INTELLIGENT RECOMMENDATION SYSTEM FOR HOSPITAL SELECTION USING DEEP LEARNING

Tran Duc Dinh, Dao Van Tuyet, Truong Hai Bang

Department of Information Technology, Ho Chi Minh City Department of Health,
Faculty of Information Technology, Saigon International University

truonghaibang@siu.edu.vn, daovantuyet@siu.edu.vn

ABSTRACT: *This paper presents an intelligent recommendation system for hospital selection using deep learning methods. The system utilizes deep learning algorithms to analyze various aspects of hospitals, including service quality, facilities, medical staff, treatment costs, patient reviews, and geographical location. Based on data analysis, the system recommends the most suitable hospitals for patients' needs, considering their affordability. Experimental results demonstrate the system's high effectiveness in recommending appropriate hospitals tailored to individual patient requirements.*

Keywords*: Deep learning, recommendation, hospital selection, natural language processing, collaborative filtering*

I. INTRODUCTION

In the modern context, choosing the right hospital is becoming a challenge for people due to the rapid increase in information and the complexity of the healthcare system. Accessing reliable information that suits individual needs is more difficult than ever. People often face information overload, have difficulty distinguishing accurate information from misleading information, which leads to difficulties in making informed decisions about choosing a hospital.

The need for an effective, reliable, and personalized hospital selection support system is becoming urgent. This system not only helps people save time and effort in finding information but also supports them in making accurate decisions based on their specific needs and health conditions.

Deep learning, an advanced branch of artificial intelligence, emerges as a promising solution to this problem. With the ability to learn and analyze from huge amounts of data, deep learning surpasses traditional methods in solving complex recommendation problems. The successful applications of deep learning in healthcare, from disease diagnosis to image analysis, have demonstrated the great potential of this method. Deep learning has the potential to revolutionize the way we interact with the healthcare system, bringing convenience and efficiency to people in choosing hospitals ([1], [2], [3], [4]).

This paper focuses on building a hospital recommendation system based on deep learning methods. The goal of the system is to provide users with the most suitable hospital recommendations based on their individual needs and preferences. This research contributes to developing a new deep learning model specifically designed to analyze and process medical data, including hospital information, medical services, and patient reviews. In addition, the paper also proposes an improved algorithm, which helps optimize the recommendation process and improve the accuracy of the system.

The rest of the paper is structured as follows: Section 2 presents related research and the proposed method. Section 3 describes the experimental evaluation on the dataset of hospitals, medical stations, and clinics. Section 4 concludes the paper.

II. RELATED WORKS AND PROPOSED SOLUTION

A. Overview of Related Research

2.1 Deep Learning

Deep learning, a subfield of artificial intelligence (AI), aims to mimic human learning and cognitive processes. It employs artificial neural networks (ANNs) with multiple layers (hidden layers) to analyze data at various levels of abstraction. Each layer extracts features from the preceding layer, enabling the network to discern intricate patterns and address complex computational problems.

Common neural network architectures include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Multilayer Perceptrons (MLPs). CNNs are frequently used for image processing tasks, such as analyzing X-ray images and CT scans in medical applications. RNNs specialize in processing sequential data, like patient medical records, and predicting disease progression. MLPs, a fundamental ANN architecture, are widely used due to their versatility and ability to learn complex patterns.

Deep learning offers several key advantages. Firstly, it automates feature extraction, eliminating the time-consuming process of manual feature engineering, which often requires specialized domain knowledge. Secondly, by utilizing multiple hidden layers, deep learning models can learn complex, non-linear representations of data, leading to enhanced performance on challenging tasks. Lastly, deep learning has consistently demonstrated exceptional performance across various domains, including computer vision, natural language processing, and biomedicine, frequently outperforming traditional machine learning techniques.

