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Article

Applying RNN-Based Technology to Construct A Recommendation Mechanism for Fitness Venues

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Abstract: This research is focused on developing an Android-based system that leverages RNN and deep learning technologies to deliver personalized gym recommendations. By analyzing user preferences, the system employs deep learning algorithms to make precise predictions and suggest the most appropriate fitness venues. Integrated with GPS location tracking, the system provides real-time, location-specific recommendations, enhancing the accuracy and user experience of these suggestions. The study uses web scraping techniques to gather data on gyms from publicly available Taiwanese government resources, creating a comprehensive database with detailed information including location, types of services, equipment, user ratings, and accessibility features. The system is anticipated to make three significant contributions: (1) improving personalized user experiences by allowing swift venue filtering based on user preferences, thus enhancing convenience and satisfaction; (2) creating a complete fitness venue database that supports diverse decision-making and query needs; (3) boosting the interpretability and accuracy of the prediction model by examining how different features affect the prediction process, providing transparency into the model's function and performance. This platform is designed to streamline the selection process for fitness venues, and provide an innovative digital solution for the fitness industry, further promoting the widespread accessibility and convenience of a healthy lifestyle.

Keywords: Fitness venues, Wellness management, Recommendation mechanism, Recurrent neural network

1. Introduction

As COVID-19 restrictions have been gradually lifted, the Taiwanese public has increasingly prioritized maintaining a healthy lifestyle, and exercise has become a crucial part of daily routines for many. By 2023, data from Taiwan's Fitness Venue Information Network indicated that 1,381 fitness venues were registered across the island, encompassing a total of 1,814 fitness facilities (Taiwan Sports Administration, 2023a). According to the Research and Markets (2023), the global fitness club industry saw consistent growth from 2013 to 2019, largely driven by the rising number of people joining fitness clubs. However, the global fitness industry suffered a significant downturn in 2020 due to the COVID-19 pandemic. With the gradual easing of the pandemic and the widespread rollout of vaccines, the industry began to recover in 2021. Projections suggest that the global fitness club market will grow at a compound annual rate of 7.67% between 2023 and 2030, reaching a market value of USD 169.7 billion by 2030, indicating the immense potential of the global fitness industry. Although a wealth of information on fitness venues is available online, it is scattered across different platforms, varies in quality, and lacks systems that offer recommendations based on individual preferences. This has led to widespread challenges among Taiwanese consumers when selecting fitness venues. As a result, they often need to spend considerable time and energy sifting through information, which complicates their decision-making process. To solve the issues of fragmented fitness venue information and the absence of personalized recommendations, this study aims to leverage Recurrent Neural Network (RNN) technology from deep learning to develop an integrated, intelligent, objective, and efficient fitness venue recommendation system. This system will improve the service quality and user experience in the fitness industry by helping users quickly and accurately find venues that suit their needs, reducing decision-making time, enhancing overall user satisfaction, and driving further growth in the fitness industry.

This research focuses on creating a recommendation system utilizing Recurrent Neural Networks (RNN) to build a personalized platform for fitness centers using deep learning methods. The system will compile user feedback and other relevant data to provide custom recommendations that match individual user preferences. Additionally, the project will integrate a real-time search function for fitness centers and related services, allowing users to quickly find suitable venues based on their location and specific needs. The objective is to simplify the decision-making process for users, boost their confidence in their choices, and improve overall customer satisfaction and experience. By harnessing cutting-edge technology, this research aims to optimize the way users discover and select fitness services, contributing to the development of the fitness industry.

2. Literature Review

This section will thoroughly examine the relevant literature from multiple angles. First, it will provide a detailed analysis of the current landscape of Taiwan's fitness industry. Next, it will explore the factors influencing the public's choice of fitness venues, aiming to understand the key considerations individuals take into account when selecting these locations.Finally, this section will offer an in-depth discussion on the architecture of recurrent neural Networks.

2.1. The Current Landscape of Taiwan's Fitness Industry

In recent years, fitness venues in Taiwan have increasingly become key locations for the public to pursue a healthy lifestyle. Whether for muscle building, weight loss, maintaining health, or joining the national fitness trend, more people are choosing fitness venues for their workouts. According to Taiwan Sports Administration (2023b) reports, from 2013 to 2023, the participation rate in physical activities among Taiwanese has surpassed 80%, highlighting the growing societal emphasis on health and fitness. Fitness venues have become a crucial choice for individuals of all ages in modern Taiwanese society to achieve physical and mental well-being. This trend not only raises public health awareness but also drives the growth of the fitness industry, illustrating the widespread adoption of a healthy lifestyle and the social integration of fitness and exercise.

According to Taiwan Sports Administration (2024) reports, the number of profit-making businesses in Taiwan's sports service industry grew from 2,280 in 2018 to 3,916 in 2023, with an average annual growth rate of 14.5%. Despite a decline in sales revenue to 28.65 billion NTD in 2021 due to the pandemic, sales rebounded to 36.86 billion NTD in 2022 as the pandemic subsided, reaching a five-year high and representing a 28.6% increase from the previous year. As awareness of fitness and health continues to rise, self-monitoring has emerged as a significant trend. According to a survey by Taiwan Sports Administration (2020), 34.5% of respondents use information devices to record exercise data and search for related information, with 37.4% being men and 32.7% being women. This shows that people are increasingly using information devices as tools to support their fitness activities and are keeping pace with technological advancements. For fitness venue operators, it is crucial to provide excellent service experiences, integrate comprehensive venue information, and utilize technology to assist in operations. In the era of rapid technological progress, integrating all functionalities to enhance overall operational efficiency and member satisfaction is becoming especially important.

In conclusion, the growth of fitness venues in Taiwan and the shifts in consumer behavior illustrate not only the inherent resilience and potential of the fitness industry but also the significant influence of changes in social structure and cultural perceptions on market dynamics.

2.2. Factors Influencing Public Choice of Fitness Venues

In today's fast-paced society, the decision-making process for users selecting fitness venues has become more intricate. Recent studies indicate that this choice is shaped not only by personal preferences but also by a myriad of factors. Users take into account the basic information about the fitness venues, the quality and convenience of services, the range of services offered, and the specific features of the fitness venues. These considerations can be divided into the following key points:

2.2.1. Fundamental Information of Fitness Venues

The presence of a coach is a key factor when selecting fitness venues, as coaches are vital in offering effective fitness guidance and motivation. Sampaio et al. (2020) confirms that coaches play a multifaceted role in fitness behavior, encompassing technical guidance, motivational support, and behavior management. This demonstrates that fitness venues with professional coaches are more capable of meeting members' needs, enhancing both the effectiveness and sustainability of their fitness routines. Furthermore, the number of rest days is a significant factor when selecting fitness venues, as it directly impacts the convenience and frequency of use for members. As highlighted in MacIntosh and Doherty (2007), the service environment is crucial in the fitness industry, particularly the operating hours and accessibility of the venues, which are key to attracting and retaining members. Fitness venues with fewer rest days and flexible operating hours contribute to higher member satisfaction and sustained participation. Moreover, the presence of fees is a crucial decision criterion, as the cost directly influences members' choices. Piotrowski & Piotrowska (2021) defined the fee structure and membership costs of fitness venues are key factors. The study found that a reasonable fee structure can attract more members, thereby assisting fitness venues in maintaining operations during challenging times.

2.2.2. Quality of Service and Convenience

When selecting fitness venues, reviews from other users serve as a crucial decision-making criterion, offering valuable insights into the service quality and member satisfaction of the venues. According to study Dewi et al. (2020), review data can significantly impact the decision-making process. These reviews aid potential members in understanding the strengths and weaknesses of fitness venues, allowing them to make more informed decisions. Transportation convenience, including access to public transport and the availability of free parking, is also a key criterion in users' decision-making process. Jiang et al. (2023) indicates that the spatial distribution characteristics of public fitness venues show that the accessibility of a venue significantly impacts users' choices. Convenient transportation options and free parking facilities not only increase the attractiveness of fitness venues but also encourage more people to engage in fitness activities, thereby enhancing overall public health.

