An intelligent time aware food recommender system using support vector machine

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ABSTRACT

This paper formulated a support vector machine powered time-aware food recommender system (SVMTAFRS) to recommend healthy food for the customers. The rated food item incorporates the user preference (UP) in terms of calories, nutrition factor, and all food contents required for a healthy diet. This also takes into account the user age, time of day and week day while predicting the food rating. The SVMTAFRS involves two steps for computation of user identity document (UID) and predicted food rating (PFR). UID is computed considering the customer age (CA), UP in terms of calories and suitable weight factors. PFR is computed considering the UID and time of day (TOD). PFR for week end day is computed by multiplying the PFR by week end multiplying factor (WEMF). Support vector machine (SVM) is used for recommending the suitable healthy food for customer in terms of correct values of PFR. Efficacy of PFR is tested in terms of mean absolute error (MAE) and root mean squared error (RMSE). This is established that performance of the SVMTAFRS is superior compared to the rule-based food recommender system (RBFRS).

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1. INTRODUCTION

Revolution of internet technology has eased the retrieval of information. This resulted in surge of number of the users to assess the available data. This created the requirement of recommender systems to help the users to extract relevant information from large available data quickly and accurately [1]. Food recommender system (FRS) helps the users to find information of healthy foods from large sized information available in food domain. However, recommendation of food is a complex problem with specific characteristics which causes multiple challenges [2]. The recommendation of food is challenging due to multiple characteristics and availability of large number of recipes. Food and diet are complex domains, food preference is mainly person specific choice which varies from person to person, decision of what to eat and what not to eat is a complex process, influenced by multiple biological, personal, and socio-economic factors [3], [4]. These factors include taste preference, cultural background, and genetic influence [5]. Further, many ingredients are used to produce the available recipes. These have combined many methods which are exponentially increasing the complexity of food recommendation. The visual attributes for food recommendation are also becoming popular for which the systems must be able to use the information contained within more complex data formats like images or videos [6].

Techniques to develop effective FRS are under development phase and multiple FRS algorithms have been reported in literature. These methods include content-based filtering, collaborative filtering, graph-based methods and hybrid methods. A statistic of these methods reported in last five years is elaborated in Figure 1 [7].

A basic taxonomy-based study for type of FRS algorithm, user test, item typologies, item types and methods for assessment of effectiveness of an FRS is reported by Ghannadrad *et al*. [2]. This is established that most of present scientific FRS are less efficient and merely focused on dataset recommendation and software recommender system. Lin *et al.* [8] designed a fuzzy markup language (FML) based FRS for restaurants which considers the estimated calories in food, the distance of restaurant from user, and price of food to be served. This serves the delicious food to the user and also suggest the exercise to be made. Panwar *et al.* [9] presented a fuzzy inference system (FIS) based FRS which is effective to suggest the food preference with an accuracy higher than 95%. Sandri and Molinari designed preference neural nets (PNN)-based FRS method which effectively provides recommendations to customers considering their profile of requirement for ingredients of the dishes [10]. Abu-Issa *et al.* [11] presented a Multi-Type Context-Aware FRS for diabetic patients. This FRS is effective to recommend the food, drink, physical exercise, and medication. Sharma *et al*. [12] designed an FRS which is based on Collaborative Filtering and taste profile which enables the user to walk into any restaurant and order an item as per his/her taste palette. A detailed study on issues, challenges, and opportunities in FRSs is presented [13]. Malathi *et al.* [14] designed a Nearest Neighbor based Restaurant and Food Recommendation System considering the ratings. A detailed study of self-supervised learning (SSL) based FRS is presented [15]. Authors developed a comprehensive taxonomy to divide existing SSL methods into four categories which includes the contrastive, generative, predictive, and hybrid. Concept, formulation, empirical comparison, pros and cons of methods are elaborated. Haris *et al.* [16] designed an FRS which helps the Restaurant owners to offer tasty and nutritious food options to their consumers. A mobile application was developed which can be used by the different rooms, and kitchens. This includes the stages of data processing, feature selection, and model training. Forouzandeh *et al.* [17] designed a Health aware food recommender system (HFRS) using dual attention in heterogeneous graphs. This is effective for unsupervised representation learning on heterogeneous graph-structured data. Hence, it is more effective when labelled food data is scarce or unavailable. It can be used for inductive and transudative learning. Singh and Dwivedi [18] designed K-nearest neighbor’s method-based FRS which is effective to recommend food using food name, food id, cuisine type, diet type (veg. or non-veg.) using content-based filtering. Neha *et al.* [19] presented a study to explore the use of machine learning (ML) techniques for forecasting meal results using on recipe data. This is achieved by the use of available recipe data to design prediction algorithms for predicting flavor, popularity, and nutritional information. Nohria *et al.* [20] designed an FRS which is effective to group food into different categories based on calories, nutrients, price, vitamins, diseases, and other factors of foods.