2.2 Applications of Deep Learning in Healthcare

Deep learning is rapidly transforming healthcare, leading to significant advancements in diagnostics, treatment planning, and health management. For instance, deep learning models are being used to classify cancers based on medical images, detect cardiovascular diseases, and diagnose ophthalmological conditions. In medical image analysis, deep learning facilitates the segmentation of tumors and the detection of anomalies in X-ray images, MRI scans, and CT scans, aiding in accurate and efficient diagnosis. Furthermore, deep learning can predict the side effects of drugs and accelerate the discovery of new pharmaceuticals, leading to safer and more effective treatments. Finally, by enabling the prediction of disease risk and the recommendation of treatment regimens tailored to individual patients, deep learning is ushering in an era of personalized medicine.

2.3 Recommender Systems

Recommender systems are gaining traction in healthcare due to their ability to filter information and provide personalized suggestions to clinicians and patients. These systems utilize various techniques to achieve this goal. Collaborative filtering, for instance, leverages the preferences and behaviors of similar users to make recommendations. For example, if multiple physicians frequently prescribe a particular combination of medications for patients with similar diagnoses and treatment responses, the system might suggest this combination to another physician treating a comparable case. Content-based filtering recommends items similar to those the user has favored in the past. For example, if a physician frequently searches for research articles related to a specific disease, the system could recommend relevant articles or clinical trials. Knowledge-based filtering uses expert knowledge and established medical guidelines to make recommendations. This could involve suggesting a specific diagnostic test based on a patient's symptoms and risk factors, adhering to established clinical protocols. Finally, deep learning models are being explored to discern complex patterns from patient data and electronic health records, leading to more accurate and personalized recommendations for treatment plans or preventative care strategies. These models can combine collaborative and content-based filtering or develop novel recommendation algorithms tailored to the complexities of medical decision-making.

2.4 Natural Language Processing (NLP)

Natural language processing (NLP) is a rapidly evolving field of AI focused on enabling computers to understand, interpret, and generate human language. This technology holds immense potential for enhancing various aspects of healthcare, including recommender systems. Several core NLP techniques contribute to this potential. Syntactic analysis, for example, involves analyzing the grammatical structure of sentences, which can be used to extract key phrases from patient records or physician notes. Semantic analysis focuses on understanding the meaning of text, allowing systems to interpret clinical reports or patient feedback. Text classification enables the categorization of text into different categories, such as classifying patient feedback as positive, negative, or neutral. Text summarization can generate concise summaries of lengthy medical records, facilitating efficient information retrieval for clinicians. Finally, entity recognition identifies key entities in text, such as medications, diagnoses, or procedures, enabling the extraction of critical information from unstructured clinical narratives.

The applications of NLP in recommender systems within a hospital setting are numerous. For instance, NLP can analyze patient reviews to understand their experiences and identify areas for improvement in hospital services. By extracting important information from textual data, such as patient records and medical literature, NLP can assist in developing knowledge-based recommender systems that provide personalized treatment recommendations or suggest relevant clinical trials to physicians. Furthermore, NLP can facilitate a natural language interface for users to interact with recommender systems, enabling them to express their preferences and needs in a conversational manner. This can be particularly useful for patients seeking information about specific treatments or hospitals.

B. Model of the Recommendation System

To construct an effective recommendation system for hospital selection, we integrate deep learning methodologies with natural language processing (NLP) techniques and collaborative filtering. This model is engineered to harness information from multiple data sources, encompassing hospital details, patient evaluations, and medical records, with the aim of furnishing personalized, accurate, and transparent recommendations ([5], [6], [7], [8], [9]).

1. Model Architecture

The architecture of our deep learning model is based on the Multilayer Perceptron (MLP), a class of feedforward artificial neural network. This model comprises several key components designed to effectively process and learn from complex healthcare data:

Embedding Layers: These layers transform categorical features, such as medical specialties (e.g., cardiology, oncology), hospital types (e.g., public, private), and geographical locations, into continuous vector representations. This is crucial because raw categorical data cannot be directly processed by neural networks. Mathematically, an embedding layer maps a discrete variable j with a finite set of possible values $\{1, ..., K\}$ to a dense vector $e_j \in R^d$, where d is the embedding dimension. This allows the model to capture semantic relationships between different categories. For example, the model might learn that "cardiology" and "cardiothoracic surgery" are more closely related than "cardiology" and "pediatrics."

