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ORIGINAL

A proficient recommendation system for athletes utilizing an adaptive learning model integrated with wearable IoT devices

Un sistema de recomendación competente para atletas que utiliza un modelo de aprendizaje adaptativo integrado con dispositivos IoT portátiles

Deepak .V[1], X.S. Asha Shiny[2], Vidyabharathi Dakshinamurthi[3], S. John Justin Thangaraj[4], Dinesh Kumar Anguraj[1]

[1]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation. Vaddeswaram, AP, India.
[2]Department of Information Technology, CMR Engineering College, Autonomous Institution. Hyderabad, Telengana - 501 401.
[3]Computer Science and Engineering, Sona College of Technology. Salem, India - 636005.
[4]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS). Chennai.

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Corresponding Author: Deepak .V

ABSTRACT

In the current digital context, recommendation algorithms must be used. It has found use in various contexts, including music streaming services and athletics. Athletic recommendation systems have received little study attention. Sedentary lifestyles are now the primary cause of many flaws and a significant portion of expenses. Based on user profiles, connections to other users, and histories in the current study, we create a system to suggest daily workout plans to athletes. The created recommendation system uses profiles of users and temporal processes in Adaptive Support Vector Machine (a-SVM). Additionally, compared to streaming recommendation algorithms, we cannot gather input from athletes using the wearable IoT Devices and sensors for collecting the data of exercise and workout the system is proposed, which sets them apart significantly. As a result, we suggest an active learning process that involves an expert in real. The active learner estimates the recommendation system's level of uncertainty for every user at each successive step and, finally, when it is high, gets assistance from a professional. We construct and use the marginal distance distribution of its probability function in the present research to determine whether to consult subject-matter experts. Our test findings on a real-time dataset demonstrate increased accuracy after incorporating a live and engaged learner into the search engine.

Keywords: Recommendation System; Learning Model; Prediction Accuracy; Uncertainty Model; Attention Model.

RESUMEN

En el contexto digital actual, deben utilizarse algoritmos de recomendación. Se ha utilizado en diversos contextos, como los servicios de transmisión de música y el atletismo. Los sistemas de recomendación atlética han recibido poca atención en los estudios. Los estilos de vida sedentarios son ahora la principal causa de muchos defectos y una parte importante de los gastos. Basándonos en los perfiles de los usuarios, las conexiones con otros usuarios y los historiales del estudio actual, creamos un sistema para sugerir planes de entrenamiento diario a los atletas. El sistema de recomendación creado utiliza perfiles de usuarios y procesos temporales en la máquina de vectores soporte adaptativo (a-SVM). Además, en comparación con los algoritmos de recomendación de streaming, no podemos recopilar información de los atletas que utilizan los dispositivos y sensores IoT portátiles para recopilar los datos de ejercicio y entrenamiento que se proponen en el sistema, lo que los diferencia significativamente. Como resultado, sugerimos un proceso de aprendizaje activo que involucre a un experto en tiempo real. El alumno activo estima el nivel de incertidumbre del sistema de recomendación para cada usuario en cada paso sucesivo y, finalmente, cuando es alto, obtiene ayuda de un profesional. En la presente investigación, construimos y utilizamos la distribución de distancia marginal de su función de probabilidad para determinar si se debe consultar a expertos en la materia. Los resultados de nuestras pruebas en un conjunto de datos en tiempo real demuestran una mayor precisión tras incorporar un alumno en directo y comprometido en el motor de búsqueda.

Palabras clave: Sistema de Recomendación; Modelo de Aprendizaje; Precisión de Predicción; Modelo de Incertidumbre; Modelo de Atención.

INTRODUCTION

Healthcare costs are significantly influenced by harmful behaviors, such as lack of physical activity, excessive eating, and unhealthy dietary choices.(1) Genetic factors do not account for as many fatalities as environmental and behavioral factors. It is possible to use pervasive computational, sensing, and communication technologies to assist people in leading healthier lives daily.(2) Another possible setting for implementing behavior-change strategies in large-scale economies is the pervasive usage of cell phones.(3) Commercial platforms for mobile health (mHealth) seek to offer psychological support. The Fittle+ system and other research platforms have shown how well-established behavior-change methods may be used for individual mHealth applications.(4) However, the majority of effort in the mHealth field is restricted to the creation of mobile applications and the linking of topics and specialist expertise.

However, recommendation systems are gaining popularity across a range of applications. E-commerce websites use recommendation algorithms to advise new goods to exist and potential customers to increase sales.(5) Service providers must keep consumers interested in their products in light of the rise of streaming music and video services like Spotify and Netflix, or they risk losing customers and income. As a result, these streaming service providers use recommendation systems to make the fresh movie and music suggestions to existing and new customers based on those users' prior movie and music viewing and listening habits. The development of recommendation systems for exercise activities hasn't received much attention from research studies.(6,7,8)

Here, an adaptive recommendation system that suggests physical activities to prospective users when used with the application. The method for suggesting recommendations is based on an adaptive Support Vector Machine (a-SVM) that uses attributes including profiles of users, exercise routines, and temporal attention mechanisms. The recommendation engine cannot gather user feedback, a key distinction between physical activity activities and other fields. The feedback that user click data provides to recommendation systems related to other applications is perpetual. The user can click on the recommended activities to wrap up it when a recommendation system proposes a fresh model. The suggestion engine is improved with input from data and time. Users can offer ratings in these systems, but they are not required to. Because of this, the algorithms will analyze click data, play length, etc., to evaluate whether the recommendation was accepted.

