\text{BP}} \\ [0.0783 & 0.2721 & 0.3643 & 0.0499 & 0.2353] \end{matrix}$$

2.2.4 *Risk Quantif cation using ASD*

Let the Radar R be a set of disjoint polygons A_{ij}, where $i = 1, \ldots, n$ and $j = (i+1) \bmod n$. Let the polygon A_{ij} in the radar chart R be a polygon consisting of vertices O, A_i, and A_j, such as $\triangle OA_iA_j$, where $\overline{OA}_i = r_{i_A}$, $\overline{OA}_j = r_{j_A}$, $\angle O = \theta_i$, $i = 1, \ldots, n$, $j = (i+1) \bmod n$, and r_i is the value of the i-th indicator.

Let the ASD of two polygons A_{ij} and B_{ij} be the ratio of intersection of the two polygons A_{ij} and B_{ij} over the area of B_{ij}. Therefore, the ASD of the two polygons is

$$S(A_{ij}|B_{ij}) = \frac{\text{Area of intersection of polygon } A_{ij} \text{ and } B_{ij}}{\text{Area of intersection of polygon } B_{ij}} \tag{2}$$

where polygon B_{ij} is reference polygon determined by the thresholds of MRFs and polygon A_{ij} is determined by the MRF measurement values of an individual. So, given the two polygons A_{ij} and B_{ij}, let polygon A_{ij} include B_{ij}, iff $r_{i_A} \geq r_{i_B}$ and $r_{j_A} \geq r_{j_B}$.

Therefore, given two indicators i and j, the ASD of two polygons A_{ij} and B_{ij}, specifically, $S(A_{ij}|B_{ij})$ can be calculated as follows:

$$S(A_{ij}|B_{ij}) = \begin{cases} 1 & \text{if } \mathrm{A_{ij}} \text{ includes } \mathrm{B_{ij}} \\ \frac{\text{Area of } \mathrm{A_{ij}}}{\text{Area of } B_{ij}} & \text{if } \mathrm{B_{ij}} \text{ includes } \mathrm{A_{ij}} \\ \frac{r_{j_B} \cdot r_{i_B} - Q}{r_{j_B} \cdot r_{i_B}} & \text{if } \mathrm{r_{i_A}} > \mathrm{r_{i_B}} \text{ and } \mathrm{r_{j_A}} < \mathrm{r_{j_B}} \\ \frac{r_{j_B} \cdot r_{i_B} - Q'}{r_{j_B} \cdot r_{i_B}} & \text{if } \mathrm{r_{i_A}} < \mathrm{r_{i_B}} \text{ and } \mathrm{r_{j_A}} > \mathrm{r_{j_B}} \end{cases}, \tag{3}$$

where

$$Q = \frac{r_{i_A} \cdot r_{i_B}(r_{j_B} - r_{j_A})^2}{r_{j_A}(r_{i_A} - r_{i_B}) + r_{i_A}(r_{j_B} - r_{j_A})}, \tag{4}$$

and

$$Q' = \frac{r_{j_A} \cdot r_{j_B}(r_{i_b} - r_{i_A})^2}{r_{i_A}(r_{j_A} - r_{i_B}) + r_{j_A}(r_{i_B} - r_{i_A})}. \tag{5}$$

Finally, let the ASD of two radar charts R_1 and R_2 be the ratio of the intersection area of the two radar charts, R_1 and R_2, over the area of radar chart R_2. Then, $S(R_1|R_2)$ is the weighted sum of A_{ij} and B_{ij}, where w_i is the weight of A_{ij} and B_{ij}, and $i = 1, \ldots, n$ and $j = (i+1) \bmod n$, and $w_i = \frac{\theta_i}{360}$. Therefore, the final ASD value which is the weighted sum of all the ASDs for each MRF of each is given by