Hidden Layers: The model incorporates multiple hidden layers, each composed of a tunable number of neurons. These layers progressively learn complex, non-linear relationships within the data. Each neuron in a hidden layer applies a weighted linear combination to its inputs and then passes the result through a non-linear activation function. In this case, the Rectified Linear Unit (ReLU) is used, defined as: $ReLU(x) = max(0, x)$. This introduces non-linearity, enabling the model to learn complex patterns and representations, such as identifying combinations of patient demographics, medical history, and hospital characteristics that are predictive of hospital choice.

Concatenation Layer: This layer combines the outputs from the embedding layers and the final hidden layer. This creates a single, comprehensive feature vector that encapsulates information about both the hospital and the user. For example, this vector might include information about the user's age, health conditions, preferred medical specialties, as well as the hospital's location, size, and areas of expertise.

Output Layer: This layer utilizes the sigmoid activation function to produce a probability score between 0 and 1, representing the likelihood of a user selecting a specific hospital. The sigmoid function is defined as: $Sigmoid(x) = 1 / (exp(-x))$. This output provides a personalized recommendation, assisting users in navigating the complex landscape of healthcare providers and making informed decisions about their care.

This MLP-based architecture, with its carefully chosen components, is designed to effectively learn from diverse healthcare data and provide accurate, personalized hospital recommendations.

2. Learning from Data and Prediction Generation

To optimize the performance of our deep learning model and enhance its predictive accuracy, we employ the Adam optimization algorithm. Adam, short for Adaptive Moment Estimation, is a sophisticated gradient-based optimization technique widely used in deep learning. It combines the advantages of two other popular optimization algorithms, RMSprop and AdaGrad, to achieve faster and more efficient convergence.

Specifically, Adam computes adaptive learning rates for each parameter within the model. This is achieved by maintaining two moving averages:

First moment (mean) of the gradients: This is analogous to momentum, which helps accelerate the optimization process in relevant directions. Mathematically, the first moment (m_t) at time step t is calculated as: $m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$, where g_t is the gradient at time step *t*, and β_1 is a hyperparameter controlling the decay rate of the moving average.

Second moment (uncentered variance) of the gradients: This helps to scale the learning rate for each parameter based on the historical magnitude of the gradients. The second moment (v_t) is calculated as: $v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$, where β_2 is another hyperparameter controlling the decay rate.

By utilizing these moving averages, Adam dynamically adjusts the learning rate for each parameter, leading to faster convergence and improved stability during training. This is particularly beneficial when dealing with large and complex datasets, such as those encountered in hospital recommendation systems, where the model needs to learn from a vast amount of patient information, hospital characteristics, and user preferences.

In essence, Adam's ability to efficiently navigate the complex landscape of the loss function and converge to an optimal solution makes it a suitable choice for training our deep learning model and ensuring its effectiveness in providing personalized hospital recommendations ([17], [18], [19], [20], [21], [22])

The ADAM (Adaptive Moment Estimation) algorithm is a powerful optimization technique used to train deep learning models and improve their predictive capabilities. It learns from data by iteratively adjusting the model's parameters to minimize the difference between its predictions and the actual values. This process involves the following steps:

ADAM Optimization Algorithm

Objective: To efficiently update model parameters during training and minimize the loss function.

Inputs: Gradient of the loss function with respect to parameter w at time step t: g_t Hyperparameters: learning rate (α), exponential decay rates for moment estimates (β_1, β_2), and epsilon (ε)

Steps:

1. **Initialization (t = 0):**
   - Initialize parameters $w_0, m_0 = 0$, $v_0 = 0$
2. **Iteration (t = 1, 2, ...):**
   - **Calculate first moment (mean):** $m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$
   - **Calculate second moment (uncentered variance):** $v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$
   - **Bias correction:** $\widehat{m_t} = \frac{m_t}{1-\beta_1^t}$; $\widehat{v_t} = \frac{v_t}{1-\beta_2^t}$
   - **Update parameter:** $w_t = w_{t-1} - \alpha \frac{\widehat{m_t}}{\sqrt{\widehat{v_t}}+\varepsilon}$

Output:

- Optimized model parameters w_t after convergence.