Whenever a recommendation system proposes a method to get feedback; the person using it selects to rate exercise. Otherwise, program cannot gather data since it cannot see the user.(9) To put it another way, the recommendation algorithm is unaware of whether the user performed the activity, which would indicate whether the recommendation was sound. Users were required to enter this information in some athletic apps manually. However, a significant amount of data must be included because most users must know this feedback. When a fresh user without any history is presented to the recommendation system, the issue becomes more difficult.(10) This study uses real-time method to overcome this problem. People rely on qualified personal trainers to give them training regimens based on the professional's expertise and experience. When the system is unsure, our suggested solution will take advantage of this trust by using the knowledge of experts. As a result, more people will have access to workout programs that include knowledgeable personal trainers.(11,12,13,14,15)

Our suggested network will use the marginal distance probability distribution or variance among exercise sessions with the greatest and second-greatest probabilities to evaluate the confidence in recommendation. The marginal distance's probability distribution is determined from the distribution of the final layer's probabilities to describe the degree of certainty. Although active learning has used the concept of marginal distance before, this paper is the first to illustrate the distribution of its probabilities in that context. To convey the level of certainty, the marginal distance's distribution of probabilities is derived from the recommender's last layer's distribution of probabilities. Although active learning has used marginal distance before, this paper is the first to illustrate the distribution of its probabilities in that context.

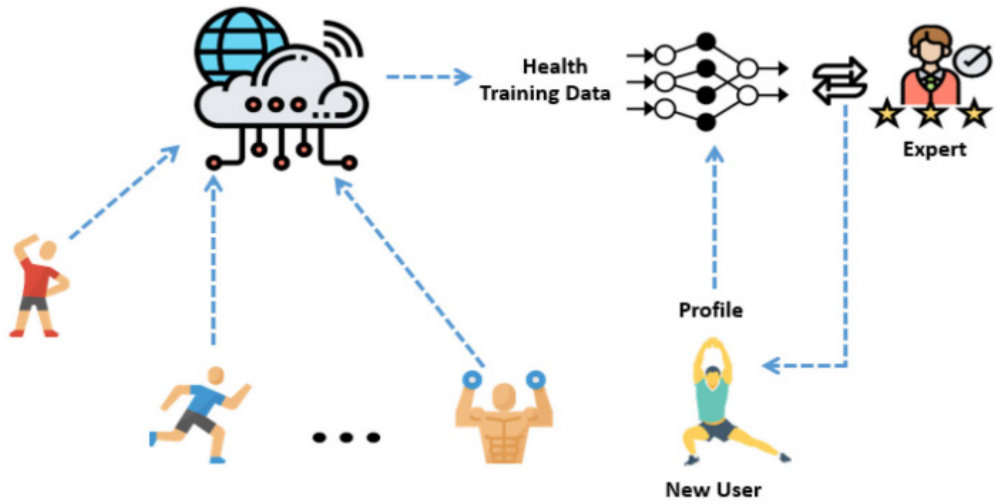

Figure 1. Generic view of the athletic recommendation system

Initializing the recommendation system for new users is another area for improvement with most recommendation systems. This problem has been the subject of much research, such as metal-learning methods. This study uses demographic data from user surveys to identify current users who share our interests and other characteristics. The history of similar users is then used to fine-tune the global recommendation algorithm. This method is easier than other ones that are already in use. The entire design of the recommendation system is depicted in figure 1.

The work is organized as follows: section 2 depicts the wider analysis of diverse approaches, and the architecture model is shown in section 3. The numerical outcomes are depicted in section 4. The work is summarized in section 5.

Related Works

Since the development of smartphones, Health systems now become prevalent in various healthcare settings. It was created by Dunsmuir et al.[16] to identify and treat the condition known as pre-eclampsia in pregnant women. The inter-pulse-interval security keys were employed for several Health applications to authenticate entities. A uniform framework for a national healthcare system for the European Union was put forth by Schiza et al.[17]. In Wei et al.[18], the transportable 7-lead ECG gadget WE-CARE was created to offer a system for continuous cardiovascular monitoring. To provide users with exercise suggestions according to their BMR, BMI, and the amount of energy expended in each activity or sport, such as cycling, working out, jogging, swimming and aerobic dance, a mHealth system was developed and implemented in Mezei et al.[19]. However, no machine learning algorithms are utilized in this work. However, recommendation algorithms have been utilized in online purchasing and e-commerce.[20]

Making recommendations for products that appeal to customer preferences is the goal of recommendation systems. Conventional RS have employed collaborative filtering to recommend products comparable to customers who purchased. Multiple studies have suggested the application of deep learning for recommendation systems in light of current developments in deep learning algorithms. Applying a multi-stack RNN framework, a recommendation system is developed in Zhao et al.[21] to propose businesses on Yelp according to user reviews. RNN with LSTM was utilized by Wu et al.[22] to forecast potential behavioral patterns. Some studies have anticipated systems for recommending exercise.[23] Sami et al.[24] collaborative strategies were utilized to promote several activities, including swimming. FitRec is an LSTM-based model Ni et al.[25] designed for analyzing a user's heartbeat profile during prospective actions and forecasting actions using that analysis. Then, 2050 workout records and related sensor measurements like heart rate, were used to test the model.

