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A DEEP LEARNING–BASED FRAMEWORK FOR EVALUATING AND RECOMMENDING PET SERVICE SELECTION

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Abstract

As public awareness of pet welfare continues to increase, pet owners face growing challenges in identifying reliable and high-quality pet service providers. Existing selection processes often rely on fragmented online information and subjective judgments, resulting in suboptimal decision-making. To address this issue, this study proposes a deep learning–based evaluation and recommendation framework that integrates recurrent neural networks (RNNs) with web crawling techniques to support systematic and evidence-based pet service selection. The proposed framework utilizes the official government dataset of licensed pet businesses as a foundational data source and enriches it with large-scale consumer reviews and supplementary attributes collected from major social media platforms and online review websites. Key decision factors influencing pet owners' choices are identified and incorporated into the model training process. By leveraging the sequential learning capability of RNNs, the framework captures individual user preferences and generates ranked evaluations and personalized recommendations for pet services.

The effectiveness of the proposed approach is demonstrated through an Android-based application that delivers tailored recommendations to end users. The results indicate that the framework enhances recommendation accuracy and improves user decision satisfaction. Beyond assisting individual pet owners, this study contributes an objective and scalable decision support framework that promotes service quality improvement and transparency within the pet service industry.

Keywords

Pet Service Selection, Deep Learning, Personalized Recommendation, Recurrent Neural Networks

1. Research Background and Motivation

1.1 Research Motivation

Taiwan is undergoing profound demographic transformations characterized by population aging, declining birth rates, and increasingly fragmented social relationships. These structural changes have intensified individuals' demand for emotional companionship, leading to a notable rise in pet ownership and the growing social significance of companion animals (Yang, 2018). For many households, pets have gradually assumed roles traditionally fulfilled by family members, becoming integral to everyday emotional support and social interaction. Official statistics from the Council of Agriculture indicate that by the end of 2023, the registered population of dogs and cats in Taiwan reached 2.22 million underscoring the expanding role of pets within contemporary family structures. Concurrently, empirical studies suggest that pet owners are increasingly attentive to animal welfare and demonstrate a stronger willingness to invest in products and services that enhance pets'quality of life (Wangyi, Hengyuan, & Lu, 2022).

Driven by these societal shifts, Taiwan's pet services industry has experienced rapid expansion, accompanied by trends toward product refinement, human-centered design, and health-oriented service innovation. Younger generations, in particular, exhibit higher consumption willingness, while pet-related businesses are transitioning toward diversified, specialized, and integrated operational models. Service providers increasingly emphasize professionalism and service quality, thereby offering pet owners a wider array of alternatives (Yang, 2024). Despite this expansion, a critical challenge persists in consumers' limited ability to efficiently evaluate and select appropriate pet stores. Although abundant pet store information is available across social media platforms and online review websites, such information is often fragmented, inconsistent in quality, and insufficiently tailored to individual preferences. Consequently, consumers face elevated cognitive and time costs during the decision-making process, which diminishes decision efficiency and satisfaction.

In recent years, deep learning has emerged as a transformative paradigm within artificial intelligence, demonstrating superior performance in pattern recognition, preference modeling, and decision support across diverse application domains (Al-Selwi et al., 2024). To address the dual challenges of information fragmentation and inadequate personalization in pet store selection, this study adopts recurrent neural network (RNN) models to capture sequential user behavior and preference patterns. By integrating official government data with large-scale online review information, the proposed approach seeks to develop an intelligent, objective, and efficient recommendation framework that enhances service quality and user experience within the pet services industry.

1.2 Research Objectives

Building on the research motivation discussed above, this study aims to address the following research objectives:

(1) To develop a deep learning–based recommendation framework for pet service evaluation. This study seeks to design and validate a recurrent neural network (RNN)–based model that integrates consumer-generated reviews and key service-related attributes to capture user preference patterns and generate personalized pet store recommendations.
(2) To examine the effectiveness of real-time, data-driven information integration in supporting pet service selection. By incorporating location-aware and service-related information, this study investigates how real-time data retrieval can enhance the efficiency and relevance of pet store recommendations under diverse consumption contexts.
(3) To assess the impact of personalized recommendation systems on consumer decision-making outcomes. This research evaluates whether an objective and user-centered recommendation framework can reduce decision-making complexity, improve decision confidence, and enhance overall satisfaction in the process of pet store selection.

2. Literature review

This section reviews relevant literature from multiple perspectives. It begins with an examination of the current status of Taiwan's pet industry, followed by an analysis of the key factors influencing pet owners' store selection, and concludes with a discussion on the application of recurrent neural networks (RNNs).

2.1 Current Status of Taiwan's Pet Industry

Taiwan's pet industry has experienced significant expansion in recent years, accompanied by notable shifts in consumer behavior. Despite broader economic uncertainties, expenditures related to pets have consistently exhibited steady growth. Global market reports underscore this trajectory: Statista (2022) identifies the pet economy as a rapidly growing sector worldwide, with Taiwan demonstrating substantial market potential. Complementing this, statistics from the Department of Statistics, Ministry of Finance (2023) reveal that from 2018 to 2022, the number of operating businesses and sales revenue within Taiwan's pet sector grew by approximately 30% and 46%, respectively. Particularly noteworthy is the segment of pet-related products, which accounted for 84% of total sales and recorded a growth of 49%, underscoring its centrality to the overall industry.

The COVID-19 pandemic, though disruptive to numerous industries, further catalyzed the global pet sector. In 2020, the market reached USD 142.1 billion, with a 6.9% growth rate (YongHyun, Kwangtek, Jungwook, & Eunchan, 2025), reflecting its resilience amidst crisis. Increased time spent at home encouraged consumers to enhance domestic quality of life, which included heightened attention and financial investment toward pets. Moreover, structural shifts such as declining birth rates and growing needs for companionship have reshaped the social role of pets from traditional companions to integral family members (Liu, et.al, 2024).

Broader demographic and cultural transformations also reinforce this trend. Population aging and shifting fertility perceptions among younger generations have heightened demand for pet companionship, further stimulating market expansion (Hsu, 2022). According to the Market Intelligence & Consulting Institute (MIC, 2020), Taiwanese households increasingly treat pets as family members, resulting in greater expenditure on veterinary services, household integration, and pet entertainment. Consumption patterns also reveal segmentation by age: owners aged 51–55 record the highest annual spending, while younger owners aged 26–35 are particularly active in purchasing technologically advanced pet products. This highlights the intersection of smart-living trends and pet-related consumption, signaling considerable growth potential in the pet technology market.

In sum, the expansion of Taiwan's pet industry and the evolving patterns of consumer behavior illustrate both the sector's inherent resilience and its responsiveness to broader socio-cultural dynamics. These developments not only provide fertile ground for scholarly inquiry but also open significant opportunities for future industrial innovation.