2.2.3. The Range of Services Offered by Fitness Venues

Offering professional training programs is also a key factor in decision-making, as these programs can significantly enhance members' service experience and satisfaction. Baena-Arroyo et al. (2020) analyzed the effects of service experience and convenience on consumer loyalty and found that professional training programs greatly increase members' loyalty. Fitness venues that provide high-quality training programs can attract and retain more members, thereby boosting overall satisfaction. Moreover, the provision of professional equipment is a key decision-making criterion, as such equipment can improve the effectiveness and safety of training. According to study Gray et al. (2015), the equipment, physical environment, and training practices in fitness facilities significantly impact customer safety. Fitness venues equipped with professional and well-maintained equipment are more successful in attracting and retaining members, ensuring they achieve their fitness goals in a safe and effective environment.

2.2.4. For sufficient accessible facilities

When selecting fitness venues, the availability of accessible facilities is also a crucial factor. Referring to the research Rimmer et al. (2005), many fitness venues have insufficient accessible facilities, creating obstacles for individuals with special needs to engage in fitness activities. The accessibility of these facilities not only impacts their fitness experience but also affects their health and quality of life. Consequently, fitness venues equipped with comprehensive accessible facilities are better positioned to attract and accommodate members with diverse needs. The size of the fitness venue is also a crucial decision-making factor, along with the available space and the fitness experience of members. According to research Bladh (2022), the spatial scale and layout of fitness venues significantly impact members' inclusiveness and comfort. Larger fitness venues typically offer a wider variety of facilities and more spacious environments, thus improving the overall fitness experience and satisfaction of members. Finally, the occurrence of adverse events is a significant decision-making criterion, as safety and risk management are vital for the health and trust of members. Zhu (2023) pointed out that members consider the safety records and risk management practices of fitness venues when making their choice, ensuring their fitness experience is both safe and worry-free.

Based on the aforementioned research, essential factors when choosing fitness venues include basic information such as the availability of coaches, rest days, and costs. Service quality and convenience aspects, such as reviews, transportation, and free parking, also impact the decision-making process. In the scope of services, the diversity and quality of classes and professional equipment are crucial considerations. Venue characteristics, including accessibility facilities, size, and the record of adverse events, are equally important criteria for members when selecting fitness venues.

2.3. Recurrent Neural Networks

Recurrent Neural Networks are deep learning models specifically designed to process sequential data, with their unique ability to leverage past information to predict future events. The theoretical foundation of Recurrent Neural Networks was established by Hopfield (1982). The training process involves two key stages: forward propagation and backward propagation. During forward propagation, data is processed sequentially to compute outputs, while backward propagation involves error backpropagation and parameter optimization (Vlachas et al. 2020). Although Recurrent Neural Networks show great potential in handling time series data, they encounter challenges with vanishing and exploding gradients when dealing with long-term dependencies. These issues significantly restrict their performance and stability (Alameen 2022). To address these challenges, researchers developed two enhanced models: Long Short-Term Memory and Gated Recurrent Unit. Long Short-Term Memory introduces three gating mechanisms—forget gate, input gate, and output gate—to effectively control information flow, mitigating gradient problems and capturing long-term dependencies (Shewalkar, Nyavanandi, & Ludwig 2019). Gated Recurrent Unit, on the other hand, simplifies the gating mechanism by retaining only the reset and update gates, reducing computational complexity, accelerating training, and often achieving performance comparable to Long Short-Term Memory in various applications (Astawa, Pradnyana, & Suwintana 2022).

Recurrent Neural Networks offer significant advantages in recommendation systems. This article examines their ability to provide precise recommendations by integrating online reviews with geographic location services. First, Recurrent Neural Networks can capture dynamic changes in time-series data, adapting to the temporal variations in user needs and preferences (Wang, Wang, & Lv 2019). Moreover, by analyzing users' historical behaviors and interactions, Recurrent Neural Networks achieve personalized recommendations, thus enhancing the relevance and user satisfaction of the recommendations (Yang et al. 2019). The learning capabilities of Recurrent Neural Networks enable them to extract valuable patterns from complex data, thereby improving the accuracy and efficiency of recommendation systems (Mozaffar et al. 2018).

When delving deeper into the applications of Recurrent Neural Networks (RNN), it is important to also consider the challenges and limitations that arise in practical implementation. While RNN exhibit powerful capabilities in processing sequential data, their use on large-scale datasets is often constrained by high computational resource demands and extended training durations. Moreover, as the dataset size increases, the complexity of the RNN model escalates, potentially leading to overfitting issues (Alsharef et al. 2022). To tackle these challenges, researchers have developed various optimization strategies, such as incorporating regularization techniques to mitigate overfitting risks and leveraging distributed computing to expedite the training process (Kratzert et al. 2019). These advancements not only improve the stability and efficiency of RNN models but also establish a foundation for their broader application in real-world scenarios. In conclusion, although RNN offer unmatched advantages in handling time-series data, unlocking their full potential requires addressing challenges related to computational demands and model complexity, as well as integrating more advanced optimization methods to enhance overall performance.

In summary, Recurrent Neural Networks have been extensively validated as an effective tool in the field of recommendation systems. However, traditional Recurrent Neural Networks face limitations when handling long-term dependencies. To overcome these challenges, researchers have introduced Long Short-Term Memory and Gated Recurrent Unit, which significantly mitigate the issues of vanishing gradients and exploding gradients, thereby greatly improving the performance of models in processing sequential data.

3. Research Methodology

This study aims to design and develop a comprehensive fitness venues recommendation system, enabling users to efficiently select the most suitable fitness venues. The system seeks to improve both convenience and geographic suitability, and will establish optimal processes and recommendation mechanisms to achieve these objectives.

3.1. System structure

This study developed a recommendation system for fitness venues by utilizing a combination of modern technologies. The development began with Python-based web crawlers designed to automatically gather information from various online sources, including venue addresses, user reviews, and geographic coordinates. These crawlers were built to efficiently collect large amounts of data, ensuring that the information was both comprehensive and up-to-date. The collected data was stored in a MySQL database, chosen for its reliability and scalability. This database was structured to handle extensive data retrieval operations, which is crucial for the system's real-time recommendation processes. The core of the recommendation system is based on Recurrent Neural Networks (RNNs), which are well-suited for analyzing sequential data such as user interactions over time. The RNN models were implemented using TensorFlow, a widely used machine learning framework that supports the development of complex neural network architectures. These models were trained to analyze user behavior and preferences, enabling the system to generate personalized recommendations. For the front-end, a mobile application was developed using Android Studio. This platform was selected due to its comprehensive development tools and support for Android devices. The application was designed to provide an intuitive interface, allowing users to easily search for nearby fitness venues, access detailed information, and receive tailored recommendations. The back-end of the system was developed using cloud-based infrastructure to manage the computational demands of the RNN models and data processing. The back-end system includes API interfaces for communication between the mobile App, the database, and the recommendation engine. Node.js was used for its efficiency in handling asynchronous operations, while Django was used for managing database interactions and implementing the system's logic. As illustrated in Fig. 1, the system's architecture integrates these components to deliver accurate and personalized recommendations in real time. The system is designed to continually improve its recommendations by adapting to user behavior over time, enhancing the overall user experience.