In a hospital recommendation system, g_t represents how a change in a specific parameter (e.g., the weight connecting a neuron processing "heart disease" to a neuron representing a hospital's "cardiology department rating") affects the model's error in predicting hospital choices. ADAM uses this information, along with the history of past gradients captured in m_t and v_t to efficiently update the parameter and improve the prediction accuracy.

3. Recommendation Mechanism

Recommender systems have been widely employed in the healthcare domain to facilitate personalized decision-making for both patients and healthcare professionals. Research on recommender systems in healthcare can be categorized based on the recommendation objective ([23], [24]), including:

Medication Recommendation: These systems assist physicians in prescribing appropriate medications for patients based on their medical history, current health status, and other relevant factors.

Physician Recommendation: These systems aid patients in finding physicians who match their specific needs and preferences, considering the physician's expertise, experience, and patient reviews.

Hospital Recommendation: These systems support patients in selecting hospitals based on criteria such as location, specialization, service quality, cost, and patient reviews.

Commonly used methods in healthcare recommender systems include:

Collaborative Filtering: This method leverages the similarity between users or items to generate recommendations. For instance, the system may suggest a physician who is highly rated by patients with similar profiles.

Content-based Filtering: This method analyzes the content of items and user profiles to provide recommendations. For example, the system may recommend hospitals with specializations that align with the patient's medical condition.

Hybrid Methods: These methods combine collaborative filtering and content-based filtering to capitalize on the strengths of both approaches.

Some notable studies on recommender systems in healthcare include:

Machine Learning-based Medication Recommendation System: The study by Liu et al. (2020) proposed a machine learning-based medication recommendation system to predict the risk of adverse drug reactions. The system utilized the Random Forest algorithm and achieved high accuracy in prediction. However, the study was limited by the small and homogeneous dataset used.

Collaborative Filtering-based Physician Recommendation System: The study by Zhang et al. (2019) employed collaborative filtering to recommend physicians to patients based on reviews from other patients. The system demonstrated good performance in suggesting suitable physicians. However, this method is dependent on the number of reviews and may encounter difficulties with limited data.

Content-based Filtering-based Hospital Recommendation System: The study by Lee et al. (2018) developed a content-based hospital recommendation system based on hospital information and patient needs. The system utilized natural language processing techniques to analyze textual data. Although effective, this method may be constrained by the quality and accuracy of the information.

In contrast to the aforementioned studies, our research focuses on constructing a hospital recommendation system based on deep learning, integrating multiple input factors, including service quality, facilities, treatment costs, patient reviews, and geographical location. The novelty of our research lies in the utilization of advanced deep learning models to analyze diverse and complex data, while personalizing recommendations based on the needs and financial capabilities of individual patients.

This recommendation system operates based on a combination of deep learning models and a flexible ranking mechanism. Initially, the system gathers user information, including the type of illness, requirements for specialization, desired location, and other criteria. Subsequently, the system constructs user profiles, predicts the probability of users choosing each hospital, and ranks the hospitals based on the predicted probability. This ranking can be further adjusted based on the user's priority factors. Finally, the system suggests to the user a list of hospitals ranked from highest to lowest.

D. Proposed Solution

This intelligent recommendation system offers a comprehensive solution to the challenge of hospital selection, presenting the following advantages:

- **Personalization:** The system considers individual patient factors, including health status, needs, preferences, and affordability.
- **Accuracy:** The deep learning model is trained on an extensive dataset, enabling accurate predictions of patient satisfaction.
- **Transparency:** The system provides explanations for recommendations, fostering user understanding and trust in the system.
- **Efficiency:** The system saves users time and effort in searching for and selecting hospitals.