In-depth review of the literature indicates that the FRS should consider all the factors such as customer age (CA), food preference (in terms of calories), time of day (TOD), and week day to recommend a suitable food rating for the customers intelligently. This is considered in this paper for the research investigations.

Following are the research contributions of this paper:

- A support vector machine powered time-aware food recommender system (SVMTAFRS) is designed which is effective for data pre-processing, feature engineering, model training, and food recommendation generation using the predicted food rating.
- Predicted food rating (PFR) is designed which considers the user identify document (UID) and time of day.
- UID is designed considering the user age and user preference (UP). UP indicates the calorie requirement.
- Root mean squared error (RMSE) and mean absolute error (MAE) indicates high efficiency of the designed SVMTAFRS.
- Performance of SVMTAFRS is superior compared to rule-based food recommender system (RBFRS).

This paper is framed in five separate sections. First section, discussed the Introduction of research work, review of literature, research gaps, research contribution and framing of paper in different sections. Second section, elaborated all the steps of proposed SVMTAFRS algorithm in detail and related mathematical formulations. This section also described the support vector machine (SVM) used for the proposed time aware food recommender system (TFRS) and mathematical formulation of SVM is discussed in detail. Discussion of simulation results related to the UID, PFR, RMSE, and MAE is included in the third section. Section four, discussed the performance comparative study of the designed SVMTAFRS with RBFRS method reported in literature. Section five, concluded the research work.

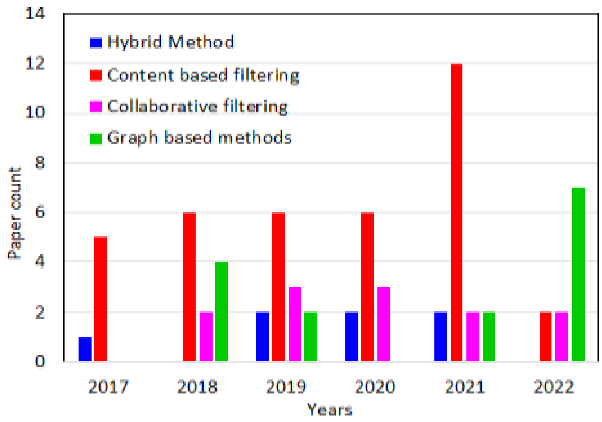

Figure 1. Statistics of FRS methods reported in five years

2. SUPPORT VECTOR MACHINE POWERED TIME-AWARE FOOD RECOMMENDER SYSTEM

Design of a SVMTAFRS includes steps such as data pre-processing, feature engineering, model training, and recommendation generation. All steps of SVMTAFRS including inputting of data, computation of UID, computation of PFR, use of SVM to identify the correctly predicted food rating, computation of RMSE, and MAE are elaborated in Figure 2. These steps are described here in detail.