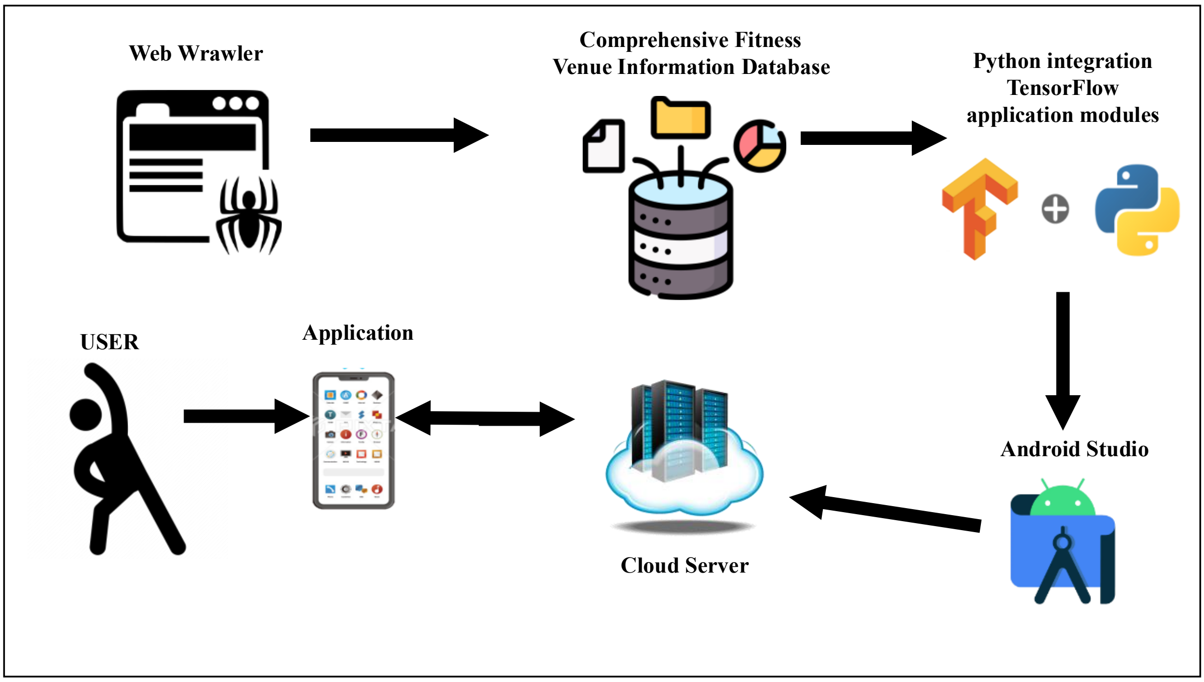

Fig. 1. System architecture.

3.2. System Process

This study undertakes the comprehensive task of collecting, integrating, and analyzing information related to fitness venues across Taiwan. The data collection process involves aggregating basic details and user-generated reviews from various online forums and rating systems. This multi-source approach ensures that the data gathered is both comprehensive and representative of the broader fitness landscape. The integration of these diverse data sources is critical to constructing a dataset that not only captures the fundamental characteristics of each fitness venue but also reflects the opinions and experiences of users, thereby providing a nuanced view of the available options. Once the data is compiled, the system employs advanced deep learning techniques, specifically Recurrent Neural Networks (RNNs), to process and analyze user preferences. The user preferences are transformed into mathematical vectors through a series of computational steps, allowing the system to quantify and compare the similarities between different fitness venues. This vectorization process is essential for the recommendation algorithm, as it enables the system to identify patterns and correlations within the data that may not be immediately apparent through traditional analytical methods. In addition to the preference analysis, the system incorporates GPS positioning technology to enhance the relevance of the recommendations. By determining the user's real-time geographic location, the system can perform a proximity comparison between the user's coordinates and those of nearby fitness venues. This feature is particularly valuable in filtering and prioritizing venues based on their physical proximity to the user, ensuring that the recommendations are not only aligned with user preferences but also practical in terms of accessibility. The final output of the recommendation process is visually represented on an interactive map. This map-based interface allows users to intuitively explore the recommended fitness venues, providing a clear visual context for each venue's location relative to the user. The map also integrates user reviews and preference similarity scores, offering a multi-dimensional view of each option. This combination of visual and data-driven elements facilitates an informed decision-making process, enabling users to select fitness venues that best meet their needs based on both subjective preferences and objective proximity. The entire recommendation process, from data collection to the final presentation, is illustrated in Fig. 2, which depicts the flow of information and the integration of various technological components. This structured approach ensures that the system is not only comprehensive in its data handling but also user-centric in its final output, providing a seamless and efficient tool for fitness venue selection.

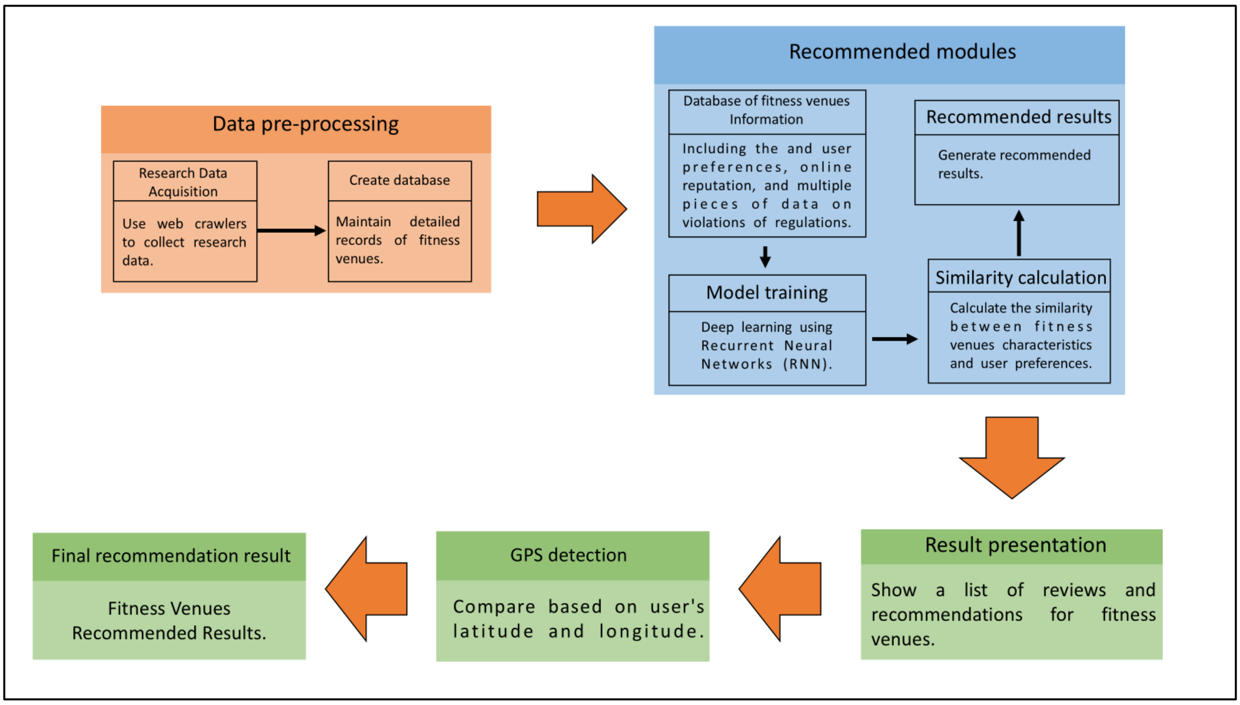

Fig. 2. Recurrent Neural Networks recommendation process.