2.2 Factors Influencing Pet Owners' Selection of Pet Stores

In contemporary consumer environments, pet store selection has evolved into a complex decision-making process influenced by both individual preferences and broader structural conditions. Prior research indicates that consumers' evaluations of service providers are shaped by an interplay of informational, experiential, and contextual factors. Accordingly, the literature suggests that an effective analytical framework for pet store evaluation should incorporate multiple dimensions rather than relying on isolated criteria. Drawing on existing studies, this research synthesizes four key domains that are consistently identified as influential in pet owners' store selection decisions: basic store information, service quality and convenience, product and service scope, and store characteristics.

(1) Basic Store Information：

Accurate and transparent store information constitutes a foundational element in consumer evaluation and regulatory oversight. Purnamasari, Sumarto, and Zailani (2023) emphasize that access to reliable store data enables consumers to assess compliance and service legitimacy while supporting informed decision-making. In addition, effective promotional communication enhances consumer awareness and market visibility, thereby facilitating acceptance and market development (Liu, 2024).

(2) Service Quality and Convenience：

Service quality has long been recognized as a critical determinant of customer satisfaction and behavioral outcomes. Empirical evidence demonstrates that favorable service experiences and convenience significantly enhance satisfaction and perceived value (Gabay et al., 2014; Elliott et al., 2019). Furthermore, Budiyono, Sarbullah, and Novandalina (2022) confirm a strong positive association between service quality, customer satisfaction, and loyalty, highlighting the role of accessible and high-quality services in sustaining long-term customer relationships.

(3) Product and Service Scope：

The breadth of product offerings and the availability of complementary services represent key evaluative criteria in store selection. Kwak and Cha (2021) identify product variety as a major factor influencing consumer choice, while Tu (2024) demonstrates that the framing and presentation of product attributes affect perceptions of informational usefulness and, consequently, purchase intentions. These findings suggest that both the scope and the communicative presentation of offerings play significant roles in shaping consumer evaluations.

(4) Store Characteristics：

Store-specific attributes, including physical scale, geographic accessibility, and overall image, further influence consumer perceptions and experiences. Purnamasari et al. (2023) underscore the importance of store size and location in shaping customer evaluations, while Kandulapati and Bellamkonda (2014) find that convenience, product completeness, store atmosphere, and service quality exert significant positive effects on satisfaction across environmental, interpersonal, and value-related dimensions.

Synthesizing these perspectives, this study conceptualizes pet store selection as a multidimensional decision process and positions these four domains as critical inputs for subsequent analytical modeling. By grounding the proposed recommendation framework in established literature, the study aims to provide a more objective and theoretically informed basis for guiding pet owners in the selection of suitable pet stores.

2.3 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) were originally introduced by Hopfield in 1982 and further developed through empirical and theoretical advancements in the 1990s, notably by Elman and subsequent scholars. Distinct from traditional feedforward neural networks, RNNs incorporate recurrent connections that allow information to persist across time steps, thereby enabling the modeling of temporal dependencies and sequential patterns. This architectural property renders RNNs particularly suitable for time-dependent tasks such as speech recognition, natural language processing, and time-series forecasting (Hewamalage, Bergmeir, & Bandara, 2021).

In RNN training, hidden states are computed through forward propagation across sequential inputs, while parameter updates are achieved via the Backpropagation Through Time (BPTT) algorithm. Despite their theoretical appeal, conventional RNNs often encounter challenges related to vanishing and exploding gradients, especially when modeling long sequences, which can limit their ability to capture long-range dependencies. To mitigate these limitations, advanced RNN architectures have been proposed. Long Short-Term Memory (LSTM) networks introduce gating mechanisms—namely the input gate, forget gate, and output gate—to regulate information flow and preserve relevant signals over extended sequences, thereby alleviating the vanishing gradient problem and enhancing long-term dependency learning (Adebawo et al., 2006). Alternatively, Gated Recurrent Units (GRUs) offer a simplified gating structure composed of reset and update gates, reducing computational complexity while maintaining competitive performance, particularly in scenarios involving shorter or moderately long sequences (Alameen, 2022; Astawa, Pradnyana, & Suwintana, 2022).

Collectively, RNN-based models constitute a robust and flexible class of methods for sequential data modeling. Their capacity to capture temporal order and evolving patterns makes them especially well-suited for recommendation systems that rely on dynamic user behavior and preference evolution (Donkers, Loepp, & Ziegler, 2017). Existing literature not only validates the effectiveness of RNNs in recommendation contexts but also underscores ongoing architectural innovations that continue to expand their applicability and performance. Consequently, RNN-based approaches provide a theoretically grounded and empirically supported foundation for developing personalized and adaptive recommendation frameworks.

2.4 Implications for the Present Study

As societal concern for pet welfare continues to intensify, pet owners increasingly demand diversified and specialized services. Nevertheless, identifying appropriate pet stores remains a nontrivial decision-making challenge due to information fragmentation and heterogeneous service quality. To address this gap, this study proposes a deep learning–based evaluation and recommendation framework that integrates recurrent neural network (RNN) and long short-term memory (LSTM) architectures with web-crawling techniques. The proposed framework is designed to effectively model sequential user behavior and preference evolution while mitigating long-term dependency issues commonly encountered in sequential data analysis. By incorporating large-scale, real-world consumer-generated information, the approach enhances both computational efficiency and predictive performance. Ultimately, the framework provides an objective and comprehensive decision-support mechanism that assists pet owners in identifying pet stores aligned with their pets' needs and overall quality of life.

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3. Research Methodology

The present study proposes a service-oriented decision-support framework aimed at facilitating pet owners' evaluation and selection of pet stores that best match their individual needs. Rather than focusing solely on system implementation, the study emphasizes the development of an efficient and user-centered analytical approach that enhances decision quality and reduces search costs in pet service selection. To achieve these objectives, the research adopts a structured methodological design and delineates a series of systematic procedures aligned with the proposed framework.

3.1 Research Environmental Context Analysis

The literature review highlights that pet owners seeking reliable and comprehensive information frequently encounter fragmented data environments, requiring them to consult multiple and often inconsistent information sources. In the Taiwanese context, the absence of a centralized and standardized database for pet stores further exacerbates this challenge. As a result, consumers predominantly rely on informal channels, such as word-of-mouth communication and dispersed online content, which may vary substantially in reliability and completeness. Although government open-data initiatives provide partial information related to licensed pet businesses, these datasets remain decentralized and insufficiently integrated, thereby constraining their practical usefulness for non-expert users engaged in pet store selection. To address this data fragmentation gap, the present study systematically organizes and integrates available data sources into a unified analytical structure. This process enables comparative assessment across key evaluation dimensions and supports subsequent model development and analysis. The categorization and integration of data sources adopted in this study are summarized in Table 1, which illustrates how heterogeneous information is consolidated to facilitate objective and data-driven pet store evaluation.