RS for customized medical decision-making in healthcare was developed by a study. The technology stores the electronic medical records of diverse patients and its medical assessments to offer clinical options to new patients. Recent research used logistic regression, SVMs and random forests to make skin-health product recommendations by customer genetic attributes. A recommendation method for planning activities hour by hour was developed in Cai et al.[26] using steps taken each day over time and customer-specific data. The model divides users into smaller groups and recommends activity according to the previous user activity comparable to theirs. The proposed method needs more time series modeling, including RNNs, to identify trends. The cold-start problem in recommendation systems has received attention in various works on a related subject.[27]

The term "cold-start problem" indicates prospective customers for whom the recommendation engine lacks access to their past data. As a result, the recommendation algorithm cannot accurately suggest products to new

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users, such as movies, music, etc. Meta-learning strategies aim to learn a global framework from every user to instantiate new recommendation systems.[28] These methods have the drawback of needing to be personalized from the start. The second strategy uses transfer learning, zero-shot, or one-shot approaches.[29] These methods give new users access to a global model developed from historical data collected from previous users. Although these methods perform quite well as classifiers, they still have issues when used as recommendation systems for data sequences. The suggested method actively learns customized training regimens for new users by leveraging specialists (human personal trainers). While many people consult trainers for advice on their daily exercise routines, the suggested approach uses the knowledge of the expert to reach a greater user base at less expensive because the experts are only required to suggest new activities at first as the system is doubtful of prospective customers.[30]

METHOD

An AI-based multi-objective data prediction model creates a recommendation system for improving athletic performance. To gather athletes' physiological data, a wearable sensor gadget is used. Based on the most recent and historical physiological data, this approach suggests motivating athletes throughout training and competition to help them perform to the best of their abilities. Information about the athlete's past and present is considered for this. A cloud computing system is used to store and analyze data. A machine learning method based on an SVM and adaptive classifier model is used to process the data. Gender, age, calorie intake, heart rate, pressure, temperature, pulse rate, breathing problems, and state of health are all considered for this study. A wearable device collects live data from participants while they are engaged in athletic activity, and feature subsets are hauled out from the dataset.

An adaptive support vector machine is used to model RS for athletes, where the feature correlations (gender, age, calorie intake, heart rate, pressure, temperature, pulse rate, breathing problems, and state of health) are examined. The kernel computation measures the hyperplanes among the feature vector (labels). The classification is based on identifying the linear measure and the radial bias function among the features. Initial normalization of the dataset is performed, and the normalized data is then fed into the adaptive SVM model. In this instance, classification is carried out, and performance indicators are assessed and contrasted with other methods. Accuracy based 23 performance indicators are assessed. Due to the suggested adaptive model's efficient feature representation, performance is improved over other approaches. Here, data from the athletes is collected and stored for later computation (dataset construction using attributes obtained from the person, whereas the benchmark dataset is reached from online resources).

Data acquisition

Here, Olympic dataset records the nation's participation where an international sports event with 1000's of athletes from diverse regions participates and competes. It is made of 15 attributes with 2, 71, 116 unique data. Table 1 depicts the attribute descriptions.

Learning

The idea of a bilinear score function has been presented. Here, $S(e_1, r, e_2) = e_1^T W_r e_2$ is a fundamental form of a bilinear score function, where with k×k dimensions, W_r is a bilinear projection matrix. Efforts were made to expand the bilinear scoring operation to increase the modeling capacity. In this study, we augment the bilinear function with constant and linear terms to improve the basic scoring function.

$$S(e_1, r, e_2) = e_1^T W_r e_2 + v_r^T e_1 + v_{r2}^T e_2 + b_r \quad (1)$$

Where the k-dimensional projection matrix to design second-order correlations among entity embedding is W_r, the models' projection vectors are related to bias entities are v_{r1} and v_{r2}, constant representing the relation bias is b_r, and k-dimensional embedding vectors specifies the entities are e_1 and e_2. To simplify the computation, we use $e_a = e \oplus 1$, which denotes inserting 1D of fixed value 1 at k-dimensional embedding vectors of e. The scoring function is given as follows which is equivalent to the following translation of equation 2 and equation 3:

$$S(e_1, r, e_2) = e_{1a}^T W_{ra} e_{2a} \quad (2)$$

$$S(e_1, r, e_2) = [e_1^T \ 1] \begin{bmatrix} W_r & v_{r1} \\ v_{r2}^T & b_r \end{bmatrix} \begin{bmatrix} e_2 \\ 1 \end{bmatrix} \quad (3)$$

This score function can be considered a condensed version and an extension of the bilinear model. The model seeks to train a bilinear score function and a ranking framework's embedding vector e for each entity. If r represents the ideal relation among e_1 and e_2, but r' is not, then W_{ra} should look for the condition that $S(e_1, r, e_2) > S(e_1, r', e_2)$. We scale the proportional bilinear score functions of r and r' to set a minimum margin between $S(e_1, r, e_2)$ and $S(e_1, r', e_2)$ and normalize the value of the margin as 1, converting the ranking function to $S(e_1, r, e_2) - S(e_1, r', e_2) > 1$. It reduces computation and stabilizes the model. As a result, the following bilinear ranking function is used to train the model:

$$e_{1a}^T(W_{ra} - W_{r'a})e_{2a} \geq 1 \quad (4)$$

We recommend max-margin term which is determined to enhance ranker's capabilities. This work translate the margin of (e_1, R, e_2) as follows, analogous to the linear SVM system:

$$\min_{(r,r')\in R*R} \frac{e_{1a}^T(W_{ra} - W_{r'a})e_{2a}}{||W_{ra} - W_{r'a}||F} \quad (5)$$