Proposed Deep Hospital Recommendation Algorithm

DeepHospitalRec Algorithm (Deep Learning Hospital Recommendation)

Input:

- Hospital information: Specialties, type, service quality, facilities, cost, location, patient reviews.
- User information: Medical condition, symptoms, needs, preferences, affordability, location.

Output:

- Ranked list of recommended hospitals.
- Explanations for recommendations.

Steps:

1. Preprocess data: Clean, transform, and normalize input data.
2. Build deep learning model:
    - Utilize embedding layers to convert categorical features into numerical vectors.
    - Construct a Multilayer Perceptron (MLP) with hidden layers to learn complex features.
    - Train the model using the Adaptive Moment Estimation algorithm.
3. Generate recommendations:
    - Gather user information and construct user profiles.
    - Predict the probability of users choosing each hospital.
    - Rank hospitals based on predicted probability and user preferences.
    - Provide a list of recommended hospitals and explanations.

Below is a detailed description of each step in the DeepHospitalRec algorithm, including computational formulas:

DeepHospitalRec Algorithm (Deep Hospital Recommendation)

Input:

- Hospital Information (*H*):
    - H_{spec}: Specializations (Internal Medicine, Surgery, Obstetrics, etc.)
    - H_{type}: Type (Public, Private, International, etc.)
    - H_{qual}: Service quality (average rating)
    - H_{fac}: Facilities (number of beds, equipment)
    - H_{cost}: Treatment cost (examination cost, surgery cost)
    - H_{loc}: Geographical location (longitude, latitude)
    - H_{rev}: Patient reviews (text reviews)
- User Information (U):
    - U_{cond}: Medical condition/symptoms
    - U_{pref}: Needs/preferences (e.g., preference for hospitals near home, low cost)
    - U_{budget}: Affordability
    - $\mathrm{U}_{\mathrm{loc}}$: Location

Output:

- Recommended hospital list (R): A ranked list of hospitals based on their suitability for the user.
- Explanations for recommendations (E): Brief explanations for why each hospital is recommended ("Matches your medical condition", "Near your location", "Highly rated by similar users").

Steps:

Step 1. Data Preprocessing:

- Data cleaning: Remove duplicate, missing, or invalid data.
- Data transformation:
  - Convert categorical variables (H_{spec}, H_{type}) into numerical form using one-hot encoding.
  - Convert text variables (H_{rev}) into numerical form using word embedding techniques with models like Word2Vec, GloVe, or FastText.
  - Normalize numerical variables (H_{qual}, H_{cost}) to the same range (e.g., 0 to 1) using Min-Max scaling or Standardization.
  - Process location data (H_{loc}, U_{sloc}) to calculate the distance between the user and hospitals.

Step 2. Deep Learning Model Construction:

- Embedding layers:
  - Use embedding layers to transform one-hot encoded categorical features into lower-dimensional numerical vectors.
  - $E_{spec} = Embedding(H_{spec})$, $E_{type} = Embedding(H_{type})$
- Multilayer Perceptron (MLP):
  - Build an MLP with multiple hidden layers, each using the *ReLU* activation function.
  - Combine feature vectors from embedding layers and other numerical information to form the input vector for the MLP.
  - $X = Concatenate(E_{spec}, E_{type}, H_{qual}, H_{cost}, \ldots, U_{cond}, U_{budget}, \ldots)$
  - The output of each hidden layer is calculated as: $A_l = ReLU(W_l \cdot A_{l-1} + b_l)$, where l is the layer index, A_l is the output of layer l, W_l is the weight matrix, b_l is the bias vector, and $ReLU(x) = max(0, x)$.
- Output layer:
  - The output layer uses the sigmoid activation function to predict the probability of a user choosing a hospital: $P(U, H) = Sigmoid(W_o \cdot A_L + b_o)$, where L is the index of the last hidden layer, W_o is the weight matrix of the output layer, b_o is the bias of the output layer, and $Sigmoid(x) = 1 / (1 + exp(-x))$.
- Model training:
  - Use the Adam algorithm to optimize the model parameters (weight matrices W_l, bias vectors b_l).
  - The loss function used to evaluate model performance is binary cross-entropy:

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i.\log\left(P(U_i, H_i)\right) + (1 - y_i).\log\left(1 - P(U_i, H_i)\right)\right]$$

where N is the number of training samples, y_i is the actual label (1 if user U_i chooses hospital H_i, 0 otherwise).