Table 1. Functional Analysis of Pet Store Information Sources and Usage Efficiency

	Word-of-Mouth Marketing	Online Information
Overview	Information is disseminated through customer recommendations and personal sharing.	Derived from digital platforms, including official websites, social media, and review systems.
Context of Occurrence	Primarily within close-knit social environments, such as family, friends, and community circles.	Accessible online via websites, social media platforms, and integrated review systems.
Information Provided	Insights into service quality, product satisfaction, and overall customer experiences.	Comprehensive data including store location, operating hours, product range, pricing, consumer ratings, and store type.
Functional Value	Strengthens consumer trust, fosters brand loyalty, and shapes a favorable brand image.	Facilitates rapid access to diverse information, enhances store visibility, and supports preliminary consumer decision-making.
Limitations	(1).Information flow is constrained by the size of social networks, limiting access to new insights. (2).Word-of-mouth dissemination makes authenticity difficult to verify and control. (3).Information updates are relatively slow.	(1).Excessive and unstructured information complicates consumer filtering. (2).Online reviews may contain biases, reducing reliability. (3).Fragmentation of information results in low integration.

The proposed framework aims to generate accurate and personalized pet service recommendations through the analysis of large-scale user-generated data. By moving beyond reliance on informal word-of-mouth information, the approach enhances the reliability and accessibility of decision support, enabling consumers to make more informed and evidence-based service selection decisions.

3.2 Research Framework

This study develops a structured research framework for pet store evaluation and recommendation by integrating data acquisition, analytical modeling, and decision-support implementation. The framework comprises several interrelated methodological components designed to support systematic analysis and personalized recommendation. First, large-scale and heterogeneous data were collected through automated web-crawling techniques to capture comprehensive pet store information, including location attributes, consumer-generated reviews, and contextual service-related features from multiple online platforms. These data were subsequently organized into a multidimensional relational database to enable efficient data management, retrieval, and analytical processing. Second, advanced deep learning methods were employed to model user behavior and preference dynamics. Specifically, a recurrent neural network (RNN)–based architecture was implemented to analyze sequential user interaction patterns and generate personalized recommendation outcomes. This modeling approach allows the framework to capture temporal dependencies and evolving preferences inherent in pet store selection behavior. Third, to ensure practical applicability and user accessibility, the analytical results were operationalized through a mobile-based interface, enabling users to interact with the recommendation outputs in real-world decision contexts. The framework further incorporates a cloud-based backend infrastructure to support data processing, model execution, and application-level integration, thereby ensuring scalability and system robustness.

The overall research framework and the relationships among its core components are illustrated in Figure 1.

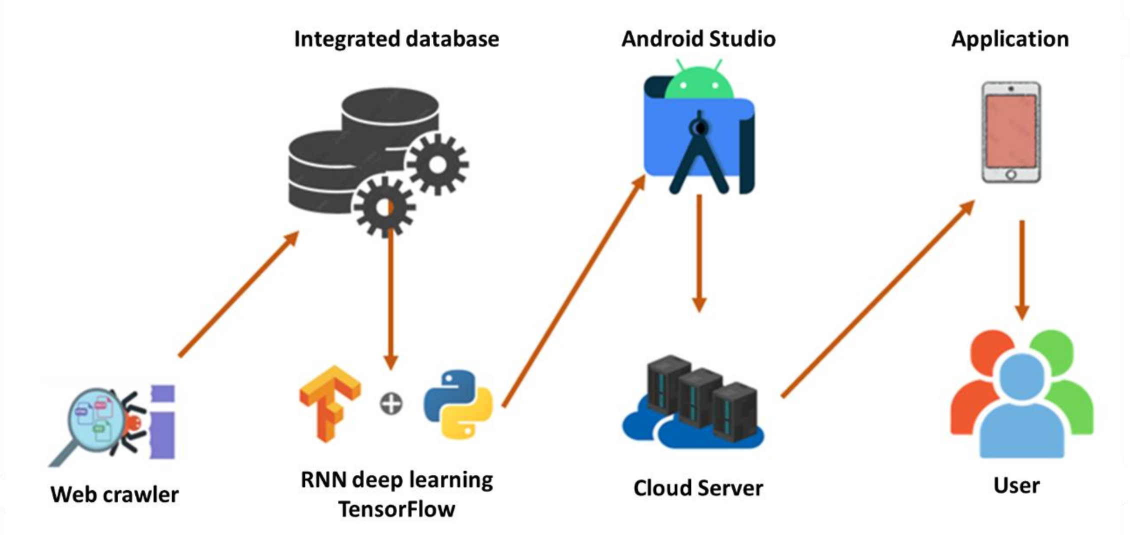

Figure 1. Prototype of the System Architecture

This study employs automated web-crawling techniques to systematically collect and integrate nationwide pet store information, thereby constructing a comprehensive and multidimensional database. In addition to basic store attributes, such as geographic location and contact information, the database incorporates large-scale user-generated content obtained from online review platforms and discussion forums, ensuring both breadth and depth of analytical input. To support personalized recommendation, user preferences toward pet stores are modeled using a recurrent neural network (RNN)–based deep learning approach. Individual preference patterns are represented as latent feature vectors, which enable similarity computation and comparative evaluation across alternative stores. Furthermore, the framework integrates location-aware analysis by incorporating geospatial information to identify candidate stores within a user's proximity, thereby refining recommendation relevance under real-world decision constraints. The recommendation outcomes are presented through an interactive spatial interface that visualizes store locations, aggregated evaluation indicators, and their alignment with individual user preferences. This visualization facilitates efficient interpretation of recommendation results and enhances decision reliability in pet store selection. The overall RNN-based recommendation workflow is illustrated in Figure 2.

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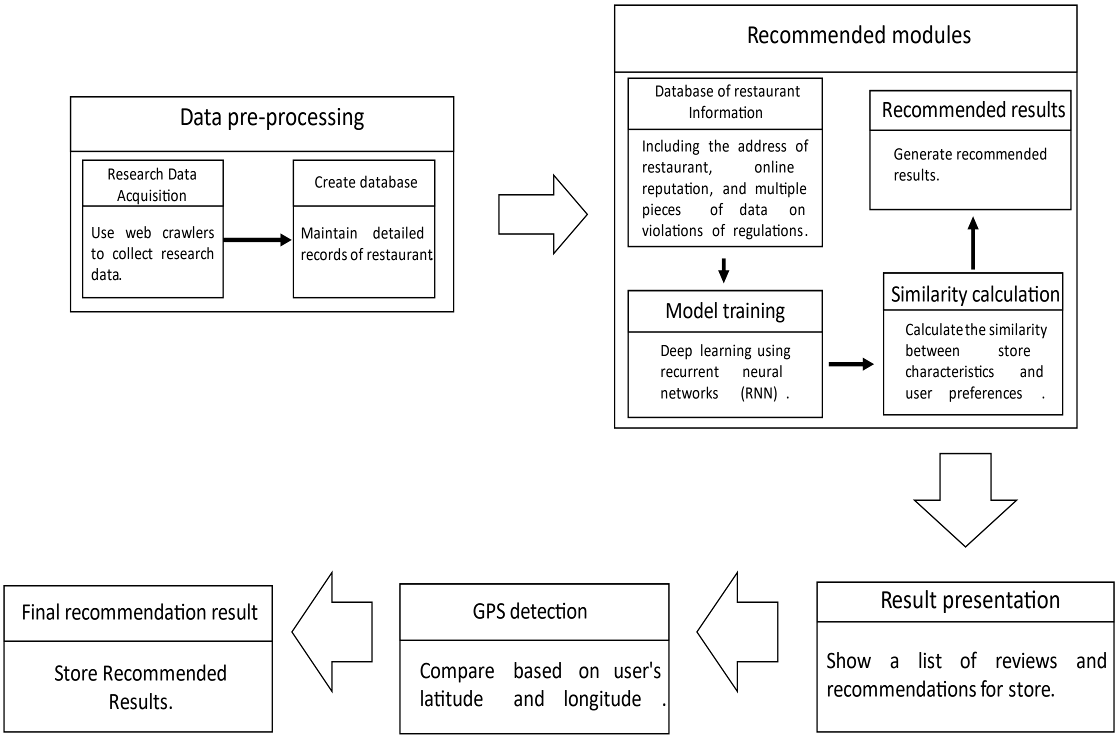

