Assessment of In-Meal Eating Behaviour using Fuzzy SVM

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Abstract— **Certain patterns of eating behaviour during meal have been identified as risk factors for long-term abnormal eating development in healthy individuals and, eventually, can affect the body weight. To detect early signs of problematic eating behaviour, this paper proposes a novel method for building behaviour assessment models. The goal of the models is to predict whether the in-meal eating behaviour resembles patterns associated with obesity, eating disorders, or low-risk behaviours. The models are trained using meals recorded with a plate scale from a reference population and labels annotated by a domain expert. In addition, the domain expert assigned scores that characterise the degree of any exhibited abnormal patterns. To improve model effectiveness, we use the domain expert's scores to create training error regularisation weights that alter the importance of each training instance for its class during model training. The behaviour assessment models are based on the SVM algorithm and the fuzzy SVM algorithm for their instance-weighted variation. Experiments conducted on meals recorded from 120 individuals show that: (a) the proposed approach can produce effective models for eating behaviour classification (for individuals), or for ranking (for populations); and (b) the instance-weighted fuzzy SVM models achieve significant performance improvements, compared to the non-weighted, standard SVM models.**

I. INTRODUCTION

Obesity (OB) and eating disorders (ED) are preventable, noncommunicable diseases that affect a large percentage of the global population. The World Health Organisation estimates that over 1.9 billion adults and 380 million children were overweight or obese in 2016 and emphasises the need for prevention at individual and population level [1].

In addition to daily energy intake and physical activity, the in-meal eating behaviour has proven to be associated with OB and ED patients [2], [3]. For example, studies have shown that both OB and ED populations demonstrate patterns of linear eating behaviour during meals [4], while similar behaviours have been associated with increased risk of long-term abnormal eating development in healthy individuals [5].

To this end, the SPLENDID system [6] aims to automatically identify early signs of problematic eating behaviour that resemble known OB or ED behaviour patterns. First, the meals are recorded using the Mandometer® device [2], which is a plate scale that provides continuous recordings of the food weight during the meal. Then, signal processing algorithms process the recordings to produce behaviour indicators characterising in-meal behaviour [7]. The goal is to use these indicators as input to the *behaviour assessment models* that automatically identify any abnormal eating patterns.

These behaviour assessment models aim to assist the health professionals' decisions in two use cases: (a) for personal guidance of an individual, by predicting if the individual's recorded meals resemble OB or ED patterns; and (b) for population screening, by ranking the participating individuals according to the degree they exhibit any abnormal patterns.

In our previous work [8], we showed that unsupervised behaviour assessment models, based on the one-class SVM algorithm, were able to achieve good accuracy and ranking performance for the binary problem of distinguishing between low-risk (LR) and abnormal meal behaviours (either OB or ED). However, these models cannot specify if the abnormal behaviours are of the OB or ED class. Furthermore, the unsupervised models cannot exploit the importance of the training patterns for their class, which was provided by the domain expert.

In this work, we present supervised learning methods for building behaviour assessment models that overcome the above limitations. These models provide multiclass predictions, able to distinguish between OB, ED and LR class. In addition, we use the fuzzy SVM algorithm [9] that features an importance weighting mechanism for the training instances. Using instance weights, we are able to incorporate the domain expert's knowledge for the importance of separate training instances, during model training.

The experiments were conducted on 120 individuals from 4 populations with different characteristics, such as age and gender. The experimental results show that: the proposed behaviour assessment models achieve good multiclass classification and ranking performance; and the exploitation of the instance-weighting mechanism of fuzzy SVM algorithm can lead to significant performance improvements, compared to the non-weighted, standard SVM algorithm.

II. PROPOSED APPROACH

A. Training set generation

Recorded meals from a reference population of N healthy, normal-BMI individuals with specific age and gender characteristics are used to generate the training set. A meal from each participating individual was measured using the Mandometer® plate scale.

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First, the recordings of each meal were automatically processed in order to find the food intake curve (i.e., weight of food consumed at each time during meal) and extract eating-related behaviour indicators, using the algorithms described in [7]. The feature vector $\mathbf{x}_i$ of a meal consists of 4 behaviour indicators: "Food intake deceleration", "Initial food intake rate", "Total food intake" and "Average food intake rate". Details regarding the eating-related indicators and the feature selection procedure are given in [8].