3.3. Training Methods for Recurrent Neural Networks Models

This study employs a user scenario dataset containing 3,000 individual usage records to train and evaluate the performance of the recommendation model. The dataset was constructed using data generation algorithms developed by Iftikhar et al. (2018), which enabled the augmentation of the initial case data. These algorithms simulate the periodic variations typically observed in real-world settings, allowing the model to capture the dynamic nature of user behavior. By leveraging a limited set of real-world case data, these algorithms successfully generated additional synthetic records that reflect the variability of user interactions with fitness venues over time. This approach ensures that the dataset is comprehensive enough to train the model effectively, despite the inherent limitations in the availability of real-world usage data. The dataset comprises a wide range of variables, documenting essential aspects of fitness venues. These variables include basic information such as the presence of a coach, the number of rest days per week, and whether membership fees are required. Such fundamental data provide an important foundation for the recommendation system, as these factors are often primary considerations for users when selecting a fitness venue. In addition to basic information, the dataset captures detailed information about service quality and convenience, both of which are crucial for assessing the overall user experience. Variables in this category include user-generated ratings, transportation options, and the availability of free parking, all of which play a significant role in determining the attractiveness of a fitness venue. For instance, venues with higher ratings and more convenient transportation options are likely to attract more users, while the availability of free parking can further enhance user satisfaction. The scope of services offered by each venue is another critical component of the dataset. This category includes the diversity and quality of fitness courses, the availability of professional training programs, and the presence of specialized equipment. These variables provide insight into the range of activities and resources available at each venue, allowing the system to recommend venues that align with the specific fitness goals and preferences of users. Furthermore, the dataset documents the physical characteristics of each venue, including accessibility features for individuals with disabilities, the size of the venue, and records of any adverse incidents. Accessibility is particularly important for users with special needs, as venues with comprehensive facilities ensure an inclusive environment. Similarly, venue size can influence the comfort and experience of users, with larger venues generally offering more space and a greater variety of equipment. Incident records, such as violations or safety-related issues, are also tracked, providing an additional layer of safety assurance for users. This comprehensive dataset not only supports the analysis and prediction of service quality and customer satisfaction but also serves as the basis for the model's recommendation process. By computing user preferences based on historical interactions, the model is able to generate personalized recommendations tailored to each user's specific needs and behaviors. The system also cross-references these user preferences with a database of 8,565 fitness venues located across Taiwan. This large-scale venue database includes a wealth of information, allowing the model to provide highly relevant recommendations by combining user preferences with real-time geographical data. Specifically, the user's current location is used to identify nearby venues, ensuring that the recommendations are not only personalized but also practical in terms of accessibility and convenience. The integration of this rich dataset into the model allows for a nuanced analysis of user preferences and venue characteristics, resulting in a recommendation system that is both user-centric and data-driven. This structured approach enhances the model's ability to accurately predict user satisfaction and provide relevant suggestions, thereby improving the overall user experience in selecting fitness venues (Table 1).

Table 1. Types of data used for model training.

Variable	Type	Directions
Coaching	0-1	One-hot coding is performed on whether coaching is provided, 0 means no, 1 means yes.
Rest Days	1-3	Classified by the number of rest days, 1 is few (less than 1 day), 2 is moderate (2-3 days), and 3 is many (more than 3 days).
Fees	0-1	One-hot coding is performed on whether fees are required, 0 means no, 1 means yes.
Reviews	0-5	If it is above 3.5, it means that the evaluation is good and it is recommended first; if it is below 3.5, it means that the evaluation is poor and it is not recommended first.
Transport	1-3	Classified by number type, 1 is inconvenient, 2 is ordinary, and 3 is convenient.
Parking	0-1	One-hot coding is performed on whether parking is provided, 0 means no, 1 means yes.
Courses	1-3	Courses are classified by number: 1 for few (less than 3 classes), 2 for moderate (3-5 classes), and 3 for many (more than 5 classes).
Equipment	0-1	One-hot coding is performed on whether professional equipment is provided, 0 means no, 1 means yes.
Accessibility	0-1	One-hot coding is performed on whether barrier-free access is provided, 0 means no, 1 means yes.
Size	1-3	Classified by number type, 1 is small amount, 2 is medium, and 3 is large amount.
Incidents	0-1	One-hot coding is performed on whether a violation event has occurred, 0 means no, and 1 means yes.

$$h_t = o_t *\tanh(c_{t-1}*f_t + i_t*\tanh(W_c x_t + U_c h_{t-1} + b_c)) \quad (1)$$

In this study, Equation (1), a fundamental component of Recurrent Neural Networks (RNN), is adapted and reformulated based on the research presented in Cui et al. (2018), specifically describing the update mechanism in Long Short-Term Memory (LSTM) networks. The variables involved in this equation are defined as follows: h_t represents the hidden state at the current time step t, while ot denotes the activation value of the output gate. The variable c_{t-1} corresponds to the memory cell state from the previous time step t-1, and f_t signifies the activation value of the forget gate. Similarly, it represents the activation value of the input gate. The weight matrices, W_c and U_c, are associated with the input and hidden states, respectively. The input at the current time step is denoted by x_t, and h_{t-1} refers to the hidden state from the previous time step. The bias term is represented by b_c.

Together, these variables define the dynamics of the hidden state h_t, which is essential for capturing sequential dependencies in the input data. The LSTM mechanism enables the model to manage long-term dependencies by controlling the flow of information through the input, forget, and output gates. This gating mechanism effectively mitigates issues related to vanishing and exploding gradients, thereby facilitating robust sequential data modeling. By adjusting these gate values at each time step, the LSTM network can selectively retain or discard information, which is crucial for accurate prediction in time-series data. This process underpins the RNN's ability to model complex temporal patterns effectively.

As illustrated in Fig. 3, this study employed Python in conjunction with the TensorFlow framework as the primary tools for the development and implementation of the predictive model. The dataset was methodically divided into training and validation sets using a 7:3 ratio, ensuring that the model had a sufficient amount of data to learn from while maintaining a separate subset for evaluating its performance. Specifically, the dataset was partitioned into 2,100 training entries and 900 validation entries, which provided a balanced approach to both training the model and testing its generalization capabilities. In the initial phase of the research process, the primary focus was on data standardization and preprocessing. This step involved the use of specialized functions to clean and normalize the raw data, ensuring that it was suitable for input into the neural network. Standardization is critical in neural network training as it ensures that the data is scaled appropriately, preventing issues such as vanishing or exploding gradients during training. This preprocessing stage also involved handling any missing values, encoding categorical variables, and ensuring that all data was in a format compatible with the TensorFlow framework. Subsequently, the study moved into the model setup phase, where the architecture of the Long Short-Term Memory (LSTM) network was defined. The LSTM model was chosen due to its effectiveness in handling sequential data and its ability to capture long-term dependencies, which are common in time-series data. The model was configured with 256 units in the LSTM layer, which were connected to a dense output layer. This configuration was selected based on its proven ability to manage the complexities of time-series forecasting, particularly in situations where data dependencies span over extended periods. To optimize the training process, the study utilized the Adam optimizer (Kingma & Ba 2014), a widely recognized optimization algorithm known for its efficiency in handling sparse gradients and its robustness in adjusting learning rates dynamically. The loss function employed was Mean Squared Error (MSE), which is commonly used in regression tasks to measure the average of the squares of the errors between predicted and actual values. Gradient clipping techniques were also applied during the training process to prevent the occurrence of gradient explosion, a problem that can lead to unstable training and poor model performance. To further refine the model and enhance its predictive accuracy, a feature importance evaluation was conducted. This involved systematically perturbing individual features in the validation set and observing the corresponding changes in the model's output. By analyzing these perturbations, the study was able to determine the relative importance of each feature in contributing to the model's predictions. This analysis provided valuable insights into the weight distribution of different user behavior patterns, allowing for a more nuanced understanding of the factors driving the model's decisions.