Figure 2. System Workflow Diagram

This study addresses the dual research objectives of enhancing decision efficiency and improving information accuracy by proposing an integrated, user-centered decision-support framework for pet store selection. The framework comprises several interrelated functional components designed to support information exploration, preference-based evaluation, and ongoing user engagement. These components collectively facilitate systematic information processing rather than isolated feature usage. Grounded in a user-centered design perspective, the framework incorporates a recurrent neural network (RNN)–based recommendation mechanism to enable precise filtering and personalized evaluation according to multiple decision criteria, including geographic proximity, aggregated user evaluations, and service categories. Supplementary modules support users in organizing preferred alternatives and tracking service-related updates, thereby extending the temporal relevance of the decision-support process beyond one-time selection. By integrating these components within a unified analytical structure, the framework reduces information search costs and enhances the transparency and interpretability of recommendation outcomes. This integrated design contributes to improved decision confidence and satisfaction in pet store selection. The functional architecture of the proposed framework and the interactions among its core components are illustrated in Figure 3.

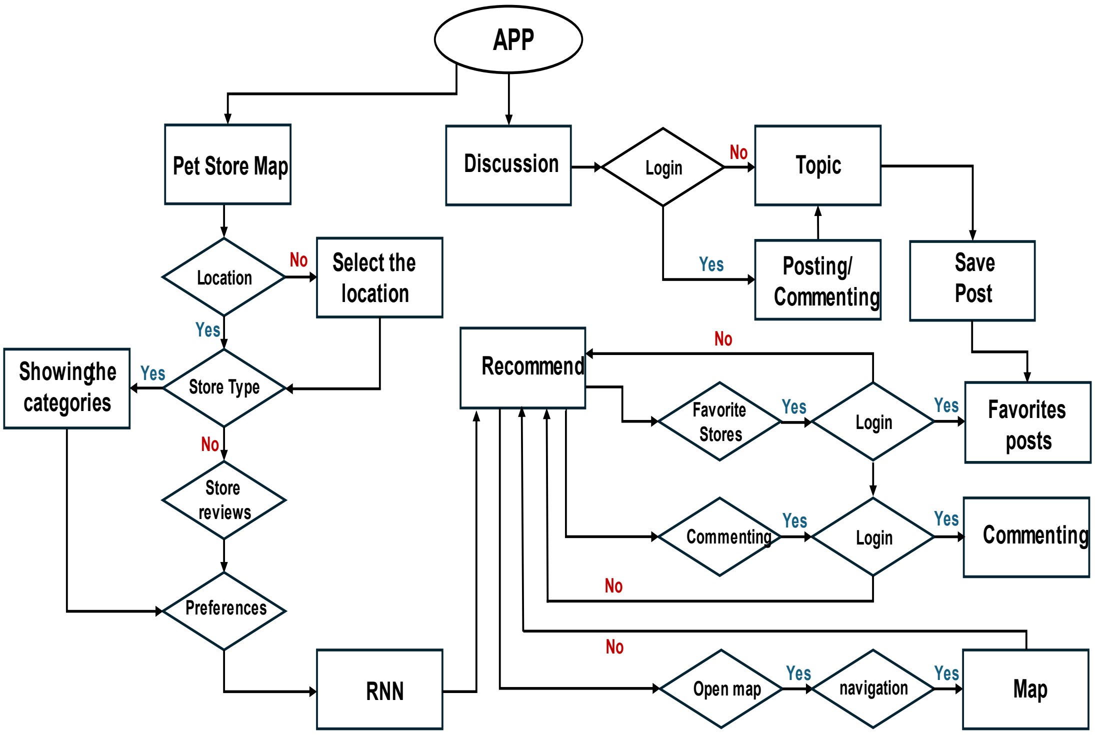

Figure 3. System Function Operation

3.3 Dataset Description

To support model training and empirical evaluation, this study constructs a user-scenario dataset consisting of 1,500 observations. The dataset encompasses a broad set of attributes capturing both objective store characteristics and consumer-perceived evaluations, including online ratings and reviews, regulatory compliance indicators, pricing structures, accessibility features, acceptance of third-party payment services, availability of pet health-related products, service categories, types of pets served, product assortment breadth, store size, and locational accessibility. By integrating these heterogeneous variables, the dataset enables a comprehensive representation of pet store service profiles and consumer evaluation contexts. This multidimensional structure provides a robust empirical basis for modeling user preferences and predicting service quality and satisfaction outcomes within the pet store industry. The composition and structure of the dataset are summarized in Table 2.

Table 2 Training Data Set

Variable Name	Variable Code	Encoding Type	Description
Pet Store ID	GV_StoreID	1 – Sequential	Unique identifier for each pet store in the database, used to distinguish individual stores.
Online Rating & Word-of-Mouth	GV_Rating	0-5	Ratings of 3.5 or higher indicate good recommendation; below 3.5, the store is not recommended.
Compliance Status	GV_Comply	0、1	Whether the store has had compliance violations. One-hot encoding: 0 = no, 1 = yes.

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Price Distribution	GV_Price	1-3	1 = low (≤ NT$1,000), 2 = medium (1,001–5,000), 3 = high (≥ 5,001).
Accessibility	GV_Access	0、1	Whether the store provides accessibility facilities. One-hot encoding: 0 = no, 1 = yes.
Third-Party Payment	GV_Pay3rd	0、1	Whether the store accepts third-party payment services. One-hot encoding: 0 = no, 1 = yes.
Pet Health Products	GV_Health	0、1	Whether the store sells pet health food. One-hot encoding: 0 = no, 1 = yes.
Pet Services	GV_Service	1-4	Service categories: 1 = grooming, 2 = boarding, 3 = medical, 4 = others.
Pet Service Types	GV_SpecPet	1-5	1 = cats, 2 = dogs, 3 = fish, 4 = reptiles, 5 = others.
Pet Product Categories	GV_ProdType	1-4	1 = food, 2 = supplies, 3 = apparel, 4 = mixed.
Store Size	GV_ProdSize	1-3	1 = small, 2 = medium, 3 = large.
Transportation Convenience	GV_Transit	1-3	1 = convenient, 2 = moderate, 3 = inconvenient.