It shows the signed distance from the decision boundary to (e_1, R, e_2). We create the model by optimizing the margin and considering T reliably rated by SVM. Ranking issues are not ill-conditioned (two relations are co-occurring) where 12 show that the optimization object can be changed into simpler form within fewer computing steps as follows:

$$\min_{e,W_{ra},e\in E,r\in R} \sum ||W_{ra}||_F^2 \quad (6)$$

$$e_{1a}^T(W_{ra} - W_{r'a})e_{2a} \geq 1, (r,r') \in R * \bar{R} \quad (7)$$

Weighted loss

The SVM model must be able to rank T accurately for equation 5 to function. However, with an actual dataset T, it is seldom feasible. To generalize the issue to the assumption that the ranking loss is defined as the SVM model's inability to rank T accurately. Our objective is to create a bilinear model with a large margin that, as closely as feasible, matches the training set of data. The standard approach is to incorporate a loss term to measure the correctness of the model, for instance, the ranking result's AUC. Our approach uses the ranking loss by including the max-margin and loss terms. The entire optimization is as follows:

$$\min_{e,W_{ra},e\in E,r\in R} \sum ||W_{ra}||_F^2 + C \sum_{(e_1,R,e_2)} \frac{1}{|R||\bar{R}|} \sum_{(r,r')\in R*\bar{R}} \xi_{trr'} \quad (8)$$

$$e_{1a}^T(W_{ra} - W_{r'a})e_{2a} \geq 1 - \xi_{trr'}, \boldsymbol{\xi_{trr'}} \geq 0 \quad (9)$$

Where the hyper-parameter that balances the weights of the function's two components is represented by C, the ranking loss, in fact, weighted hinge loss where weight $1/(|R||\bar{R}|)$ is employed to emphasize ranking fault significance in diverse triplet set scales. The model contains more information on this weight. Additionally, we propose that in addition to the weights for the triplet sets' scale and the ranking losses differ in different relational pairings. The knowledge base has multiple relations between the entities that are interdependent. Relationships like "place of event" and "place of living" may be more likely to co-occur between two items. Additionally, a relationship between two things, such as "feature of" and "environment of," would rarely or never occur simultaneously. It is feasible to benefit from handling multiple pairs of relations. One can get previous knowledge of the relations because the ranking-based predictor considers the links between relations. Our approach considers that the weights of the ranking losses among various relations vary. As a result, relationship among r and r', we change C's value in equation 6 and give the ranking losses different weights. The better optimization challenge is:

$$\min_{e,W_{ra},e\in E,r\in R} \sum ||W_{ra}||_F^2 + C \sum_{(e_1,R,e_2)} \frac{1}{|R||\bar{R}|} \sum_{(r,r')\in R*\bar{R}} C_{rr'}\xi_{trr'} \quad (10)$$

$$e_{1a}^T(W_{ra} - W_{r'a})e_{2a} \geq 1 - \xi_{trr'}, \boldsymbol{\xi_{trr'}} \geq 0 \quad (11)$$

The weights are independent of the entities and depend on (r, r'). Connections between three groups are: possible, logical contradiction, and class error. Two relations connect objects from diverse classes, as the class error category shows. For instance, "nationality" specifies nation, whereas "gender" specifies "male" or "female" specifies separate entity. The two relations—such as "has part" and "part of"—cannot logically occur simultaneously because of the logical contradiction. During the training phase, the loss weights are determined to be small for any potential group, substantial for the class error category, and extremely big for the logical contradiction category. With this level, the model is less likely to make amazing mistakes and is more accurate.

Optimization issue is presented in equation 7. In adaptive SVM, the issue is frequently addressed in dual space. SVM ranking framework will generate |R||R¯| parameters for each training sample. An excessively high level of complexity could be produced by addressing optimization issue as knowledge bases frequently contain many training samples. So, to solve the issue in original space, we employ gradient descent. The initial space problem is resolved by converting equation 7 to unconstrained form:

$$\min_{e,W_{ra},e\in E,r\in R} \sum \left|\left|W_{ra}\right|\right|_F^2 + C \sum_{(e_1,R,e_2)} \frac{1}{|R||\bar{R}|} \sum_{(r,r')\in R*\bar{R}} C_{rr'}\ (0,1 - e_{1a}^T(W_{ra} - W_{r'a})e_{2a}) \quad (12)$$