Then, a domain expert inspected the food intake curves and the extracted indicators to provide subjective scores based on his experience with OB and ED patients. The scores were given on an integer scale from -4 to $+4$ and quantify whether the meal patterns of the healthy individuals resemble pathological behaviours. More negative scores are given to meals with the higher resemblance to ED patients' behaviour; more positive scores are given to meals with higher resemblance to OB patients' behaviour; and 0 scores are given to behaviours that resemble low risk patterns.

Based on the expert scores, we assigned labels to the reference population's meals: y_i = ED for the scores in $[-4, -1]$; y_i = OB for the scores in $[+1, +4]$; and y_i = LR, indicating low risk, for the 0 scores. Note that these labels do not categorise the current health status of the individuals in the reference population (since all of them are healthy), but they denote similarity with known pathological eating behaviours.

In addition to the labels, we assigned fuzzy membership values s_i for each meal. A membership value s_i quantifies the importance of meal $\mathbf{x}_i$ is for its class y_i. To this end, we set the values of s_i as the absolute value of the expert scores when y_i is either ED or OB class; thus, $s_i \in [1, 4]$. For the meals of LR class we set $s_i = 1$, since we do not have additional knowledge regarding their class importance.

Overall, the output of the described procedure is a training set $\{(\mathbf{x}_i, y_i, s_i) | i = 1, \ldots, N\}$, which we used for training the behaviour assessment models, described next.

B. Behaviour assessment model training

We train the behaviour assessment models using the SVM algorithm [10] and an instance-weighted variation, the fuzzy SVM algorithm [9]. Next, we describe the algorithms and their adaptation for behaviour assessment model training.

SVM is a binary classification algorithm, in which a realisation of the separating hyperplane for non-separable classes is given by the following optimisation problem:

$$\min \ \frac{1}{2}\mathbf{w}^T\mathbf{w} + C^+\sum_{i=1}^{N^+}\xi_i + C^-\sum_{i=1}^{N^-}\xi_i \qquad (1)$$

$$\text{s.t.} \ \ y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1 - \xi_i, \quad i = 1, \ldots, N \qquad (2)$$

$$\xi_i \geq 0, \quad i = 1, \ldots, N \qquad (3)$$

where N^+ and N^- are the number of instances for the positive and negative class.

Due to class imbalance in our problem, we use regularisation weights C^+ and C^- per class in objective function (eq. 1). The C^+, C^- are training hyperparameters that regularise the effect of the training errors ξ_i for each class. Larger values for C^+, C^- lead to less training errors, but the separating margin between classes becomes narrower. Proper selection of the C^+, C^- values is typically performed through hyperparameter selection methods, such as K-fold cross-validation.

TABLE I

DATASETS USED FOR MODEL TRAINING AND EVALUATION

Dataset	Description	M / F	LR / ED / OB
DT1	44 meals from normal-BMI healthy adult females (age average: 22.84).	0 / 44	25 / 7 / 12
DT2	25 meals from adult males and females (age average: 30.01).	13 / 12	10 / 1 / 14
DT3	40 meals from Swedish adolescent males and females collected at a high school screening (age average: 16.67). Details in [14].	18 / 22	15 / 11 / 14
DT4	11 meals from adult females (age average: 22.8).	0 / 11	5 / 2 / 4

We train 3 pairwise binary models (i.e., ED vs OB, OB vs LR, and LR vs ED) and we construct the final behaviour assessment model using an one-vs-one (OVO) voting scheme. In our problem, the C^+, C^- of each pairwise classifier correspond to 2 out of 3 parameters from: C_{ED}, C_{OB}, C_{LR}. Finally, in order to produce rankings between new meals for ED or OB class, we use Platt scaling [11] to calculate the class probabilities and rank according to them.

In the standard SVM algorithm, all instances are considered of equal importance; however, this is not optimal for all problems. To this end, the fuzzy SVM algorithm takes advantage of the membership values, s_i, and uses them as weights that regularise each instance's contribution to the overall training error. In fuzzy SVM, the objective function becomes

$$\min \ \frac{1}{2}\mathbf{w}^T\mathbf{w} + C^+\sum_{i=1}^{N^+}s_i\xi_i + C^-\sum_{i=1}^{N^-}s_i\xi_i \qquad (4)$$

whereas the constraints (2), (3) remain the same.