3.4 System Design

The proposed framework is conceptualized as an intelligent, user-centered decision-support environment that integrates deep learning–based recommendation with interactive information management mechanisms. Rather than functioning as a standalone application, the framework is designed to support pet store selection through multiple complementary modules that facilitate information filtering, preference evaluation, and continuous user engagement. The core functional components are described as follows.

(1) Pet Store Mapping and Filtering Mechanism：

The framework incorporates a multivariate store selection mechanism that enables flexible information filtering based on geographic proximity, user preferences, and regulatory compliance status. This design reflects the heterogeneous nature of consumer decision-making, acknowledging that users may weigh trade-offs differently even when high-rated or fully compliant alternatives are available. By allowing users to adjust filtering criteria, the mechanism supports nuanced and context-sensitive store evaluation.

(2) Personalized Recommendation Mechanism：

A deep learning–based recommendation engine models user behavior and preference patterns to generate personalized pet store recommendations. Location-aware analysis is integrated to align user positions with store coordinates, thereby enhancing contextual relevance. In addition, a preference-retention function enables users to bookmark favored alternatives, facilitating repeated evaluation and improving recommendation consistency over time.

(3) Community-Based Information Exchange Mechanism：

To complement algorithmic recommendations, the framework incorporates a community interaction module that supports user-generated discussions and experience sharing. This mechanism enables users to access collective insights regarding service quality and operational practices, thereby enriching individual evaluations with socially derived information and supporting more informed decision-making.

(4) Pet Care Scheduling and Engagement Mechanism：

The framework further integrates a scheduling module designed to support pet owners in managing recurring and time-sensitive pet care activities. By facilitating reminders and event tracking, this mechanism extends user engagement beyond immediate store selection and reinforces the continuity of the decision-support environment.

3.4.1 Functional Requirement Analysis

Grounded in the identified requirements of end users, the proposed framework integrates a set of functional mechanisms designed to support usability and decision efficiency. The alignment between user needs and the corresponding analytical and interaction components is systematically structured to ensure coherence between research objectives and design choices. A summary of the mapping between user requirements and functional components is presented in Table 3.

Table 3 Requirement Analysis Matrix

Requirement Category	System Function	Identified Challenge	Proposed System Solution
Social Needs	Review Module / Store Bookmarking	Users may face issues of incomplete or non-transparent information when selecting pet stores.	The system enables registered members to share experiences, exchange evaluations, and discuss store information within the platform, while also supporting the management of bookmarked stores.
Technical Needs	GPS-Based Positioning / Personalized Recommendation	Users may experience inconvenience due to geographic constraints or mismatched preferences when selecting pet stores.	By integrating GPS-based location tracking with users' historical behaviors and preferences, the system employs an RNN model to deliver personalized store recommendations.
Interactive Needs	Forum and Topic Bookmarking	Users may prefer engaging in discussions on an open forum to obtain more diverse perspectives and tailored advice.	The system combines GPS-determined locations with user history and preferences, applying the RNN model to generate personalized recommendations while supporting broader community interaction.

3.5 Research Process

To ensure analytical rigor and information completeness, this study identifies ten key variables as the foundation for model development, including eight core indicators related to online ratings and consumer word-of-mouth. A comprehensive pet store database was constructed, in which each store was assigned a unique identifier to facilitate systematic analysis. Categorical attributes were transformed into numerical representations to support subsequent statistical analysis and machine learning procedures.

The methodological framework adopts Python as the primary programming environment and TensorFlow as the deep learning platform. Following a modified formulation based on Iwendi et al. (2020), the dataset underwent standardized preprocessing to ensure consistency across variables. The data were subsequently partitioned into training (70%) and validation (30%) subsets to support model development and performance assessment.

The analytical process was organized into two main stages. In the first stage, raw data were subjected to preprocessing and normalization procedures, followed by structured partitioning into training and validation datasets. In the second stage, model construction and training were conducted. A Long Short-Term Memory (LSTM)–based architecture was employed, consisting of an LSTM layer with 128 hidden units followed by a fully connected output layer. The LSTM architecture was selected due to its well-established capability to mitigate long-term dependency issues and effectively model sequential patterns in time-dependent data.

Model training utilized Mean Squared Error (MSE) as the loss function, with gradient clipping applied to reduce the risks associated with vanishing and exploding gradients. Parameter optimization was performed using the Adam optimizer (Kingma & Ba, 2014), while MSE was concurrently used as a monitoring metric to evaluate convergence and parameter updates throughout the training process.

To further examine the contribution of individual features, a feature importance analysis was conducted through controlled perturbations applied to each input variable within the validation set. Changes in predictive performance were subsequently observed to assess the relative influence of different features on model outcomes. This procedure enabled the identification of feature weight distributions associated with user behavioral patterns, thereby enhancing the interpretability and precision of the recommendation model.

Finally, predictive performance was evaluated by comparing model-generated outputs with observed values, expressed in terms of proportional error rates. This evaluation provides empirical evidence of the model's validity and demonstrates its effectiveness in capturing temporal dynamics and forecasting outcomes within the context of pet store recommendation.

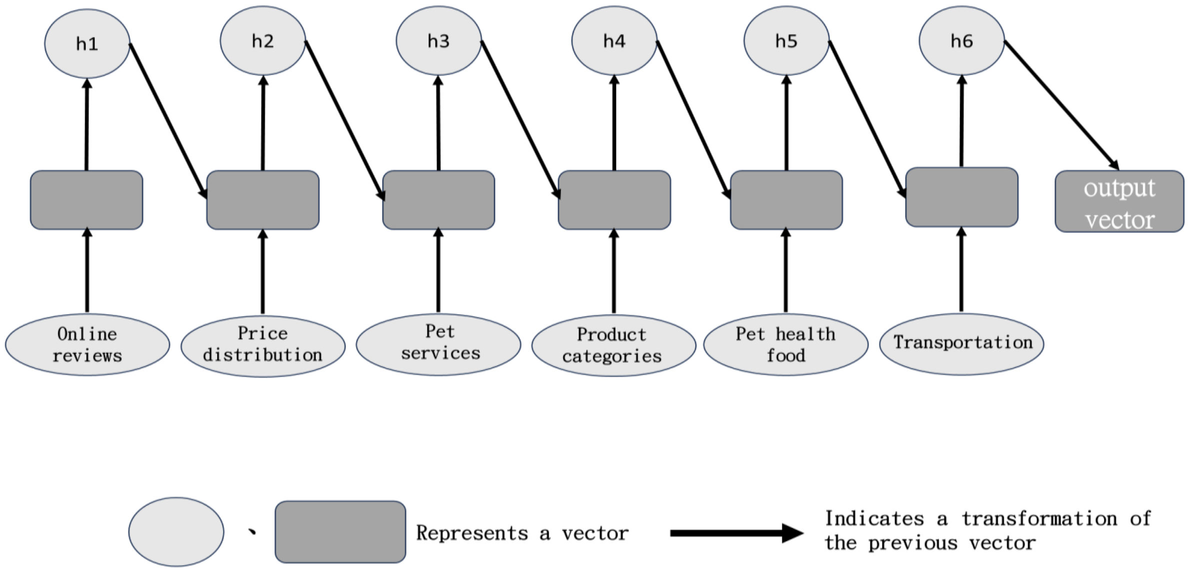

Figure 4. Architecture of the Recurrent Neural Network (RNN)

As illustrated in Figure 4, the training process of the proposed recommendation framework follows a structured deep learning workflow implemented within the TensorFlow environment. The process begins with data acquisition, in which consumer-generated reviews are collected through automated web-crawling techniques and subsequently subjected to preprocessing procedures, including data cleaning and normalization. The processed information is then organized into a multidimensional dataset suitable for sequential learning and preference modeling.