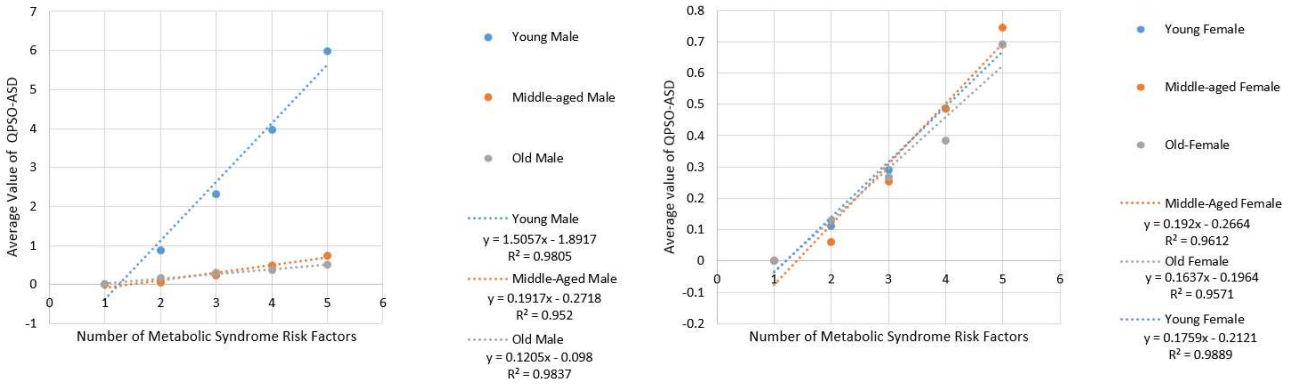
$$S(R_1|R_2) = \sum_{i=1}^{n} \frac{\theta_i}{360} \cdot S(A_{ij}|B_{ij}) \tag{6}$$

where $\sum_i^n \theta_i = 360$, $j = (i+1) \bmod n$. The ASD value for any individual is (0,1].

3. RESULTS

From the 528 samples, 73 which belonged to the child category were removed and the proposed model was run on 455 samples. Table 3 shows the ASD with QPSO results on middle-aged female subjects. As mentioned in Section 2.1, the dichotomous method (JIS MetS definition) was used to label each subject. If a subject has exceeded threshold of three or more the MRFs (or failed to meet the threshold in the case of HDL-C,), then the subject is labelled as having MetS. Also those on treatment as mentioned in Section 3 are also labelled with having MetS. Only subjects with 3 or more MRF value measurements above the threshold are classed to have MetS. All subjects did not present with being on any medication treatment.

Figure 3 show the regression analysis plots of the average ASD values and the number of MRFs. We can observe that there exists a strong positive correlation between the ASD values and the number of MRFs based on the high R^2 values. As the number of MRFs increases, the ASD values also increase from the regression lines. However, we notice that the ASD values are dependent on the sample size of each subgroup and gender. This is a limitation to the model as the ASD values will increase as the number of sample size increase.



(a) Male (b) Female

Figure 3: Regression Analysis of proposed QPSO-ASD model and the number of risk factors.

Table 3: Examples of ASD experiment results for middle-age females.

Subject	FBG	WC	HDL-C	TG	BP	JIS	ASD
1	4.4	79	1.29	1.65	150/100	Non MetS	0.83
2	9.1	79	1.30	1.80	129/79	Non MetS	0.92

Note: FBG, HDL-C and TG are measured in mmol/L; WC is measured in cm; BP is measured in mmol/L.

Table 4: Results of the ASD with QPSO algorithm based on the population sample.