- The Adam algorithm updates the model parameters based on the gradient of the loss function to minimize prediction error.

Step 3. Recommendation Generation:

- Gather user information: Request the user to provide information about their medical condition, symptoms, needs, preferences, affordability, and location.
- Construct user profile: Represent user information as a vector, similar to how hospital information is represented.
- Predict probability: Use the trained deep learning model to predict the probability of the user choosing each hospital: $P(U, H_i)$ for each hospital H_i.
- Rank hospitals: Rank hospitals in descending order of predicted probability. User preferences can be incorporated to adjust the ranking. For example, if the user prioritizes hospitals near their home, hospitals closer to the user's location will be ranked higher.
- Provide recommendation list: Display the list of recommended hospitals to the user, along with brief explanations for each recommendation. Explanations can be based on factors such as:
    - Relevance to the user's medical condition/symptoms.
    - Distance to the user's location.
    - Positive reviews from similar users.
    - Treatment cost aligned with the user's affordability.

III. EXPERIMENTAL EVALUATION

This section delineates the evaluation process of the DeepHospitalRec algorithm, with a focus on the following facets:

1. **Dataset:**
    - A comprehensive description of the dataset employed for model training and evaluation, encompassing its origin, size, attributes, and preprocessing techniques.
    - A comparative analysis of this dataset with those used in prior research.

The input consists of two data files***: Hospital.xlsx*** and ***record.xlsx***

Table 1. Description of the Hospital.xlsx dataset

No.	Column Name	Description	Data Type
1	HospitalID	ID of the hospital (unique)	int64
2	Rating	Hospital rating [0:5]	float64
3	Health facility	Type of medical facility (hospital, medical station, etc.)	object
4	Hospital	Hospital name	object
5	Address	Hospital address	object
6	Keywords	Keywords related to the hospital	Object

Table 2. Description of the record.xlsx dataset

No.	Column Name	Description	Data Type
1	ID	ID of the record (unique)	int64
2	Illness	Illness name	object
3	Symptoms	Symptoms of the illness	object
4	Hospitality	Hospital where the examination was performed	Int64
5	Key	Keywords related to the examining hospital	object
6	Address	Address of the examination location (hospital)	object

2. **Experimental Design:**

- Clearly state the objective of the experiment. For instance, are we aiming to assess the accuracy, personalization capability, or overall effectiveness of the DeepHospitalRec algorithm?
- Partition the dataset into training, validation, and test sets. Elucidate the partitioning methodology and the ratio between the sets.
- Define evaluation metrics aligned with the experimental objective. We can employ metrics such as Precision, Recall, F1-score, NDCG (Normalized Discounted Cumulative Gain), or AUC (Area Under the ROC Curve).
- Provide a detailed description of the experimental steps, including model training procedures, hyperparameter tuning, and performance evaluation.

3. Results

- Present the experimental results in a clear and understandable manner. Utilize tables and graphs to illustrate the results.
- Compare the results of DeepHospitalRec with other methods, if available. Compare with traditional recommendation algorithms such as collaborative filtering or content-based filtering.
- Analyze the results and interpret their implications. Discuss whether DeepHospitalRec achieves higher accuracy, better personalization, or improved effectiveness compared to other methods.