2.1. Data collection

Collect a dataset that includes information about users, their food preferences, and the time of the day they consumed or rated food items. The rated food items incorporate the user preference, nutrition factors, and food contents. Food datasets have been collected from https://www.food.com for this study [21]. This data set is considered due to reason that it has large data size of different types of foods. This ensures the availability of the all-components food as well as all types of foods.

2.2. Data preprocessing

Missing data are identified and considered as per trend of the customers. The categorical features like user IDs, food items, time of day, day of the week are encoded in the numerical format. The numerical features are normalized. Complete data set is splitted into the training and testing data sets. The UIDs are used on the scale of 1 to 5. Time of the day has been considered for 24 hours starting from 0 hours to 23 hours.

$$UID = \omega_1 \times CA + \omega_2 \times UF \quad (1)$$

Here, UID: user identity document, CA: customer age; UP: user preference in terms of calorie requirement; w_1, w_2: weight factors. Weight factors have been considered after testing the method on 100 data sets of the different recipes and customers. Here, $w_1 = 1.4\times10^{-4}$, and $w_2 = 1.84\times10^{-3}$ are considered for this study. Maximum age for this study is considered as 70 years.

2.3. Feature engineering

The time-aware aspect of the food recommendation system is considered as "hour of the day". The user IDs have been considered as another feature which rates the caloric requirement for food and CA. The food rating has considered the time of day, user preferences, nutrition factors and food contents to rate a food for recommendations. For a standard diet of 2000 calories per day, the nutrients considered are included in Table 1 [22]. PFR is expressed by (2).

$$PFR = \omega_3 \times UID + \omega_4 \times TOD \quad (2)$$

Here, UID: user ID, TOD: time of day in hours; UP: user preference in terms of calorie requirement; w_3, w_4: weight factors. Weight factors have been considered after testing the method on 100 data sets of the different recipes and customers. Here, $w_3 = 0.11$ and $w_4 = 0.191$ are considered for this study. Maximum value of PFR is 4.50 when all the 125 parameters considered are maximum. An additional week end multiplying factor

(WEMF) equal to 1.2 is considered for the week end day to consider the factor that on the week end day peoples fully enjoy in free mood.

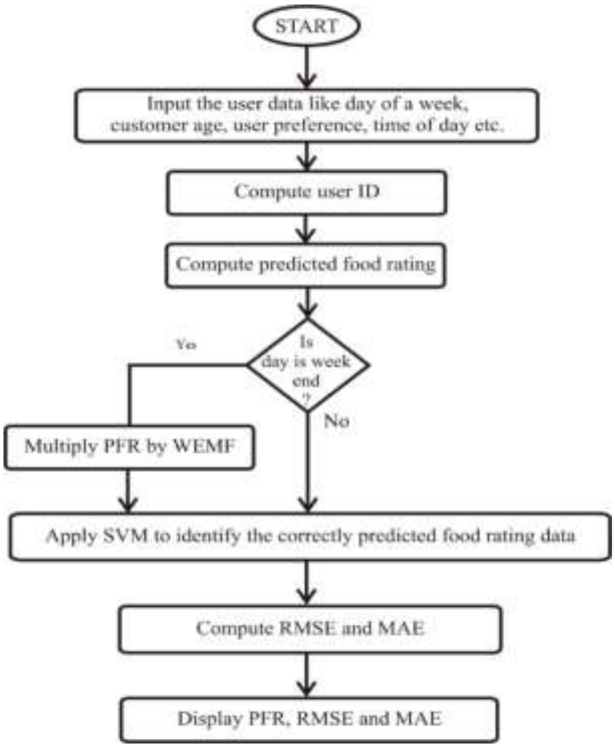

Figure 2. Algorithm of SVMTAFRS

Table 1. Nutrients of standard food diet per day

S. No.	Name of nutrient	Quantity
1	Protein	0.8 to 1.0 grams of protein per kilogram of body weight. 56 to 70 grams of protein daily for a person with weight of 70kg
2	Carbohydrates	225-325 grams
3	Fiber	25-30 grams
4	Fats	44-77 grams
5	Vitamin B12	2.4 micrograms
6	Vitamin D	15-20 micrograms
7	Iron	18 milligrams
8	Calcium	1,000-1,200 milligrams
9	Zinc	8-11 milligrams
10	Water	About 2 liters
11	Salt	5 grams

2.4. Model training

The SVM is used as a machine learning model. This is used for both regression and classification tasks. The SVM model is trained using PFR data matrix. The hyperparameters such as kernel and regularization parameters are optimized considering cross-validation. Detailed description of the SVM model used for this study is included in Section 3.4.1.