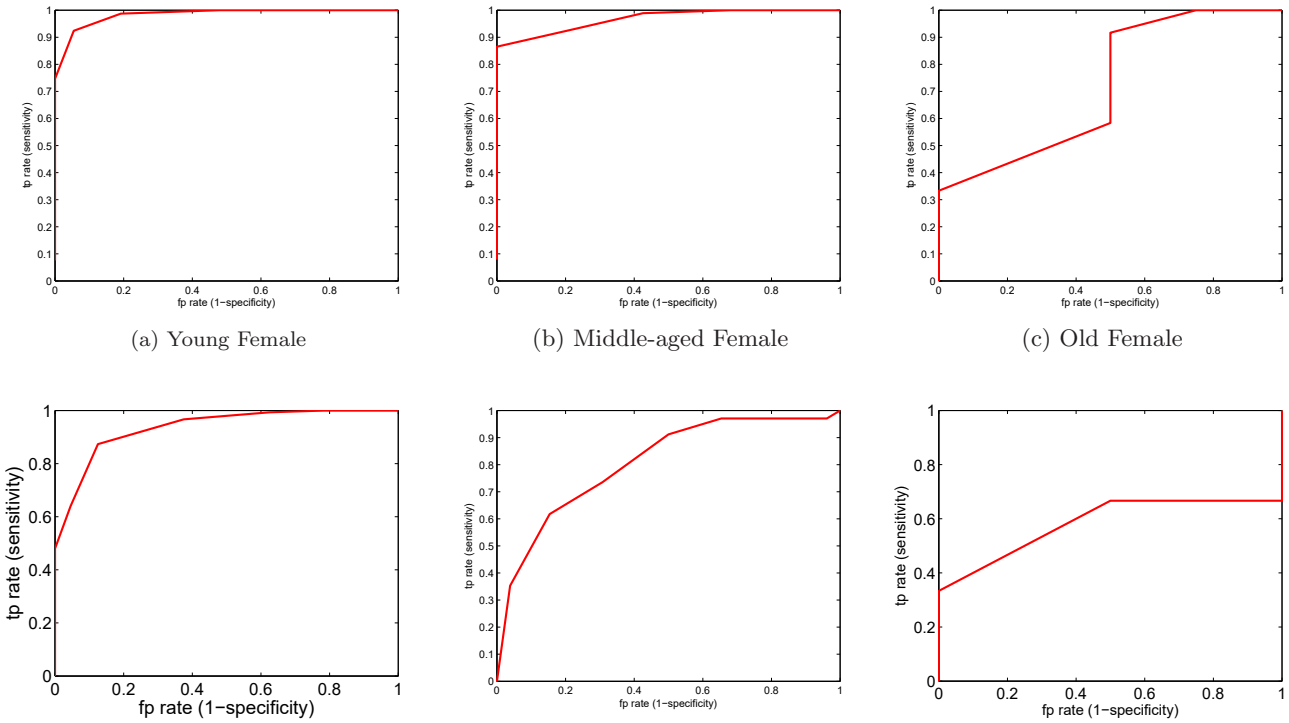
		AUC	SEN	SPEC	PPV	NPV
Male	Young	88.33	80.84	46.66	73.89	56.61
	Middle-Aged	83.18	77.27	42.65	63.82	58.93
	Old	54.54	51.52	59.09	65.38	44.84
Female	Young	98.92	84.45	54.74	66.90	76.48
	Middle-Aged	73.71	96.43	83.55	77.90	63.82
	Old	77.08	66.66	47.72	79.27	32.30

The ASD results for each individual was calculated and Receiver Operating Characteristic (ROC) curves were plotted as shown in Figure 4. The performance of a medical test is evaluated using performance metrics known as predictive biomarkers [16]; area under the ROC curve (AUC), sensitivity (SEN), specificity (SPEC), precision (PREC) or positive predictive value (PPV), and negative predictive values (NPV). However, the predictive biomarker discussed in this paper is the AUC because it is a summary measure of accuracy derived from the ROC curve. In this paper our focus is the proposed method's ability to classify individuals with MetS, especially, those who present with borderline measurement MRF values.