The weighted sum of each sample's |R||R¯| hinge losses determines its ranking loss; it does not require sampling and only pertains to a few negative samples. It allows sub-gradient descent to solve our model. The following results are obtained if $L(e_1, e_2, r, r')$ is used to represent hinge loss of relations pair (r,r') in a triplet (e_1, R, e_2):

$$L(e_1, e_2, r, r') = \frac{1}{|R||\bar{R}|} C_{rr'} \max(0,1 - e_{1a}^T\ (W_{ra} - W_{r'a})e_{2a}) \quad (13)$$

$$e_{1a}^T(W_{ra} - W_{r'a})e_{2a} \geq 1 \quad (14)$$

$$\frac{\partial L}{\partial e_{1a}} = \frac{\partial L}{\partial e_{2a}} = \frac{\partial L}{\partial W_{ra}} = \frac{\partial L}{\partial W_{r'a}} = 0 \quad (15)$$

$$\frac{\partial L}{\partial e_{2a}} = \frac{C_{rr'}}{|R||\bar{R}|}\left(e_{1a}(W_{ra} - W_{r'a})\right)^T \quad (16)$$

By adding the max-margin component's derivatives as $2W_{ra}$ and all of the hinge losses' derivatives, we compute the derivatives of the training object. The sub-gradient descent minimizes the target by choosing an appropriate step length. The final component of e_{ia} is reset to 1 after being refreshed. The algorithm displays our framework's entire process. Instead of using the sub-gradient descent, a stochastic sub-gradient descent can solve the model. It considerably speeds up training while marginally sacrificing ranking performance, especially for large datasets. Our training architecture allows both online learning and stochastic sub-gradient descent. We first determine whether our model suits the new sample, presuming the model was previously properly trained for the past samples. When the outcomes of the right relations outperform those of the wrong ones, this data set is considered the trained sample and is refrained from updating our model. In each scenario, we run mini-batch of size b randomly selected from learned data for one round of gradient descent. The procedure of choosing mini-batch to perform gradient descent which is continued until the latest sample satisfies the requirements or the total rounds reaches pre-determined threshold value, t, if the updated model isn't compatible with the novel sample after single round. To prevent over-fitting, this termination condition makes an effort to consider the new data without significantly altering the model for any particular sample. The anticipated model performs the relation identification task and classification test. The triplet classification job involves determining whether or not a relation r between two provided items, e_1 and e_2, is accurate. Since multi-label classifiers and ranking SVM are closely linked, the score function values are extremely important for classification. The classification task is given a threshold δ_r by classifying the triplet (e_1, r, e_2) as correct if $S(e_1, r, e_2)-\delta_r > 0$. In the most recent research, δ_r is often determined by an easy classification loss, meaning that δ_r should maximize precision on a certain collection. Our system uses a linear SVM to determine the classification threshold, making the classifier more reliable and stable.

Algorithm 1: Adaptive SVM
Input: Training set T, dimension k;
Output: Vector e_i for every entity and W_r matrix for every relation
1. Set $C_{rr'}$ hyper-parameters;

2. Initialize e_i represents k- a dimensional vector;
3. Initialize W_{ra} as (k+1)*(k+1) dimensional matrix;
4. Allocate $e_{ia}=e_i \oplus 1$;
5. Re-order T into triplet set in (e_1, R, e_2)
5. While no convergence do
6. for each e_i do
7. $\partial L/(\partial e_{ia})=0$ (k+1)
8. for each W_{ra} do
9. $\partial L/(\partial W_{ra})=0$ ((k+1)*(k+1))
10. for each (e_1, R, e_2) do
11. for each r∈R do
12. for r'∈ $\bar{R}$ do
13. if $e_{1a}^{T} (W_{ra}-W_{r'a}) e_{2a} \leq 1$ then
14. $\partial L/(\partial e_{1a})= \partial L/(\partial e_{2a})= \partial L/(\partial W_{ra})= \partial L/(\partial W_{r'a})=0$;
15. $\partial L/(\partial e_{\_2a})= C\_(_{rr^{\wedge},})/|R||\bar{R}| \; (e_{1a} (W_{ra}-W_{r'a}))^{T}$;
16. for each W_{ra} do
17. $\partial L/(\partial W_{ra})= \partial L/(\partial W_{ra})+2W_{ra}$
18. Reorganize e_{ia} and W_r by gradient descent;
19. Set element as e_{ia} to 1;
20. Output: e_{ia} and W_r;

The phases in our model for the classification of the triplet are as follows: Create a training set for a binary classifier for each relation r; for each sample in this set, a triplet set (e_1, R, e_2) is allocated; the feature of the sample is given the value S(e_1, r, e_2); the label is set to 1 if r ∈ R; else set to -1; the first stage is to train ranking model using training set T; Step 2 is to create training set for binary class for every relation r. 3) Utilise the pre-built training set for δ_r to determine the threshold r using a typical SVM; 4) Compute S(e_1, r, e_2) for a test triplet (e_1, r, e_2); if S(e_1, r, e_2) >δ_r, the test triplet is thought to be accurate; if not, it is seen to be faulty. In addition, if the test triplet is thought to be correct, we apply two restrictions to reduce the false positive. The ranking restriction must be satisfied, for starters, by the relation. The other is that it should be able to connect the triplet's three components, e_1, r, and e_2.