In (4), a larger s_i value makes the instance $\mathbf{x}_i$ less likely to be misclassified; i.e., it becomes more likely for the training error ξ_i to be zero. Thus, the fuzzy SVM algorithm, when applied with s_i values that are larger for the more prominent training instances, can achieve a separating hyperplane with better generalisation performance than standard SVM [9].

Fuzzy SVM algorithm has been adopted by many decision support systems for biomedical applications with training instances of different importance for their class. For example, fuzzy SVM has been used for diagnosis of neuromuscular disorders [12], and for pathological brain detection [13].

In our application, larger s_i values are given to training instances with higher resemblance to pathological OB and ED patterns, which are the instances that are more important and representative for their classes.

TABLE II

CONFUSION MATRICES FOR THE **SVM** BEHAVIOUR ASSESSMENT MODEL

Predicted label

Actual label

	LR	ED	OB
LR	8	2	0
ED	0	0	1
OB	7	0	7

(a) DT2 (Accuracy = 60%)

	LR	ED	OB
LR	13	0	2
ED	3	3	5
OB	4	0	10

(b) DT3 (Accuracy = 65%)

	LR	ED	OB
LR	5	0	0
ED	0	2	0
OB	2	0	2

(c) DT4 (Accuracy = 82%)

TABLE III

CONFUSION MATRICES FOR THE **FUZZY SVM** BEHAVIOUR ASSESSMENT MODEL

Predicted label

Actual label

	LR	ED	OB
LR	9	1	0
ED	0	1	0
OB	5	0	9

(a) DT2 (Accuracy = 76%)

	LR	ED	OB
LR	13	0	2
ED	3	3	5
OB	4	0	10

(b) DT3 (Accuracy = 65%)

	LR	ED	OB
LR	5	0	0
ED	0	2	0
OB	1	0	3

(c) DT4 (Accuracy = 91%)

III. EXPERIMENTAL ANALYSIS

A. Datasets and Experimental Setup

The datasets used in the experimental analysis consist of meals from 120 individuals, collected from 4 populations with different characteristics. Each individual contributed with one meal in the datasets. The meals were annotated by a domain expert and were assigned classes and scores, using the procedure described in Section II-A. Table I describes for each dataset: the population demographics, the male/female (M/F) ratio, the age average, and the number of meals annotated as LR, ED or OB by the domain expert.

We use DT1 as the training set and the DT2, DT3, and DT4 as evaluation sets. It is worth noting that, the population characteristics of DT1 match exactly only the characteristics of population DT4 (young adult females, with same age average); they are partly similar with the characteristics of population DT2 (young adult males and females, with slightly higher age average); and are fairly dissimilar with the characteristics of population DT3 (adolescent males and females).

Ideally, we would like to train behaviour assessment models using reference populations with similar characteristics with the populations on which we apply them. Nevertheless, it is not feasible to collect data for every type of population. Thus, it is interesting to examine the robustness of the behaviour assessment models when applied on different population types.

TABLE IV

COMPARISON OF RANKING USING AVERAGE PRECISION METRIC

	OB class		**ED class**	
Dataset	**SVM**	**Fuzzy SVM**	**SVM**	**Fuzzy SVM**
DT2	0.93	0.96	0.33	0.33
DT3	0.58	0.77	0.84	0.73
DT4	1.00	1.00	1.00	1.00

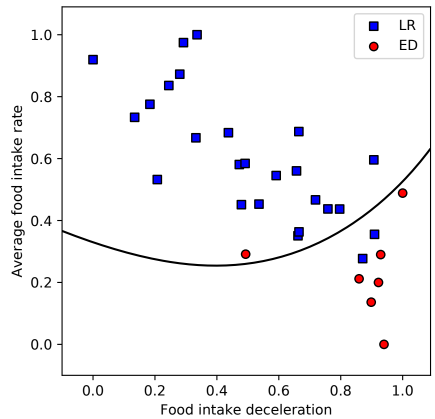
We train non-linear SVM and fuzzy SVM models with the RBF kernel. Each feature is independently rescaled in the $[0, 1]$ range before training. The optimal hyperparameters values for each algorithm are selected through a parameter selection procedure on a grid of their combinations. The C_{ED}, C_{OB}, C_{LR} receive values in $\{10^i | i = -1, \ldots, 4\}$, and the γ of RBF kernel receives values in $\{10^i | i = -2, \ldots, 2\}$. We assess the performance of each hyperparameter combination through 20 randomised repetitions of 10-fold cross-validation procedures on the training set (DT1).