To support sequence representation, textual inputs are encoded into vectorized formats that enable quantitative modeling of input–output relationships. This encoding allows the framework to capture consistency patterns within sequential data and facilitates subsequent learning and evaluation processes. During forward propagation, information from previous time steps is recursively incorporated into the hidden states, enabling the model to retain contextual information across sequences. This mechanism allows the recurrent neural network (RNN) to effectively capture temporal dependencies embedded in user-generated content.

Model optimization is achieved through Backpropagation Through Time (BPTT), in which prediction errors are aggregated across time steps and propagated backward to update network parameters. Through iterative optimization, the model adjusts its internal representations to minimize loss and improve predictive accuracy. This training strategy enables the framework to learn context-dependent behavioral patterns and refine its understanding of sequential user preferences.

The iterative interaction between forward propagation and error correction reinforces the model's ability to maintain contextual continuity across inputs, thereby enhancing its capacity to represent dynamic user behavior. Such sequential learning capability is particularly advantageous for recommendation tasks, where historical interactions inform future preference predictions. Overall, the application of deep learning techniques within this framework enables the extraction of structured representations from complex, unstructured data, positioning RNN-based models as an effective methodological approach for sequential recommendation and decision-support applications.

4. Research Results

As illustrated in Figure 5, the model was trained for 1,000 epochs, yielding a learning trajectory consistent with established deep learning optimization behavior. During the initial phase (epochs 1–50), both training and validation losses exhibited noticeable fluctuations, stabilizing around values close to 1.0. The average training and validation losses during this stage were 0.86 (SD ≈ 0.06) and 0.92 (SD ≈ 0.08), respectively.

Such variability is characteristic of early-stage optimization, during which stochastic gradient–based algorithms explore the parameter space.

In the intermediate phase (epochs 51–300), loss values declined steadily, indicating effective learning and parameter adjustment. Training loss decreased to 0.48 by epoch 150 and further converged to an average of 0.22 (SD ≈ 0.05) by epoch 300. Validation loss followed a comparable downward trend, declining from 0.87 to 0.26 (SD ≈ 0.06). The progressively reduced fluctuation range during this phase suggests that the model approached convergence and developed increasingly stable internal representations. Throughout this stage, validation loss consistently remained slightly higher than training loss, with a mean difference of approximately 0.04, indicating the absence of substantial overfitting.

In the later phase (epochs 301–1,000), further reductions in loss were marginal, accompanied by minor oscillations and occasional spikes. By epoch 1,000, both training and validation losses reached minimal values, with mean losses of 0.11 (SD ≈ 0.10) and 0.14 (SD ≈ 0.12), respectively. This pattern—characterized by rapid early decline, gradual stabilization, and late-stage fine-tuning—aligns with canonical learning dynamics observed in deep neural network training. Minor rebounds in later epochs can be attributed to stochastic gradient noise and learning rate adjustments rather than systematic divergence.

From a distributional perspective, the interquartile range (25th–75th percentile) of training loss contracted markedly from 0.80–0.95 in the initial phase to 0.02–0.20 in the final phase. Validation loss exhibited a similar contraction, narrowing from 0.90–1.02 to 0.03–0.25. The convergence of both loss distributions in later epochs further underscores the model's strong generalization capability and the lack of pronounced overfitting.

Overall, the observed learning behavior confirms the stability and effectiveness of the proposed training strategy. The resulting learning curve provides a robust empirical baseline for subsequent analyses, including model comparison, hyperparameter tuning, and the potential implementation of early stopping mechanisms.

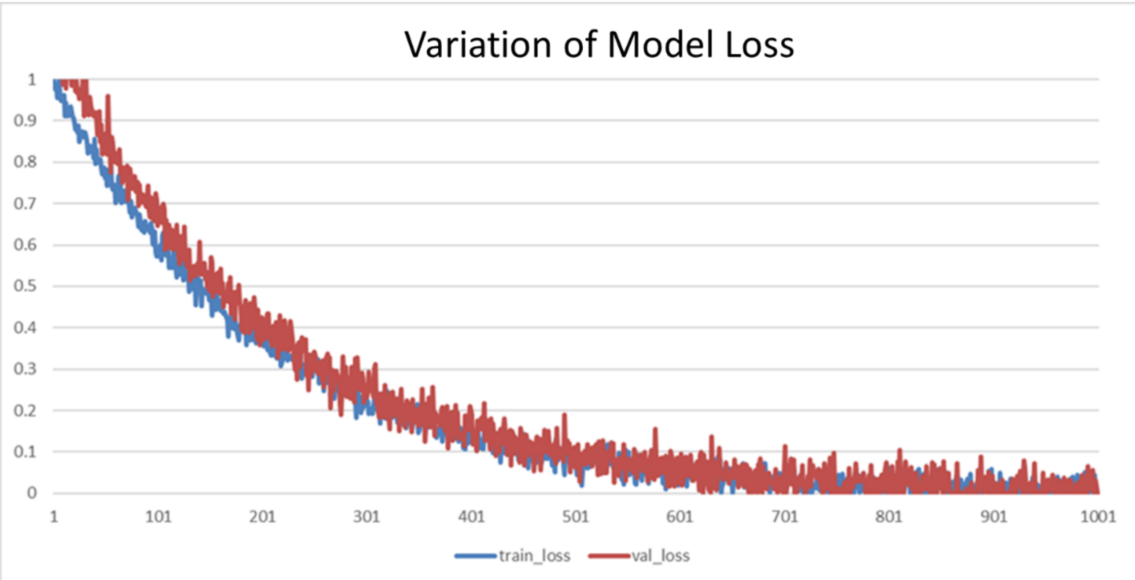

Figure 5. Variation of Model Loss During Training

Figure 6 presents the evolution of the model's root mean square error (RMSE) across 1,000 training epochs. At the initial stage of training, the RMSE begins at approximately 1.00 and exhibits a rapid exponential decline during the first 100 epochs, decreasing to around 0.70. This sharp reduction reflects the model's early-stage learning and substantial parameter adjustments as it captures dominant patterns in the data.