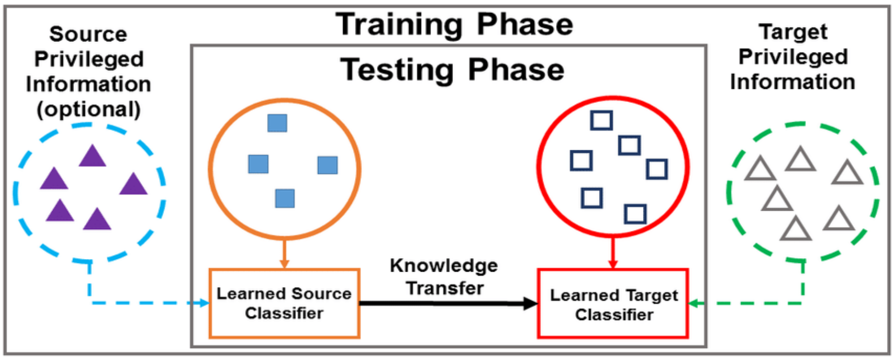

Figure 2. Adaptive SVM

RESULTS AND DISCUSSION

On the offline dataset, the anticipated techniques with various components are assessed. The dataset is used to assess the proposed architecture. Recommendation systems need more training data. Utilizing data augmentation is one method to expand the total training data. While adding noise to data or randomly cropping images can easily enhance data augmentation where significant attention is required for symbolic and sequential data, including language. Because it generates data noise which is inconsistent when compared to real data's sequential order, the random process that generates sequential data has an adverse impact.

The sequential data for exercise activities can be supplemented in one of two ways: by consulting a human expert or by using the training data's application to association mining. An exercise specialist classified a variety of workouts that had been made accessible to individuals in the first method. After analyzing the set of workouts for every participant in the workout data, the augmentation algorithm then picks 10 % of workouts and replaces them with equal activities from the same category. The second approach is to extract rules from regularly recurring item sets using association rule mining. After reviewing each participant's arrangement of exercises, the augmentation algorithms select 10 % of them and replace them by substituting identical exercises by these rules. We examined the workout sequence's autocorrelation function to determine the proper window size for the adaptive SVM model.

The time series order analysis is typically decided using auto-correlation function demonstrating the interconnectivity data degree from time series. According to the results of our study, the recommended sequence length for the adaptive SVM model is w = 3. The data processing with w = 3 produces 2343 training sample sequences. Empirically, K_u = 15, K_x = 20, K = 10 and K_e = 3 were selected for the recommended recommendation system's architecture. As a starting point, we employ the model with temporal and user profile attention mechanisms for the exercise profile. Adam optimizer and cross-entropy loss function train the model throughout 30 iterations. To evaluate the recommender's effectiveness, we employ the k-fold technique. We used data from the remaining 71 participants in our k-fold design for training; however, we did not include one of them as part of the training dataset.

The excluded person is subsequently considered a new participant and given workout recommendations by the qualified recommender. The efficacy of the recommendation algorithm is evaluated using the ground truth information from the person who was excluded. We evaluate the RS by computing the top-1, top-5, and top-10 accuracy. The experimentation is run five times and table 1 shows the top-k accuracy average. The proposed recommendation system's attention mechanism uses user demographic information in the initial testing. The accuracy is displayed in table 2. We saw a slight decrease in accuracy when we combined the attention mechanism with all the demographic information from the surveys for the second examination. We think that the majority of individuals underestimate their potential. As a result, there may be a discrepancy between what they reported on the surveys and how they executed the tasks. As an illustration, two people who give identical answers to questions (potentially inaccurate responses) may have distinct skill levels and exercise preferences. The remainder of this essay depicts user's profile using demographic data. We contrasted the baseline model to examine the impact of the network architecture using user demographic information and slightly modified. RNN module's dimension is cut to half and the size of the output module in half in the new architecture. Accuracy rankings 1 through 10 are 60,87 %, 90,55 %, and 94,71 %, respectively. The performance of the alternative architecture could be better than row 1 in table 1. The original structure suggested is chosen empirically since it performs the best for data. Two detailed methods were used to supplement the training dataset. The baseline model was assessed according to the baseline section's guidelines after it had been trained to employ the augmented and training data.

Table 1. Accuracy comparison

Method	Top-1	Top-5	Top-10
Demographic	63 %	92 %	97 %
Full profile	61 %	90 %	96 %
Data augmentation	72 %	95 %	98 %
Active learning	69 %	95,2 %	98,6 %
Data augmentation + active learning	80 %	97 %	99 %
Rule-based model	71 %	95 %	97 %
Adaptive SVM	90 %	98 %	99,5 %

Table 2. Accuracy comparison with other recommendation systems

Method	Top-1	Top-5	Top-10
GRU-4REC	78,9 %	22,7 %	40 %
Pooling	88,3 %	41 %	50 %
CNN	13 %	33 %	53 %
Mixture	54,5 %	20,4 %	40 %
Baseline model	64 %	93 %	97 %
Adaptive SVM	90 %	98 %	99,5 %

Table 3. Accuracy comparison with other recommendation systems using K

Method	Top-1	Top-5	Top-10
GRU-4REC	25 %	12 %	21,5 %
Pooling	39 %	19 %	40 %
CNN	22,6 %	11 %	20 %
Mixture	24 %	11 %	22 %
Baseline model	59 %	26 %	46 %
Adaptive SVM	90 %	98 %	99,5 %