Finally, the model's performance was rigorously evaluated by comparing the predicted values against the actual values from the validation set. The accuracy of the model's predictions was assessed using metrics such as the ratio of the difference between predicted and actual values. This evaluation not only confirmed the model's ability to effectively forecast time-series data but also highlighted areas where the model could be further improved. The overall findings demonstrated that the LSTM model, with its carefully tuned parameters and optimized training process, was capable of delivering accurate and reliable predictions, making it a suitable choice for the intended application.

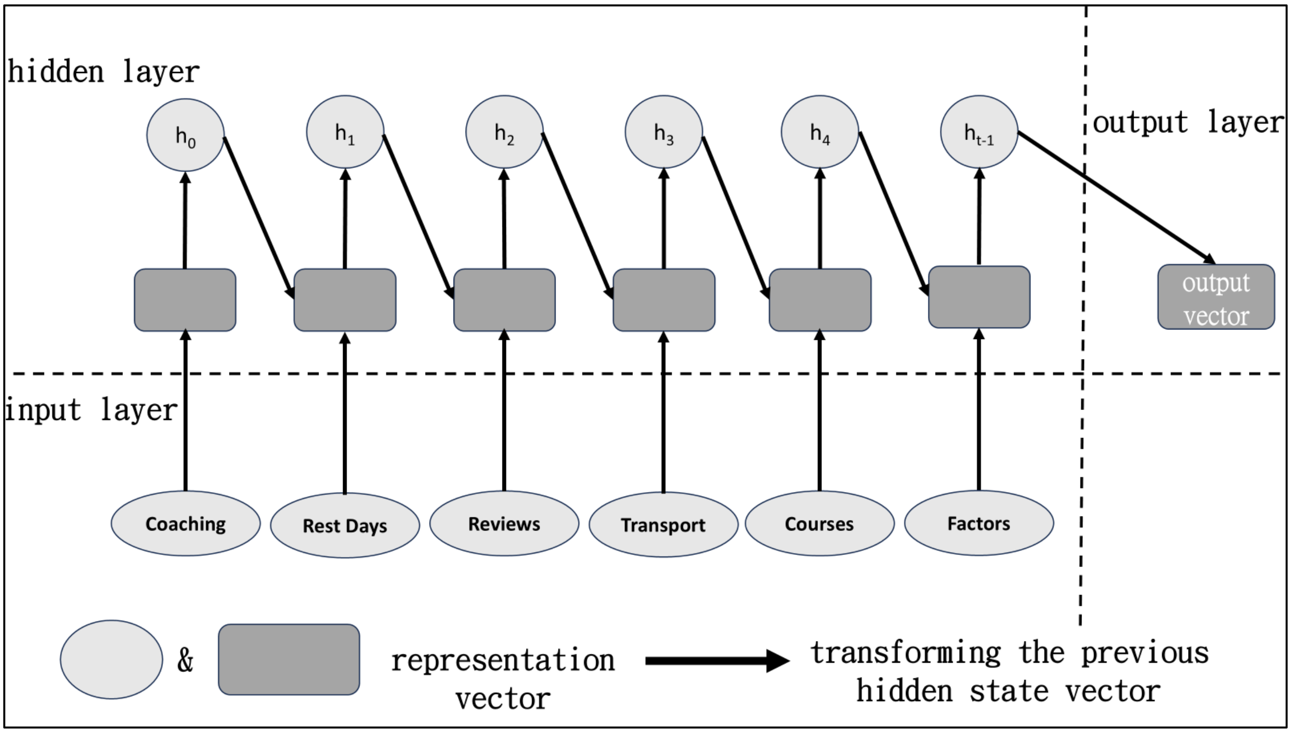

Fig. 3. Illustration of Recurrent Neural Networks model training.

4. Result

The model's learning process over 1,500 training cycles is depicted in Fig. 4. The trends in both validation accuracy and Mean Squared Error (MSE) loss throughout these iterations provide insight into the model's performance during training. In the initial phase of training, validation accuracy exhibited a gradual increase, rising from 0.000508 to 0.00138 by the 100th iteration. This steady improvement indicates the model's ability to progressively refine its classification performance as it assimilated more data. Concurrently, the model's loss value showed a modest decrease from 0.998 to 0.997, reflecting a reduction in the prediction error during the early stages of training. As the training progressed, these trends became more pronounced. By the 500th iteration, validation accuracy had increased to 0.0697, while the loss value had decreased to 0.865. This continued improvement suggests that the model was effectively learning from the training data, with a marked enhancement in its predictive capabilities. Further training led to even more substantial gains, with validation accuracy reaching 0.850 by the 1,000th iteration and the loss value dropping significantly to 0.0224. By the end of the 1,500 training cycles, the model achieved a validation accuracy of 0.919 and a loss value of 0.0064.

These results demonstrate a consistent improvement in the model's performance over the course of the training process. The steady increase in accuracy coupled with the corresponding decrease in loss underscores the model's growing ability to generalize from the training data and make accurate predictions. The observed trends highlight the efficacy of the training regimen and the model's capacity to converge towards a state of optimal performance.

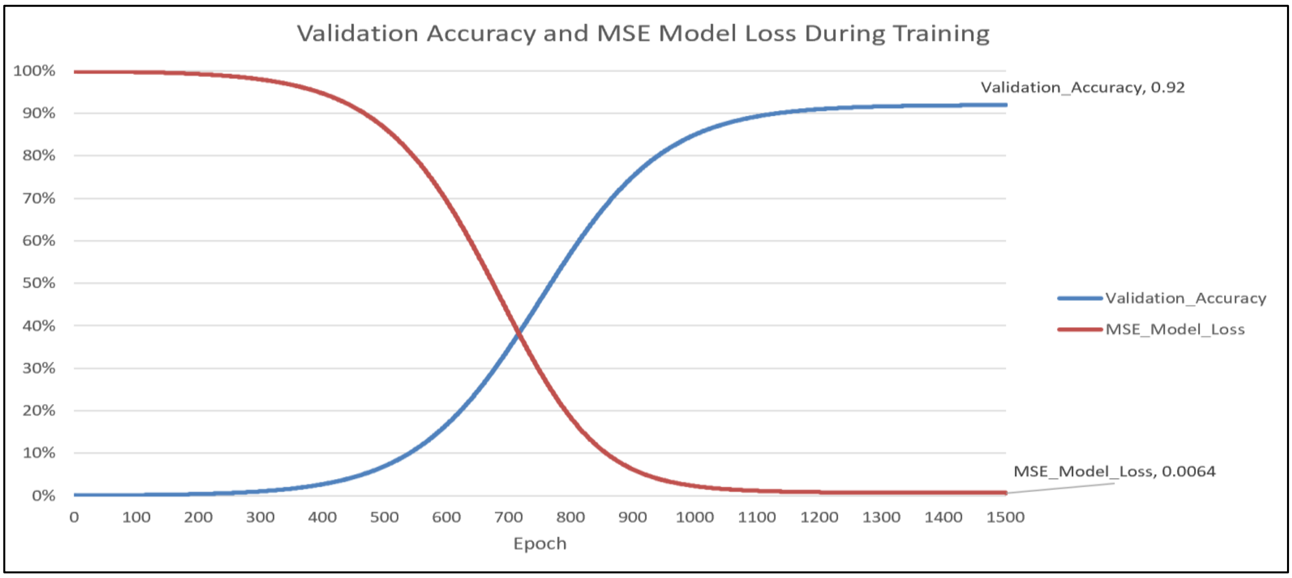

Fig. 4. Validation accuracy and MSE model loss during training.