Between epochs 100 and 500, the RMSE continues to decrease, albeit at a slower rate, with substantially reduced oscillations. During this phase, error values gradually stabilize within the range of approximately 0.60 to 0.30, indicating that the model transitions into a mid-level convergence stage characterized by increasingly stable representations. Beyond epoch 500, the decline in RMSE becomes more gradual, asymptotically approaching a lower bound of 0.0316, which is ultimately reached at the final training epoch. This late-stage behavior reflects a fine-tuning process in which incremental improvements are achieved through minor parameter updates. Descriptive statistics across the full training sequence further illustrate this convergence pattern. The RMSE exhibits a maximum value of 1.002 and a minimum of 0.0316, with a mean of 0.34 and a standard deviation of 0.23. The median RMSE is 0.30, with the first and third quartiles at 0.21 and 0.48, respectively. The resulting right-skewed distribution indicates that relatively low error values dominate the majority of training epochs, while higher errors are concentrated in the early stages of training and during occasional fluctuations. Overall, the observed RMSE trajectory is consistent with established learning dynamics of deep neural networks, encompassing rapid initial convergence, a stabilization phase, and gradual fine-tuning toward the end of training. The repeated attainment of the lower bound value suggests that the model approaches either its representational capacity under the given architecture or the numerical precision limits of the computational framework. Together, these results provide empirical evidence of effective model convergence and support the robustness of the proposed training strategy.

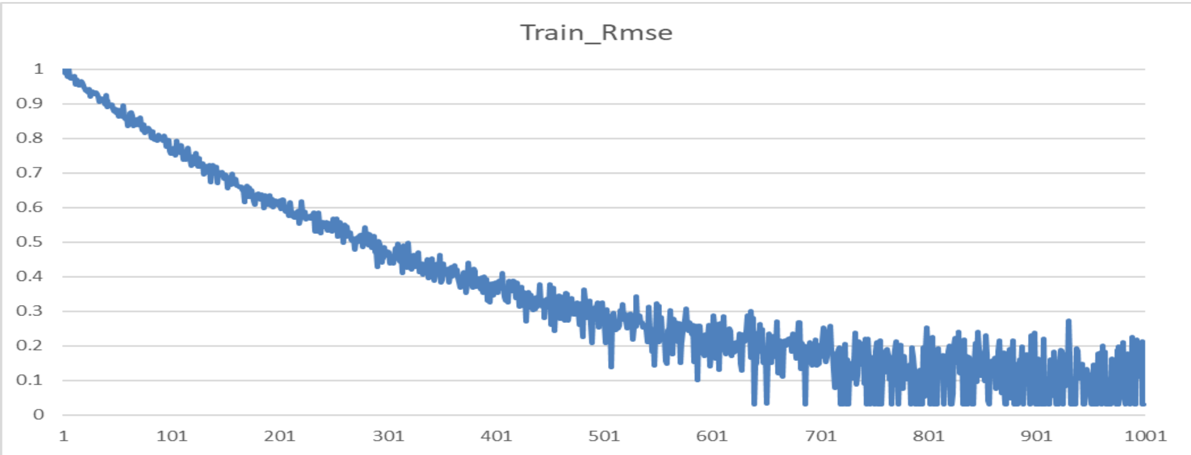

Figure 6. Train Rmse

Figure 7 illustrates the evolution of training accuracy (train_acc) and validation accuracy (val_acc) across 1,000 training epochs, revealing a learning trajectory characteristic of deep neural network optimization. At the initial epoch, train_acc and val_acc were 0.508 and 0.482, respectively, reflecting the absence of meaningful feature representations at the onset of training. During the early learning phase (epochs 1–300), both accuracy metrics increased rapidly in an approximately linear manner. Training accuracy improved from 0.508 to approximately 0.63 (range: 0.489–0.657, SD = 0.041), while validation accuracy rose from 0.482 to around 0.57 (range: 0.430–0.626, SD = 0.052). This stage was characterized by noticeable volatility, consistent with substantial parameter adjustments and exploratory learning commonly observed in early-stage deep learning training.

In the intermediate phase (epochs 301–700), training accuracy continued to improve, reaching approximately 0.78 (range: 0.57–0.90), while validation accuracy stabilized within the range of 0.55–0.74. A plateau effect emerged during this period, accompanied by a modest but persistent performance gap between training and validation accuracy (mean difference ≈ 0.04). This divergence suggests the onset of mild overfitting as the model increasingly adapted to the training data. During the late training phase (epochs 701–1,000), both metrics exhibited incremental gains and converged toward near-optimal values. Training accuracy reached 0.999, while validation accuracy converged to 0.939, with a peak value of 0.964. Concurrently, the standard deviations of train_acc and val_acc declined to 0.050 and 0.070, respectively, indicating reduced oscillations and enhanced stability in model performance. Aggregate statistics further confirm the convergence behavior. Across all epochs, training accuracy averaged 0.77 (median = 0.80, Q1 = 0.65, Q3 = 0.92), whereas validation accuracy averaged 0.74 (median = 0.77, Q1 = 0.60, Q3 = 0.87). The two accuracy series exhibited a strong positive correlation (Pearson's r ≈ 0.96), indicating that validation performance closely tracked training accuracy with a slight lag. Overall, the results delineate a canonical deep learning training trajectory comprising three stages: rapid initial improvement, intermediate stabilization, and late-stage fine-tuning. Although a small performance gap of approximately 0.02–0.05 persisted between training and validation accuracy in later epochs, the overall pattern indicates effective learning and strong generalization capability. These findings provide empirical support for the robustness and convergence efficiency of the proposed model.

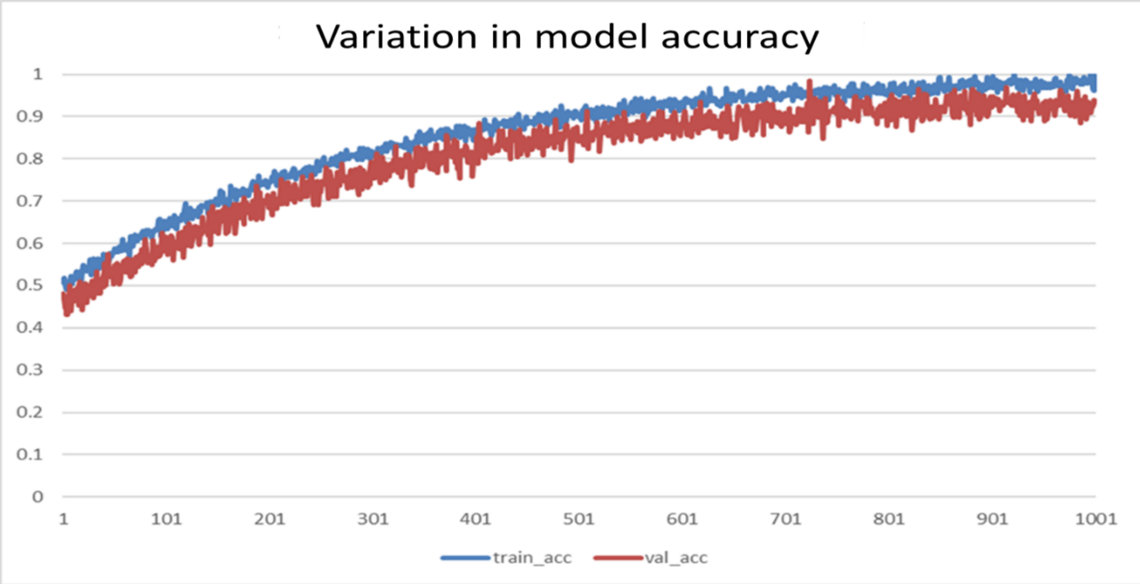

Figure 7. Variation in model training and validation accuracy across epochs.