B. Results

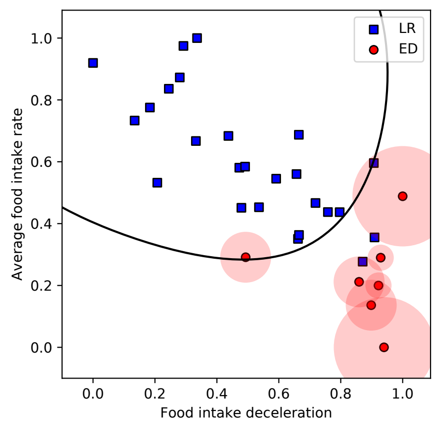
Tables II and III show the confusion matrices and the classification accuracy for each evaluation dataset, for the SVM and fuzzy SVM behaviour assessment models respectively. The more important result is that the proposed fuzzy SVM approach improves the classification performance compared to standard SVM approach. The accuracy improvement was $+27\%$ for DT2, $+11\%$ for DT4, and there was no difference for DT3.

The best classification performance of the fuzzy SVM models was observed for DT4 (91%). This can be explained by the fact that DT4 was recorded from a population with same characteristics as training set, DT1. On the other hand, the lowest classification performance was observed for DT3 (65%) which was recorded from a completely different population type. Similar performance differences between the datasets were observed in our previous work using unsupervised binary models [8].

Regarding the other classification metrics, we observe the following improvements for the fuzzy SVM approach. For DT2, the sensitivity improved: from 0.8 to 0.9 for LR (+13%), from 0.0 to 1.0 for ED, and from 0.5 to 0.64 for OB (+28%). The precision improved: from 0.53 to 0.64 for LR (+21%), from 0.0 to 0.5 for ED, and from 0.88 to 1.0 for OB (+14%). For DT4, the sensitivity improved from 0.5 to 0.75 for OB (+50%) and the precision improved from 0.71 to 0.83 for LR (+17%).



(a) SVM



(b) Fuzzy SVM

Fig. 1. The separating hyperplane of the pairwise LR vs ED classifiers, projected on two indicators. The radius of the circle markers in the bottom figure are proportional to the membership values, s_i, used for fuzzy SVM training. We observe that the existence of important ED instances near the separating hyperplane allows the fuzzy SVM model to form a stricter boundary between the two classes.

In addition, we calculated the Average Precision (AP) metric to evaluate the ranking performance of the models between each population's meals. Table IV shows the AP of the models for the OB and ED classes, for each evaluation dataset. We observe that the fuzzy SVM model achieved for OB class performance improvement of $+3\%$ in DT2 and $+33\%$ in DT3. For ED class, there was a performance decrease of -13% in DT3 — this was the only metric the fuzzy SVM approach was inferior to the standard SVM approach. Finally, it is worth noting that both models achieved perfect ranking for both classes on DT4, due to the same population characteristics with the training set DT1.

We can comprehend how the membership values, s_i, affect the decision hyperplane through visualisations. Figure 1 compares the hyperplane projections of the pairwise binary classifiers between the LR and ED classes, for the SVM and fuzzy SVM. Figure 1b uses circle markers around the instances of ED class, with radius proportional to the membership values s_i. (Markers are not used for LR instances, since it is $s_i = 1, \forall i$ such that $y_i =$ LR.) In the example, we can see that prominent ED instances (i.e., with larger s_i) are located near the boundary between the two classes. Such instances guide the fuzzy SVM algorithm to produce a stricter separating hyperplane than standard SVM in important regions of feature space.

IV. CONCLUSIONS

We introduced novel approaches for building behaviour assessment models for the eating behaviour domain. The behaviour assessment models are used for classification and ranking of recorded meals according to characteristics that resemble obesity and eating disorders patterns. The more important element of the proposed approaches is the exploitation of domain expert's scores which characterise the degree of abnormal eating behaviour for each training instance. Using these scores, we produced training error regularisation weights for the fuzzy SVM algorithm. Experiments on 120 individuals' meals from 4 populations showed that the instance-weighted fuzzy SVM approach achieved improved multiclass classification and ranking performance compared to the non-weighted, standard SVM approach.

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