We have proposed and validated a method for the early detection of MetS using the five MRFs. The results as can be seen in Table 4 are promising. The previous study on ASD [20] did not evaluate the risk quantification method using performance metrics. The young female has the highest AUC of 98.92 %, followed by that of the young male while the old female has the lowest AUC of 54.54 %. From Table 2, we observe that the number of samples for the young female is the highest ($n = 152$), which is 9 % of the study sample while the old male data sample is only 1 %. Furthermore, we notice that even though the young female presents with the highest AUC, the PPV of the young male is higher than that of the young female with about 7 %. This variation in AUC results could be attributed to the sensitivity of the proposed algorithm towards the number of data samples. The weights generated from the QPSO were calculated purely based on the number of individuals in each subgroup. This could attribute a limitation of the proposed algorithm because there will be differing ASD values for the quantification of MetS based on the volume of data sample available. However, we can conclude that the higher the data sample of the MRFs, the higher the AUC value.

4. DISCUSSION

To perform an in-depth analysis of the ASD results in Table 3, we will refer to each subject in the table with their subject numbers. The cut off point for the diagnosis of MetS using our proposed method is calculated as the mean of all the ASD values of the population subgroup. In the case of the middle-aged female subgroup, the cut-off point is set at 0.73. Subject 1 according to medical indication can be said to be hypertensive. However, the JIS dichotomous method classifies her as not being at risk or having MetS because only two of her MRF values–HDL-Cholesterol and blood pressure–exceed the recommended thresholds. On the other hand, the ASD value depicts otherwise. Subject 1 has an ASD value of 0.83 which clearly puts her at risk of MetS. Furthermore, the MRF results of subject 2 provides an indication of a diabetic. Nevertheless, the dichotomous method does not recognise the health risk of this subject because only her fasting blood glucose and triglyceride MRF values exceed the dichotomous threshold. Fortunately, subject 2 has an ASD value of 0.92 which diagnoses her as having MetS. Here, we can see the possibility of information loss in the dichotomous method where both subjects with hypertension and diabetes are diagnosed as not having MetS. This diagnosis is in contradiction with the inclusion of hypertension and diabetes as NCDs with high mortality and morbidity [13]. The ASD values of the two study subjects also correlate with the 84 % specificity of the model. Thus,



(a) Young Female (b) Middle-aged Female (c) Old Female

(a) Young Male (b) Middle-aged Male (c) Old Male

Figure 4: Receiver Operating Characteristic (ROC) curve of ASD for six subgroups.

our proposed model is able to reduce information loss in diagnosis of MetS.

5. CONCLUSION

Consider an old female aged 67 years presenting with the following MRFs examination measurements: a fasting blood glucose of 5.4 mmol/L, waist circumference of 91 cm, HDL-Cholesterol of 1.2 mmol/L, Triglyceride of 0.8 mmol/L, systolic blood pressure of 145 mm Hg, and diastolic blood pressure of 79 mmHg. Clearly from the dichotomous definition of MetS, this old female will be diagnosed as not having or even being at risk of MetS since only two of her MRF measurement values is below the threshold i.e. elevated waist circumference and systolic blood pressure. However, this middle-aged woman has borderline MRF measurement values (close to the thresholds) on three out the five MRF. We used our model to calculate the ASD value for the old female and the ASD value was 0.79. With an ASD value of 0.79, what ever cut-off value is adopted, this will still place the old female at being diagnosed with Metabolic Syndrome. Clearly, this knowledge will guide both the medical health practitioner and the individual in becoming alert. Elderly people need to know their current metabolic status at an early stage. This will help to keep both their medical health care personal, caregivers and also themselves the likelihood of being at risk of CVD and T2DM. Dietary and Life style habit management can be initiated and monitored at this early stage so as to prevent a progression of MetS which will lead to the NCDs mentioned in Section 1. The clinical indication of our proposed method is quite promising, however, this method is quantitative and not self learning. Quantified risk values are not updated at any stage and thus the method is heavily reliant on the population sample. The method also holds the flexibility of being applicable to personal healthcare systems.

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