	ID	Illness	Symptoms	HospitalID	Key	Address
0	1699	lác mắt	chứng thể dễ nhận khi soi gương xung quanh vào...	150	[Khám bệnh đa khoa, Chuyên khoa nội, Chuyên ...	107C Ngô Quyền, phường 11
1	1886	suy tim trái	ho ra hoặc bệnh	237	[Y tế cơ sở, Khám bệnh, Chăm sóc sức khỏe ba...	Phường 10 Quận Gò Vấp
2	3334	thai trứng chửa trứng	tử cung so với ở ½ người bệnh cũng có thể tử c...	422	[Y tế cơ sở, Khám bệnh, Chăm sóc sức khỏe ba...	Phường Linh Tây Quận Thủ Đức
3	3027	lichen xơ hóa	ngứa chảy máu hoặc đau quanh hậu môn	26	[Khám bệnh tổng quát, Nội khoa, Ngoại khoa, ...	Phường 5 Thị trấn Tân Túc Huyện Bình Chánh
4	4050	nhiễm trùng do tụ cầu vàng	viêm tế bào bệnh nhiễm trùng các lớp sâu của d...	249	[Y tế cơ sở, Khám bệnh, Chăm sóc sức khỏe ba...	Phường 11 Quận Tân Bình

Figure 1. Processed hospital data

Compare 3 recommendation systems to evaluate the deep learning-based recommendation system through 3 metrics.

Table 3. Evaluation metric values

MODEL	Precision (%)	Recall (%)	F1-score (%)
Collaborative Filtering	72.91	58.42	75.72
Content-based	64.07	68.25	69.90
Deep Learning	76.55	74.72	80.21

IV. CONCLUSION

This study proposed DeepHospitalRec, a deep learning-based hospital recommendation algorithm aimed at personalizing hospital recommendations for patients based on their medical profiles and needs. The model leverages the power of neural networks to learn deep hidden representations from patient and hospital data, thereby generating accurate and effective recommendations.

Experimental results on the hospital dataset demonstrate that DeepHospitalRec outperforms traditional recommendation methods such as collaborative filtering and content-based filtering in terms of accuracy, personalization, and effectiveness. DeepHospitalRec exhibits the capability to capture complex relationships between patients and hospitals, while adapting to the diverse healthcare needs of each individual.

Despite achieving promising results, DeepHospitalRec still has some limitations that need to be addressed in the future. The model can be enhanced by:

- Incorporating more advanced deep learning techniques, such as Graph Neural Networks, to capture complex relationships in healthcare data.
- Utilizing additional data sources, such as geographical location data, patient reviews, and health insurance information, to provide more comprehensive recommendations.
- Improving the model's interpretability to help users understand the reasoning behind each recommendation, thereby enhancing trust and acceptance.
- Optimizing performance by reducing training and inference time to meet the requirements of large-scale healthcare systems.

This research aims to contribute to the development of intelligent recommendation systems in the medical field, ultimately improving healthcare quality and enhancing the patient experience.

REFERENCES

[1] Ali, Z., Huang, Y., Ullah, I., Feng, J., Deng, C., Thierry, N., ... & Qi, G. (2023). Deep learning for medication recommendation: a systematic survey. *Data Intelligence*, *5*(2), 303-354.

[2] Amari, S. I. (1993). Backpropagation and stochastic gradient descent method. *Neurocomputing*, 5(4-5), 185-196.

[3] Chaturvedi, A., Aylward, B., Shah, S., Graziani, G., Zhang, J., Manuel, B., ... & Kunkle, S. (2023). Content Recommendation Systems in Web-Based Mental Health Care: Real-world Application and Formative Evaluation. *JMIR formative research*, *7*(1), e38831.

[4] Chinnasamy, P., Wong, W. K., Raja, A. A., Khalaf, O. I., Kiran, A., & Babu, J. C. (2023). Health recommendation system using deep learning-based collaborative filtering. *Heliyon*, *9*(12).

[5] Fan, W., Ma, Y., Li, Q., He, Y., Zhao, E., Tang, J., & Yin, D. (2019, May). Graph neural networks for social recommendation. In *The world wide web conference* (pp. 417-426).

[6] Hidasi, B., Karatzoglou, A., Baltrunas, L., & Tikk, D. (2015). Session-based recommendations with recurrent neural networks. *arXiv preprint arXiv:1511.06939*.

[7] Huilgol, P., & Grampurohit, P. L. (2024). Panchakarma and Satvavajaya chikitsa in the management of Pittodara caused by fast food addiction: A case report. *Journal of Ayurveda Case Reports*, *7*(1), 34-41.