As shown in Fig. 5, the predicted validation values followed a clear and systematic downward trajectory throughout the 1,500 training epochs, illustrating the model's steady improvement in predictive accuracy. The initial predicted validation value at epoch 0 was 0.428, reflecting the high level of error at the outset of training. Over the subsequent epochs, this value decreased incrementally, ultimately reaching 0.0342 at epoch 1,500, indicating a significant reduction in prediction error. During the early stages of training, particularly in the first 100 epochs, the predicted validation values exhibited a noticeable decline. For instance, by epoch 10, the value had already dropped to 0.428330568, and by epoch 50, it had further decreased to 0.428212214. This initial sharp reduction suggests that the model rapidly learned key patterns and features from the data, adjusting its internal weights and biases effectively during this early phase. As training progressed beyond epoch 100, the rate of decline in predicted validation values became more gradual. By epoch 500, the predicted validation value had decreased to 0.427662267, showing a steady, yet slower, improvement. This deceleration in the rate of error reduction is typical in neural network training, where the model makes larger gains in accuracy early on and progressively focuses on finer adjustments as it approaches convergence. Between epochs 500 and 1,000, the values continued to decline, reaching 0.426 at epoch 1,000. By this stage, the model had captured most of the underlying patterns in the training data, and the remaining epochs were primarily focused on refining the predictions. The predicted validation value at epoch 1,000 reflects a significant improvement from the early stages, indicating the model's enhanced ability to generalize across the data. From epoch 1,000 to the final epoch, 1,500, the predicted validation values showed further incremental improvements, culminating in a value of 0.0342. This final stage of training involved minimal changes in the predicted validation values, signifying that the model was nearing its optimal performance. The gradual reduction over this period reflects the fine-tuning process, where the model adjusted its parameters to further minimize residual errors.

The overall trend observed in the predicted validation values highlights the effectiveness of the model's training process. The model's capacity to reduce the prediction error consistently over a prolonged training period demonstrates its ability to adapt and improve. This progression, particularly the dramatic reduction in predicted validation values from 0.428 to 0.0342, underscores the success of the training strategy and the model's eventual convergence towards an optimal solution.

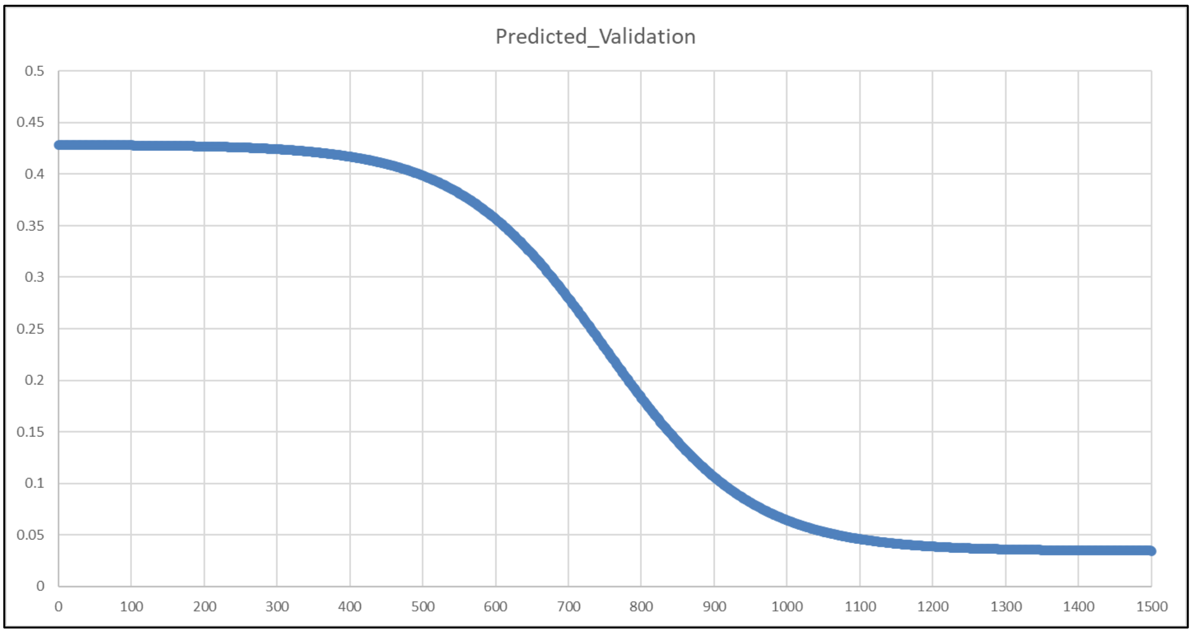

Fig. 5. Predictive model validation data.

In this study, the validation difference between the predicted validation values and the observed validation accuracy was analyzed over 1,500 epochs. This difference, termed "Validation_Difference," reflects how well the model's predictions align with actual validation outcomes. As shown in Figure 6, the data depicts a consistent downward trend in validation difference, indicating a progressive improvement in the model's predictive capabilities as training progresses.At the beginning (Epoch 0), the validation difference stands at -0.4278, revealing a notable initial gap between the model's predictions and the actual validation accuracy. Over the course of training, this difference steadily decreases, with a significant reduction observed in the first 500 epochs, where the validation difference drops at a stable rate. Figure 6 further illustrates how, by Epoch 1000, the rate of decline in validation difference slows, suggesting that the model is approaching convergence. From Epoch 500 onwards, sharper reductions in the validation difference are observed, signaling that the model's learning process is becoming more refined, with greater predictive accuracy. By Epoch 1,500, the validation difference has dropped to 0.8857, indicating that the model has substantially improved its ability to predict validation outcomes with increasing precision. This final value highlights the significant reduction in prediction error and reflects the model's overall progress. The data trends depicted in Fig. 6 provide a visual representation of the validation difference's steady decline, with the graph plateauing around the later epochs, indicating the point at which further training brings diminishing returns in prediction accuracy. This pattern suggests that the model's predictive performance stabilizes after approximately 1,000 epochs, reinforcing the notion that training beyond this point yields marginal gains in accuracy.

In conclusion, as shown in Fig. 6, the decreasing validation difference throughout the training process underscores the model's improved predictive alignment with actual validation accuracy. The final validation difference of 0.8857 demonstrates a high degree of convergence, affirming the model's reliability in forecasting validation results by the end of training.