2.4.1. Support vector machine for SVMTAFRS

This section briefly describes the SVM implemented for the proposed TFRS. SVM is a classification algorithm which was coined by Vapnik in 1963 [23]. SVM uses a linear model called the maximum margin hyperplane. This hyperplane provides the greatest separation between the classes. Instances closest to the maximum-margin hyperplane are called support vectors. These support vectors singularly define maximum-margin hyperplane for learning problem [24]. A diagram illustrating the maximum-margin hyperplane, positive hyperline, and negative hyperline is depicted in Figure 3.

The hyperplane is expressed by (3) where b indicates the minimum distance of hyperplane from origin. The positive hyperplane is expressed by (4) [25].

$$\pi : \omega^T \times x + b = 0 \quad (3)$$

$$\pi^+ : \omega^T \times x + b = +1 \quad (4)$$

The negative hyperplane is expressed by (5). The positive and negative hyperplanes are called support vectors. The perpendicular distance between the positive and negative hyperlines is called margin and expressed by (6) [25].

$$\pi^- : \omega^T \times x + b = -1 \quad (5)$$

$$\text{margin} = \frac{2}{||\omega||} \quad (6)$$

Proposed SVMTAFRS has been used the following constraint optimization to find the ratings of the foods according to time of day.

$$\omega^*, b^* = argmin_{\omega,b} \frac{||\omega||}{2} + C.\frac{1}{n}\sum_{i=1}^{n} \xi_i \quad (7)$$

The (7) is satisfied provided that below condition is also satisfied where ξ_i indicates the distance away from the correct hyperline in the incorrect direction. The foods which are mis-classified have not been included in the proposed ratings and not suggested to the customers.

$$(\omega^T \times x_i + b) \geq 1 - \xi_i \ (8) \quad (8)$$

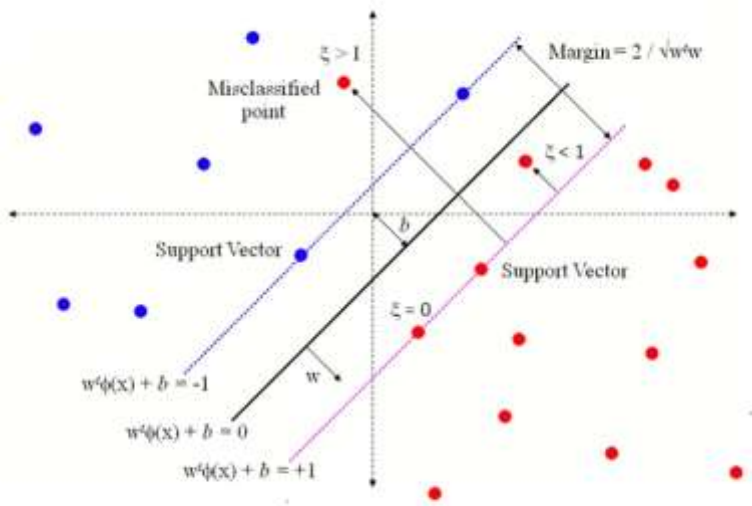

Figure 3. SVM for time aware FRS

2.5. Evaluation

The MAE and RMSE are used to evaluate the performance of SVMTAFRS for regression tasks or accuracy to rate the foods effectively and appropriately with high accuracy. RMSE is expressed by the below relation [26] where x_i is actual value of the nearest-cluster distance for i^{th} data, $x_{i\ is}$ predicated value of the nearest-cluster distance for i^{th} data, and N istotal number of data:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{I=1}^{N}(x_i - x_i')} \quad (8)$$