To advance the application of recommendation systems in spatial decision-support contexts, this study proposes a visualization framework that integrates deep learning–based evaluation indices with Geographic Information System (GIS) techniques. The framework is designed to enhance decision-making efficiency by jointly addressing spatial proximity and multidimensional service quality in pet store selection. At the core of the framework, a deep neural network trained on large-scale, real-world data is employed to compute a composite evaluation index for each pet store. This index synthesizes multiple dimensions, including geographic proximity, user ratings, service categories, pricing structures, and consumer purchasing behaviors related to pet health products. By aggregating heterogeneous attributes into a unified metric, the framework ensures both analytical rigor and interpretability in recommendation outcomes.

Building on this evaluation mechanism, location-aware filtering is applied to dynamically retrieve candidate stores based on users' GPS positions. Recommendation results are subsequently rendered through a GIS-based interface employing multi-scale clustering techniques. At higher-level spatial views, stores with close geographic proximity and similar evaluation scores are aggregated into clusters, with relative intensity visually encoded through variations in marker size and color gradients. This macro-level representation enables users to rapidly identify high-value regions and overall spatial patterns. As users zoom into finer spatial resolutions, clustered markers are progressively decomposed into individual store representations, displaying essential attributes such as store name, location, composite evaluation score, and aggregated user ratings. Interactive functions, including navigation links and on-demand review summaries, further support efficient comparison and informed selection.

The proposed GIS-based visualization strategy enhances the interpretability of spatial recommendation results while mitigating information overload through dynamic filtering and hierarchical representation. Empirical observations of user interaction behavior indicate that this approach significantly improves decision efficiency and reduces cognitive burden during store selection. Overall, the framework demonstrates the effective integration of deep learning–based recommendation models with spatial visualization techniques and provides a scalable and replicable methodological reference for future location-based service (LBS) applications in both academic research and practical deployment.

5. Conclusion and Future Directions

This study develops a comprehensive, data-driven recommendation framework to support pet store selection by integrating personalized analytics, social information, and spatial decision support. Rather than focusing solely on application development, the proposed framework addresses the broader challenge of reducing information asymmetry and decision complexity in pet service selection. By combining

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recommendation algorithms with user-generated content and location-aware visualization, the framework enhances both decision efficiency and informational reliability.

At the analytical core of the framework, recurrent neural networks (RNNs) are employed to model dynamic user preferences and generate personalized recommendations based on large-scale, heterogeneous pet store data. The recommendation mechanism is complemented by socially derived information and interactive tools that extend decision support beyond algorithmic outputs. Specifically, community-based content provides experiential insights, preference-retention mechanisms facilitate comparative evaluation over time, and spatial navigation tools enable contextualized exploration of alternatives. Collectively, these components position the framework as an integrated decision-support environment rather than a standalone recommendation tool.

The contributions of this study can be summarized across three dimensions:

(1) Personalized Decision Support：The proposed framework integrates user-defined criteria—such as geographic proximity, service categories, and aggregated evaluations—into a deep learning–based recommendation process. Preference-retention and reminder mechanisms further reduce search costs and support continuity in user decision-making.

(2) Integration of Social Information：By embedding community-driven features, including peer reviews and structured discussions, the framework incorporates socially generated knowledge into the recommendation process. This integration enriches individual evaluations and mitigates the limitations of purely algorithmic recommendations.

(3)Analytical Visualization for Decision Interpretation：The framework synthesizes multi-source data and user feedback into a unified analytical structure and employs visualization techniques to translate complex evaluation results into interpretable spatial and graphical representations. This approach enhances transparency, reduces cognitive burden, and supports informed comparison across alternatives.

Overall, this study contributes a replicable and extensible methodological framework that demonstrates how deep learning, social information, and spatial visualization can be jointly leveraged to improve recommendation quality and decision support. The proposed approach offers both theoretical implications for recommendation system research and practical relevance for location-based service applications within the pet service industry and related domains. The mobile application developed in this study is designed as an integrated pet store recommendation system that aligns with user needs for store selection and information retrieval. By combining deep learning–based analytical models with user-centered design, the system provides accurate, personalized recommendations, underscoring its dual contributions to both academic inquiry and practical implementation.

Looking ahead, the proposed framework offers several promising avenues for refinement and extension across four interrelated dimensions: data integration, algorithmic development, technological scope, and user experience. (1) Data Integration. Future research may incorporate more heterogeneous data sources beyond structured store profiles and user reviews, including social media streams and Internet of Things (IoT)–generated data. Such integration would enable richer behavioral modeling and more nuanced evaluation metrics, thereby improving recommendation robustness and accuracy. At the same time, advances in data preprocessing, governance, and privacy-preserving mechanisms will be essential to ensure data quality, security, and computational efficiency. (2) Algorithmic Development. While the present study adopts recurrent neural networks (RNNs) to model sequential user preferences, emerging paradigms such as graph neural networks (GNNs), deep reinforcement learning, and hybrid architectures provide promising directions for enhancing model expressiveness and adaptability. In addition, multi-task and transfer learning approaches could allow the framework to capture multiple aspects of user behavior simultaneously and improve generalization across diverse recommendation scenarios. (3) Technological Scope and Application Domains. From an application perspective, the proposed framework may be extended to a broader range of pet-related services, including healthcare management, digital commerce, and community-oriented platforms. The incorporation of immersive technologies, such as virtual reality (VR) and augmented reality (AR), also presents opportunities to enhance user engagement and experiential decision-making. Furthermore, cross-platform and cross-device interoperability would facilitate wider adoption and practical deployment. (4) User Experience and Interaction Design. Future studies should place greater emphasis on human-centered design by integrating principles from human–computer interaction and user experience (UX) research. Systematic usability evaluation and the incorporation of adaptive feedback mechanisms could enable continuous refinement of the recommendation process, ensuring intuitive interaction and sustained relevance across diverse user contexts.

In summary, this study outlines a forward-looking research agenda grounded in four strategic pillars: multi-source data integration, algorithmic innovation, technological convergence, and enhanced user experience. Advancements along these dimensions are expected not only to strengthen the practical applicability of pet store recommendation systems but also to contribute to the broader academic discourse on intelligent decision-support and personalized service ecosystems.

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