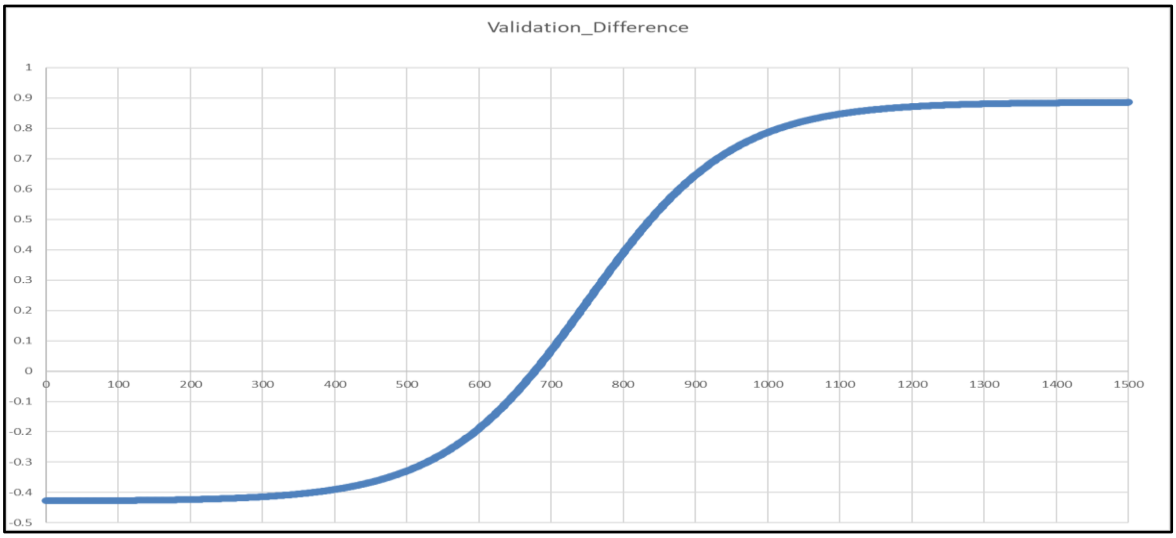

Fig. 6. Comparison of validation accuracy and predicted values differences

This study conducts a feature importance analysis to evaluate the relative contribution of various factors to the model's predictive performance. The analysis revealed that "Reviews" emerged as the most influential feature, with an importance score of 0.327, signifying its dominant role in shaping the model's predictions. "Size" was the second most impactful feature, with an importance score of 0.255, indicating that the size of the fitness venue plays a substantial role in influencing user decisions and consequently, the model's recommendations. The "Courses" feature also demonstrated considerable influence, with a score of 0.186, highlighting the significance of the variety of course offerings in the decision-making process for consumers selecting fitness venues. "Equipment" and "Transport" were similarly critical, with scores of 0.142 and 0.130, respectively, underscoring the importance of high-quality equipment and convenient transportation options in users' preferences. "Parking" was found to have a moderate impact, with a feature importance score of 0.098, suggesting that the availability of free parking, while not the most significant factor, still holds relevance in the decision-making process. Features such as "Coaching," "Accessibility," "Fees," "Rest Days," and "Incidents" had comparatively lower importance scores, but they nonetheless contribute to the overall performance of the model. These findings indicate that consumer choices are primarily influenced by factors such as well-reviewed venues, appropriate gym sizes, a diverse range of courses, and access to professional equipment. Collectively, the results of the feature importance analysis provide critical insights into the attributes that most significantly drive consumer preferences, thereby enhancing the predictive accuracy of the model.

The primary objective of this study is to develop a system that delivers personalized recommendations for fitness venues based on users' geographical locations. The recommendation system leverages not only spatial data but also incorporates a set of rating indices to ensure that the recommended venues meet both quality and service expectations. By integrating user reviews, ratings, and other relevant indices, the system enhances the reliability of its recommendations, ensuring that the suggested fitness venues align with individual user preferences regarding service quality, convenience, and overall satisfaction. The system is designed with a user-friendly interface that presents recommended venues in clustered formations when viewed from a broader, wide-angle perspective. This initial cluster view offers users a high-level overview of available fitness venues in their region, helping them identify areas with a higher density of recommended options. This feature is particularly beneficial for users seeking to compare different areas or neighborhoods for their fitness needs, allowing them to quickly evaluate the concentration of high-quality venues in various locations. As users zoom into the map, the system transitions from a general view to a more granular level of detail. At this closer level, individual fitness venues are displayed with detailed information, including specific user ratings, reviews, service features, and other critical factors such as pricing, available courses, and accessibility. This detailed view, as illustrated in Fig. 7, provides a comprehensive dataset that enables users to thoroughly assess each venue based on their personal preferences. Furthermore, the system is designed to highlight key aspects such as proximity to the user's current location, transportation options, and parking availability, facilitating an informed and convenient decision-making process.

The combination of a broad, clustered overview and an in-depth, zoomed-in analysis allows users to navigate the system intuitively and make informed choices. This dual-level interaction empowers users to first identify potential venues based on geographic and rating-based clusters and then delve deeper into the specifics of each fitness venue to determine the best fit for their needs. By integrating both geographical proximity and user-generated data into its recommendation algorithm, the system significantly enhances the user experience, providing recommendations that are both personalized and practical, ensuring that users can find the most suitable fitness venues with ease.

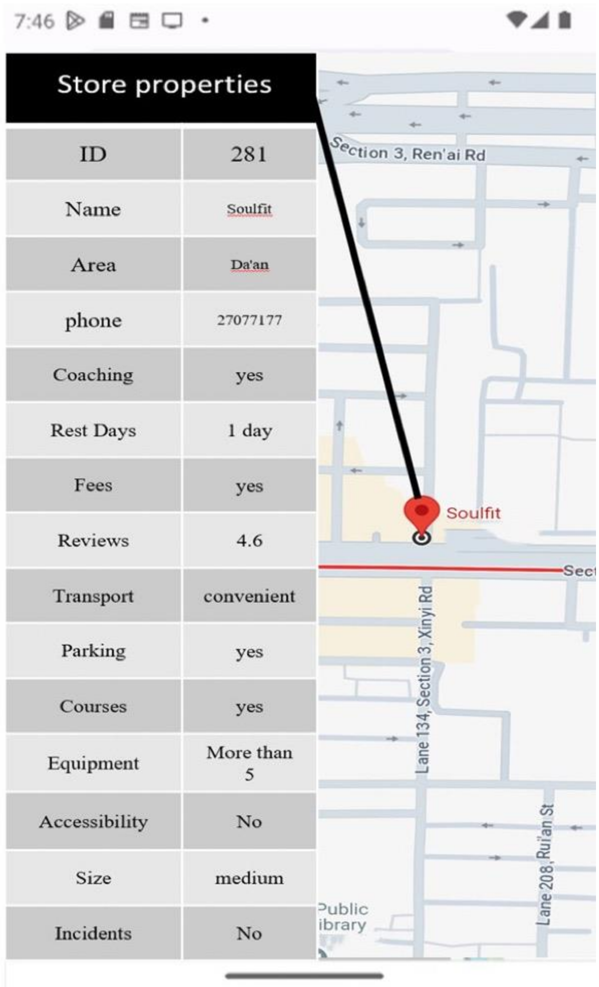

Fig.7. Visualization of recommended map in user-located area.

5. Conclusions

The application developed in this study serves as a comprehensive fitness venue recommendation system, designed to assist users in discovering and selecting venues that align with their preferences. By integrating a recommendation engine with map-based navigation, the system enhances both the convenience and efficiency of identifying suitable fitness venues. Leveraging a Recurrent Neural Network (RNN) deep learning model, the system analyzes extensive user data, including preferences and historical behavior, to provide personalized recommendations that best match the user's needs. Building upon the research data and objectives outlined in this study, the system aims to significantly improve the process of finding and selecting fitness venues by offering recommendations that are both accurate and tailored to individual users. The study contributes in the following three key areas:

5.1. Enhancing Personalized Experience

The system allows users to efficiently filter and identify the most suitable fitness venues by leveraging user-defined preferences, such as geographic location, available services, and venue ratings. Through this tailored filtering process, users are able to specify their requirements, ensuring that the recommended fitness venues align with their individual needs and expectations. The system further enhances user convenience by incorporating personalized features, such as real-time location tracking, which identifies nearby venues, and dynamic updates on service availability and user reviews. By integrating these customized elements, the system not only streamlines the decision-making process but also improves the overall user experience, providing a more efficient and accurate means of discovering and selecting fitness venues that meet specific criteria. Additionally, the incorporation of user preferences and behaviors into the recommendation algorithm ensures that the system adapts to evolving user needs over time, offering a more refined and personalized set of recommendations as users interact with the platform.

5.2. Comprehensive Fitness Venues Database

In this study, a comprehensive database was constructed, encompassing detailed information on a wide range of fitness venues. The dataset incorporates a variety of variables, including geographic location, service offerings, equipment availability, user ratings, and accessibility features, among others. This extensive collection of data not only provides a robust foundation for the recommendation system but also serves as a valuable resource for users seeking to make informed decisions. By including multiple variables, the database allows for in-depth comparisons between fitness venues, enabling users to assess key factors such as quality of service, convenience, and cost-effectiveness. The system's ability to analyze and present this data in an accessible format ensures that users can easily identify the strengths and weaknesses of different venues, leading to more confident and well-informed choices. Furthermore, the database's structure is designed to be scalable, allowing for the integration of new data and updates as the fitness industry evolves. This adaptability ensures that the recommendation system remains relevant and accurate, providing users with the most up-to-date information available for their decision-making process.