MAE is expressed by the below relation [26]. RMSE and MAE finds the error between actual and predicted values of the PFR. Small values of RMSE and MAE indicates that food rating has been predicted effectively and accurately as per the input data of the user.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|x_i - x_i^{'}| \tag{10}$$

2.6. Recommendation generation

The trained SVM model is used to predict the food rating for the user considering time of the day, customer age and user preference. Food items are ranked based on predicted ratings. A food item matching with the PFR is recommended for the user from available food items in the restaurant. UID and PFR are displayed in the form of numerical values.

2.7. User interface and display recommendations

First the UID is computed by inputting the UP and CA which is reflected in the range of 1 to 5. Further, a user interface is created to allow the users to input their UID and TOD to display the predicted food rating. Hence, UID takes care of customer age and UP. UID has maximum value for the middle-aged customer and minimum for children. Additional information such as the accuracy of the recommendations in terms of RMSE and MAE are also displayed.

2.8. Testing

The designed SVMTAFRS is tested on 100 data sets to ensure that it works as expected. This data set has considered the different types of foods to ensure the testing for large range food components. Hence, proposed SVMTAFRS is suitable to recommend all types of food items for the customers including children, middle age and old age customers. This can be deployed in the restaurants using a desktop or web application for end-users to access.

3. DISCUSSION OF RESULTS

This section details the results of simulation of the SVMTAFRS. Results are evaluated in two steps. First step includes the computation of UID and second step includes the computation of PFR. RMSE and MAE are also computed to test the algorithm. Hence, results related to the UID and PFR are discussed in the following two sub-sections.

3.1. Results of UID

The UID is computed using (1) considering the customer age and UP in terms of calorie requirement. Computed UID values for different combinations of CA and UP are included in Table 2. This is observed that the UID values varties in the range of 1.8407 for a child of age 5 years to 3.6845 for person aged 30 years. Maximum UID values are observed for middle aged persons with age 30-35 years. UID is lower for the old aged persons compared to middle aged persons and comparable with the children of age 10 years. The UID values included in Table 2 are used for computation of PFR.

3.2. Results of PFR

PFR is computed using (2) considering the UID values and time of day in hours. Computed PFR values for different combinations of UID and TOD are included in Table 3. The graphical user interface (GUI) used for computation of PFR is elaborated in Figure 4. The GUI interface is used to input the various combinations of UID and TOD to compute the PFR along with the values of RMSE and MAE. Computed values of RMSE and MAE are also included in Table 3.

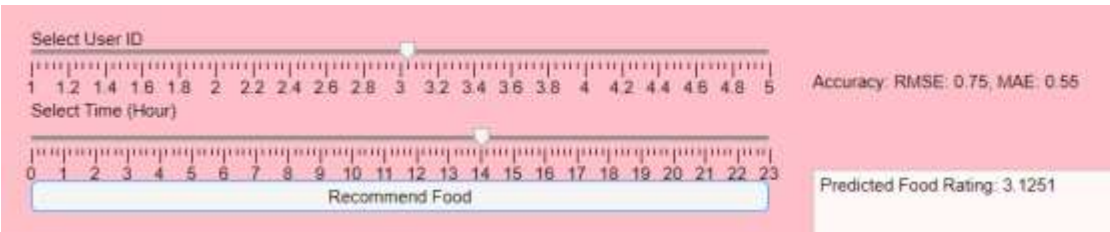

Figure 4. Input GUI interface for computation of PFR

Table 3 depicts that PFR values ranges from 1.730477 to 4.375705 depending on the input values of UID and TOD. PFR values are high for the evening time compared to values in the morning time. The PFR values for the week end day may be computed by multiplying these values by the factor of WEMF which is 1.2. These values of PFR will help the restaurant manager to serve the food as per requirement of the customer. Table 3 also depicts those average values of RMSE and MAE are 0.621 and 0.444 respectively. This established that the designed SVMTAFRS works well. RMSE equal to 0.621% indicates that the accuracy of proposed SVMTAFRS is 99.379%.