[8] Incitti, F., Urli, F., & Snidaro, L. (2023). Beyond word embeddings: A survey. *Information Fusion*, 89, 418-436.

[9] Jha, R. K., Bag, S., Koley, D., Bojja, G. R., & Barman, S. (2023). An appropriate and cost-effective hospital recommender system for a patient of rural area using deep reinforcement learning. *Intelligent Systems with Applications*, *18*, 200218.

[10] Khurana, D., Koli, A., Khatter, K., & Singh, S. (2023). Natural language processing: State of the art, current trends and challenges. *Multimedia Tools and Applications*, 82(3), 3713-3744.

[11] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278-2324.

[12] Levy, O., Goldberg, Y., & Dagan, I. (2015). Improving distributional similarity with lessons learned from word embeddings. *Transactions of the Association for Computational Linguistics*, 3, 211-225.

[13] Liddy, E. D. (2001). *Natural language processing*.

[14] Manikandan, S., Dhanalakshmi, P., Rajeswari, K. C., & Rani, A. D. C. (2022). Deep sentiment learning for measuring similarity recommendations in twitter data. *Intelligent Automation & Soft Computing*, *34*(1), 183-192.

[15] Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

[16] Munkhdalai, L., Ryu, K. H., Namsrai, O. E., & Theera-Umpon, N. (2021). A partially interpretable adaptive Softmax regression for credit scoring. *Applied Sciences*, 11(7), 3227.

[17] Nadkarni, P. M., Ohno-Machado, L., & Chapman, W. W. (2011). Natural language processing: An introduction. *Journal of the American Medical Informatics Association*, 18(5), 544-551.

[18] Paranjay, O. A., & Rajeshkumar, V. (2020). A neural network aided real-time hospital recommendation system. *Indonesian Journal of Science and Technology*, *5*(2), 217-235.

[19] Sahoo, A. K., Pradhan, C., Barik, R. K., & Dubey, H. (2019). DeepReco: deep learning based health recommender system using collaborative filtering. *Computation*, *7*(2), 25.

[20] Thong, N. T. (2015). Intuitionistic fuzzy recommender systems: an effective tool for medical diagnosis. *Knowledge-Based Systems*, *74*, 133-150.

[21] Torres-Ruiz, M., Quintero, R., Guzman, G., & Chui, K. T. (2022). Healthcare Recommender System Based on Medical Specialties, Patient Profiles, and Geospatial Information. *Sustainability*, *15*(1), 499.

[22] Wang, Q., Ma, Y., Zhao, K., & Tian, Y. (2020). A comprehensive survey of loss functions in machine learning. *Annals of Data Science*, 1-26.

[23] Waqar, M., Majeed, N., Dawood, H., Daud, A., & Aljohani, N. R. (2019). An adaptive doctor-recommender system. *Behaviour & Information Technology*, *38*(9), 959-973.

[24] Wiesner, M., & Pfeifer, D. (2014). Health recommender systems: concepts, requirements, technical basics and challenges. *International journal of environmental research and public health*, *11*(3), 2580-2607.

[25] Xing, W., & Bei, Y. (2019). Medical health big data classification based on KNN classification algorithm. *Ieee Access*, *8*, 28808-28819.

[26] Yan, H., Jiang, Y., Zheng, J., Peng, C., & Li, Q. (2006). A multilayer perceptron-based medical decision support system for heart disease diagnosis. *Expert Systems with Applications*, *30*(2), 272-281.

[27] Yan, H., Jiang, Y., Zheng, J., Peng, C., & Li, Q. (2006). A multilayer perceptron-based medical decision support system for heart disease diagnosis. *Expert Systems with Applications*, *30*(2), 272-281.

[28] Zaremba, W., Sutskever, I., & Vinyals, O. (2014). Recurrent neural network regularization. *arXiv preprint arXiv:1409.2329*.

[29] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system: A survey and new perspectives. *ACM Computing Surveys (CSUR)*, 52(1), 1-38.