5.3. Integrated Analysis and Visualization

This study integrates data from various sources, including online reviews, geographic information, and service details, to create a comprehensive data analysis platform tailored for selecting fitness venues. The platform not only aggregates large volumes of information but also refines and organizes it, ensuring that users can access reliable and up-to-date data. A key feature of the system is its incorporation of user feedback, which enhances the richness and accuracy of the data, allowing the system to adapt to evolving user preferences and behaviors over time. By capturing both qualitative and quantitative metrics, such as user ratings, service quality, and location convenience, the platform delivers a holistic view of each fitness venue. To further enhance the user experience, the study employs advanced data visualization techniques. Through the use of charts, graphs, and interactive maps, the system translates complex datasets into visually accessible formats. This approach allows users to easily interpret and explore key metrics, such as venue ratings, proximity, and service diversity, without needing to sift through raw data. For instance, geographic data is visualized through map-based interfaces, providing users with a clear spatial understanding of venue distribution, while detailed charts enable comparative analysis across different service types and user satisfaction levels. These visual tools empower users to make more informed and confident decisions by presenting them with actionable insights in a clear and intuitive manner. By merging multi-source data with sophisticated visualization techniques, the platform effectively bridges the gap between raw information and user-friendly insights. This ensures that users are not only equipped with the most relevant data but also have the tools to understand and analyze it in a way that enhances their decision-making process when selecting fitness venues.

Overall, this study contributes significantly to the field of recommendation systems by demonstrating the effective application of deep learning models, user-centered design, and data visualization in the fitness industry. The system developed in this research addresses key challenges in venue selection by offering a tailored, efficient, and scalable solution that enhances both user convenience and decision-making accuracy. Future research could explore further enhancements, such as integrating additional personalized features and expanding the system to other service-based industries, to continue improving the user experience and applicability of recommendation technologies.

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Conflicts of Interest: The authors declare no conflict of interest.

References

1. Alameen, A. (2022). Improving the accuracy of multi-valued datasets in agriculture using logistic regression and LSTM-RNN method. *TEM Journal*, *11*(1), 454–462.
2. Alsharef, A., Aggarwal, K., Sonia, et al. (2022). Review of ML and AutoML solutions to forecast time-series data. *Archives of Computational Methods in Engineering*, *29*(7), 5297–5311.
3. Astawa, I. N. G. A., Pradnyana, I. P. B. A., & Suwintana, I. K. (2022). Comparison of RNN, LSTM, and GRU methods on forecasting website visitors. *Journal of Computer Science and Technology Studies*, *4*(2), 11–18.

4. Baena-Arroyo, M. J., García-Fernández, J., Gálvez-Ruiz, P., et al. (2020). Analyzing consumer loyalty through service experience and service convenience: Differences between instructor fitness classes and virtual fitness classes. *Sustainability*, *12*(3), 828.
5. Bladh, G. H. (2022). Spatial bodies: Vulnerable inclusiveness within gyms and fitness venues in Sweden. *Social Sciences*, *11*(10), 455.
6. Cui, Q., Wu, S., Liu, Q., et al. (2018). MV-RNN: A multi-view recurrent neural network for sequential recommendation. *IEEE Transactions on Knowledge and Data Engineering*, *32*(2), 317–331.
7. Dewi, R. K., Sari, Y. A., Widodo, A. W., et al. (2020). Testing for recommendation method in m-health sports venue recommendation system. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, *9*(6), 2143–2146.
8. Gray, S. E., Keyzer, P., Norton, K., et al. (2015). The role of equipment, the physical environment and training practices in customer safety within fitness facilities: The perspectives of fitness industry employees. *Journal of Fitness Research, 4*(2), 26–33.
9. Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences of the United States of America*, *79*(8), 2554–2558.
10. Iftikhar, N., Liu, X., Nordbjerg, F. E., et al. (2016). A prediction-based smart meter data generator. In Proceedings of the 2016 19th International Conference on Network-Based Information Systems (pp. 173–179). Ostrava, Czech Republic, September 7–9, 2016.
11. Jiang, Y., Liu, Y., Liu, Z., et al. (2023). Spatial distribution characteristics of public fitness venues: An urban accessibility perspective. *Sustainability*, *15*(1), 601.
12. Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
13. Kratzert, F., Klotz, D., Herrnegger, M., et al. (2019). Toward improved predictions in ungauged basins: Exploiting the power of machine learning. *Water Resources Research*, *55*(12), 11344–11354.
14. MacIntosh, E., & Doherty, A. (2007). Reframing the service environment in the fitness industry. *Managing Leisure*, *12*(4), 273–289.
15. Mozaffar, M., Paul, A., Al-Bahrani, R., et al. (2018). Data-driven prediction of the high-dimensional thermal history in directed energy deposition processes via recurrent neural networks. *Manufacturing Letters*, *18*, 35–39.
16. Piotrowski, D., & Piotrowska, A. I. (2021). Operation of gyms and fitness clubs during the COVID-19 pandemic-financial, legal, and organisational conditions. *Journal of Physical Education and Sport*, *21*, 1021–1028.
17. Research and Markets. (2023). Global gym and health clubs market 2024–2028. TechNavio. Available online: https://www.researchandmarkets.com/ (accessed on 26 March 2025).
18. Rimmer, J. H., Riley, B., Wang, E., et al. (2005). Accessibility of health clubs for people with mobility disabilities and visual impairments. American Journal of Public Health, 95(11), 2022–2028.
19. Sampaio, A. R., Pimenta, N. J., Machado, M., et al. (2020). Development and validation of the Fitness Coaching Behavior Scale: Factor structure, validity and reliability. *Retos: Nuevas tendencias en educación física, deporte y recreación*, *37*, 687–693.
20. Shewalkar, A., Nyavanandi, D., & Ludwig, S. A. (2019). Performance evaluation of deep neural networks applied to speech recognition: RNN, LSTM and GRU. *Journal of Artificial Intelligence and Soft Computing Research*, *9*(4), 235–245.
21. Sports Administration, Ministry of Education, Taiwan. (2020). 2020 sports status survey results: Successful epidemic prevention and joyful exercise, diverse sports iTaiwan. Sports for All Division.
22. Sports Administration, Ministry of Education, Taiwan. (2023a). 2023 sports statistics. Jiabin Co., Ltd.
23. Sports Administration, Ministry of Education, Taiwan. (2023b). 112th year sports status survey: Final report. Shih Hsin University.
24. Sports Administration, Ministry of Education, Taiwan. (2024). Venue information – Sports venues. National Sports Venue Information Networks-iPlay. Available online: http://data.gov.tw/?q=principle (accessed on 26 March 2025).
25. Vlachas, P. R., Pathak, J., Hunt, B. R., et al. (2020). Backpropagation algorithms and reservoir computing in recurrent neural networks for the forecasting of complex spatiotemporal dynamics. *Neural Networks*, *126*, 191–217.
26. Wang, D., Wang, X., & Lv, S. (2019). End-to-end Mandarin speech recognition combining CNN and BLSTM. *Symmetry*, *11*(5), 644.
27. Yang, F., Jin, L., Lai, S., et al. (2019). Fully convolutional sequence recognition networks for water meter number reading. *IEEE Access*, *7*, 11679–11687.
28. Zhu, L. (2023). Research on legal liability and prevention mechanism of accidental injury accidents in commercial fitness clubs. *Academic Journal of Management and Social Sciences*, *4*(3), 34–39.

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