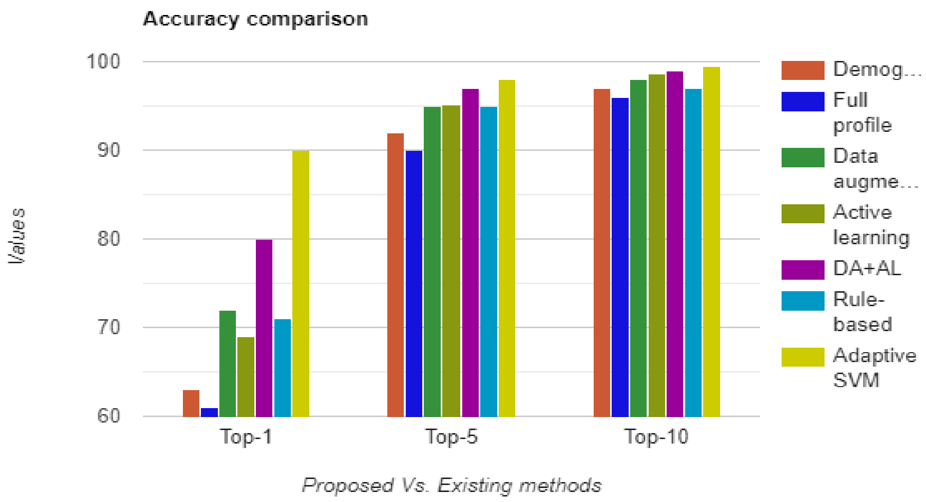

Figure 3. Accuracy comparison

The baseline model's accuracy results are displayed using training and expert-augmented data. Compared to the baseline, data augmentation increases the accuracy and broadens its application, as shown. On the other hand, whenever a baseline model is trained utilizing association rule mining techniques on the training dataset, we observe a reduction in accuracy. This statement highlights how important the need to exercise recommendation systems inform the expert. Since the augmented dataset with knowledge from experts delivers more precise results in the present study, we do additional experiments using this methodology in our assignment. Dirichlet distributions' parameters were estimated using the training data: $[y_{(N)}, y_{(N-1)}, y]^T$~D(1,5, 0,42, 0,31). The marginal distribution is quantitatively approximated, and the following outcomes of the α = 0,01-level hypothesis test are obtained:

$$\begin{cases} H_0: & z^i(t) \geq 0{,}18 \\ H_1: & z^i(t) < 0{,}18 \end{cases} \quad (17)$$

In which (z_i (t) ≥ 0,18) > 1 - α. If z_i (t) goes below 0,18 during the test, the recommender contacts the expert for feedback used to adjust the network. We are testing the suggested model using data gathered in the past; therefore, we cannot get input from the expert. As a result, whenever z_i (t) is less than 0,18 where the actual exercise is used that test subject completed at 't' time step and input it into our active learning system as expert feedback. Compared to our baseline model, the results show a 10 % improvement in top-1 accuracy. The suggestion system was adjusted with the expert's feedback to make it more accurate and personalized, which improved accuracy.