Table 2. Computation of user IDs

S. No.	Customer age	User preference	UID
1	5	1000	1.8407
2	10	1200	2.2094
3	15	1400	2.5781
4	20	1600	2.9468
5	25	1800	3.3155
6	30	2000	3.6842
7	35	1800	3.3169
8	40	1700	3.1336
9	45	1600	2.9503
10	50	1500	2.7670
11	55	1450	2.6757
12	60	1400	2.5844
13	65	1350	2.4931
14	70	1300	2.4018

Table 3. Output results of SVMTAFRS

S. No.	UID	Time of day (hour)	Predicted rating	RMSE	MAE
1	1.8407	8	1.730477	0.68	0.47
2	2.2094	13	2.726034	0.64	0.45
3	2.5781	14	2.957591	0.65	0.45
4	2.9468	20	4.144148	0.68	0.46
5	3.3155	21	4.375705	0.59	0.44
6	3.6842	8	1.933262	0.71	0.46
7	3.3169	13	2.847859	0.52	0.39
8	3.1336	14	3.018696	0.75	0.55
9	2.9503	20	4.144533	0.58	0.44
10	2.7670	21	4.31537	0.54	0.41
11	2.6757	8	1.822327	0.63	0.44
12	2.5844	13	2.767284	0.55	0.42
13	2.4931	14	2.948241	0.56	0.41
14	2.4018	20	4.084198	0.61	0.43
		Average error		0.621	0.444

4. PERFORMANCE COMPARATIVE STUDY

Performance of proposed SVMTAFRS is compared with the RBFRS reported in [27] in terms of accuracy of the FRS. Accuracy of the RBFRS reported in [27] is 96.579% whereas the proposed SVMTAFRS works with a higher accuracy of 99.379%. Hence, efficacy of designed SVMTAFRS is superior compared to the RBFRS. Performance of the SVMTAFRS is also validated by computing the precision and recall. Precision (P) is defined by (11).

$$P = \frac{TP}{TP+FP} \tag{11}$$

Here, true positive (TP) categories of the confusion matrix; false positive (FP) categories of the confusion matrix. Recall ratio (R) is defined using mathematical relation (12) where FN indicates the false negative (FN) categories of the confusion matrix.

$$R = \frac{TP}{TP+FN} \tag{12}$$

Results of SVMTAFRS and RBFRS for the Food.com data sets are included in Table 4. Table 4 depicts that SVMTAFRS has higher values of efficiency, precision and recall ratio compared to the RBFRS indicating supremacy of the SVMTAFRS.

Table 4. Performance of FRS methods

S. No.	Name of FRS method	Efficiency	Precision	Recall Ratio
1	SVMTAFRS	99.379%	0.0668	0.0632
2	RBFRS	96.579%	0.0621	0.0614

5. CONCLUSIONS

A SVMTAFRS to recommend the healthy food for the customers is formulated in this paper. The SVMTAFRS recommends the healthy food considering UID and PFR. SVM is used to train the model to recommend suitable healthy food for customer in terms of correct values of PFR. This is concluded that designed SVMTAFRS is effective to recommend healthy food to the customer considering UP in terms of calories, nutrition factor, and all food contents required for a healthy diet, time of day, and week day. Incorporation of time factor makes the SVMTAFRS more effective. This is established that proposed SVMTAFRS recommends food with an accuracy as high as 96.579%. Efficacy of the SVMTAFRS is established by computing error using RMSE and MAE. The SVMTAFRS performs better compared to the RBFRS reported in literature. Proposed SVMTAFRS can be implemented using the mobile application or the desktop computer by the Restaurant to support the customers to find the most suitable and economical recipe.

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