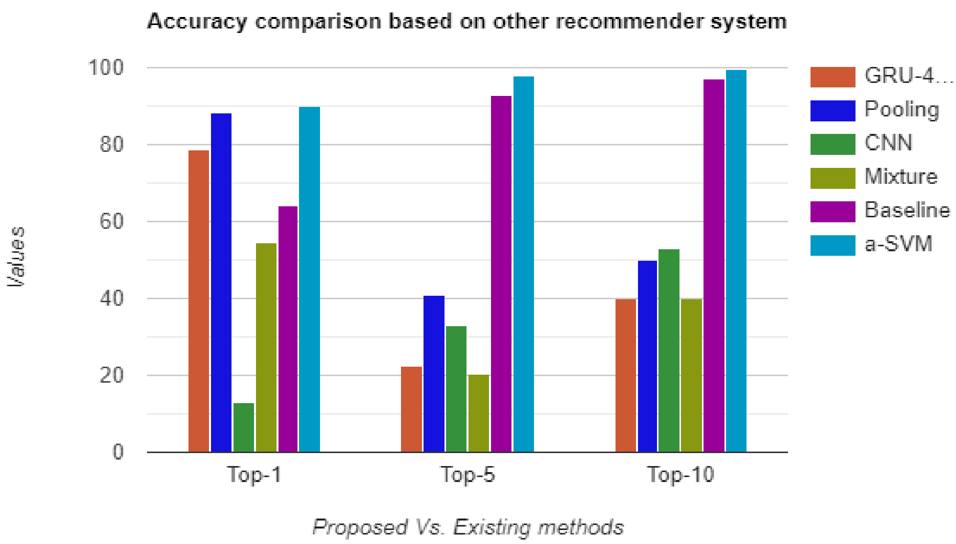

Figure 4. Comparison with another recommender system

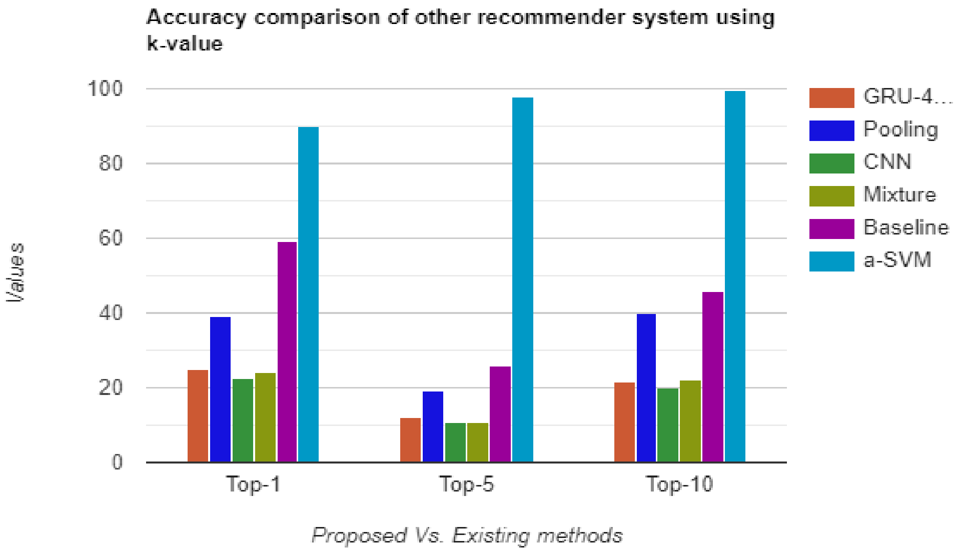

Figure 5. Comparison with other recommender systems using k-values

All individuals' pairwise similarity was calculated. We adjusted the recommendation system for every new participant, taking into account the training data of each of the three individuals who, according to their profiles, had the most in common with each additional person. The tuned network presents a recommendation system to the new user. In this research, we went further, using active learning and data augmentation to investigate the outcomes of new user activation. In table 1, we note a little improvement in top-1 accuracy. However, we think the suggested initialization technique considerably improves the accuracy for more diverse individuals, such as those from different age groups, races, and ethnicities. In this experiment, we coupled active learning and data augmentation since we thought the accuracy would increase. Results are shown in table 3. Only augmentation and active learning have shown increased accuracy, as expected. In the previous test, we integrated every module. Results are shown in table 2 and compared, which shows a very slight loss of accuracy due to the new user setup technique. More research using various surveys, medical records, etc., could boost the new user initialization method's accuracy.

A few popular sequential recommendation systems are used to compare the proposed model. The sequential models, including the suggested method, cannot be directly compared to matrix factorization techniques, such as SVM, because they propose the next item based on the history of items for each user. The factorization methods make implicit recommendations for the following item when estimating the ratings of various things. Sequential models, on the other hand, employ the historical items' chronological order to suggest the next item without anticipating user evaluations. This experiment employs user demographics from the baseline model to ensure an even comparison. The Top-k accuracy for several models is shown in table 2. The baseline model performs better than the current model in the top 1, top 5, and top 10 accuracies. CNN method performs better when compared to the recommended baseline approach in table 2. However, the suggested method performs better than the existing strategy. Compared to other iterations of the model, for instance, the baseline with active learning, the proposed baseline model performs better. Our suggested recommendation method was created especially for recommending workouts when there aren't many available (unlike movies). It is tested using the dataset to demonstrate the strength of the suggested strategy in scaling to different applications.

To do this, the dataset was pre-processed, and only the top 100 values were considered. As a result, the newly created subset of the dataset will be more relevant to the exercise activity dataset while the total elements is limited. In keeping with the dataset, we used a window length of w = 3, resulting in 29931 sequence samples divided into training and test samples. Empirically, the architecture $K_e = 3$, $K = 300$ and $K_x = K_u = 1000$ was selected for the suggested recommendation system. Table 3 lists the top-1, top-5, and top-10 recommendation systems' accuracy rankings. In the subset of the dataset, the suggested strategy outperforms cutting-edge methods for suggesting new films. The pooling approach, less accurate than the suggested baseline method, comes in second place behind the proposed method.

CONCLUSIONS

This article established a mechanism for recommending physical activity. Making recommendation systems personalized is the key challenge, especially when the training dataset is lacking for new users. Examining the experimental findings reveals the significance of user and workout profiles as attention processes. As a result, the designed system used the demographic and health surveys users completed before enrolling in the course as a vector mechanism. The experiment's findings show that perfect personalization is only feasible with the attention mechanism and its fine-tuning. While it is possible to collect constantly updated information from user interaction in electronic commerce, movie and music recommendation systems, including a professional in exercise recommendation systems is inevitable, given that we cannot determine if the user completed the exercise. Combined with one of our original recommendation algorithms, real-time active learning, the system's accuracy increased noticeably. Expert knowledge provides insight when the recommender is unsure and makes unreliable forecasts. The major research constraint is the inability to adopt various other activities related to athletic performance. However, in the future, some novel deep-learning approaches will be adopted to measure the research gaps identified in the prevailing approaches.

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AUTHORSHIP CONTRIBUTION
Data curation: Deepak .V, X.S. Asha Shiny, Vidyabharathi Dakshinamurthi, S. John Justin Thangaraj, Dinesh Kumar Anguraj.

Methodology: Deepak .V, X.S. Asha Shiny, Vidyabharathi Dakshinamurthi, S. John Justin Thangaraj, Dinesh Kumar Anguraj.

Software: Deepak .V, X.S. Asha Shiny, Vidyabharathi Dakshinamurthi, S. John Justin Thangaraj, Dinesh Kumar Anguraj.

Drafting - original draft: Deepak .V, X.S. Asha Shiny, Vidyabharathi Dakshinamurthi, S. John Justin Thangaraj, Dinesh Kumar Anguraj.

Writing - proofreading and editing: Deepak .V, X.S. Asha Shiny, Vidyabharathi Dakshinamurthi, S. John Justin Thangaraj, Dinesh Kumar Anguraj.