Online Physician Recommendation System based on User Rating using Cascaded Res-BiLSTM

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Abstract: Online doctor recommendation system is a platform created to help patients identify suitable doctors according to their individual needs and preferences. This system utilizes deep learning and data analysis, to evaluate patient reviews and doctor-customized recommendations. Patients fluently locate and connect with doctors, particularly in remote regions, thereby improving the overall access to medical services. Maintaining the accuracy and reliability of data gathered from patient reviews and doctor profiles is challenging. Inaccurate or biased information may result in suboptimal recommendations. Numerous doctors may have few reviews or ratings, leading to sparse data that impede the system's capacity to generate precise recommendations. The proposed physician recommendation model is developed with a focus on user ratings to improve the accuracy and relevance of the recommendations offered to patients. Cascaded Residual Bidirectional Long Short-Term Memory (Res-BiLSTM) architecture is proposed to identify complex patterns within the data, including the interrelationships among various features that affect user ratings. The accuracy in recommending suitable physicians to patients using the proposed model is 91.2%. Thus, a high precision score signifies that the system is successful in identifying suitable physicians who support patient preferences and requirements.

Keywords:Online Physician Recommendation System; Cascaded Residual Bidirectional Long Short-Term Memory; Medical Services;

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Nomenclature

Abbriviation	Expansion
Res-BiLSTM	Residual Bidirectional Long Short-Term Memory
WHO	World Health Organization
MAE	Mean Absolute Error
CS	Clustering
MF	Matrix Factorization
TM	Text Mining
KBS	Knowledge-Based System
MAE	Mean Absolute Error

1. Introduction

A recommendation framework is an information filtering system, which is designed to predict the user preferences in a particular entity [1]. This system is commonly used in various fields. Healthcare departments emerged as significant areas to use recommendation systems [2]. The implementation of a recommendation system guides the healthcare sector through their research and clinical research. It helps patients in selecting medical services based on their specific treatment needs. This system provides patient-oriented clinical guidelines [3]. WHO highlights the need for a strong health system to provide quality healthcare services effectively [4]. It provides the benefits of using digital health technologies, such as telemedicine and online health services, in boosting healthcare delivery [5]. Online physician recommendation models are essential to this digital health ecosystem, utilizing various technologies to connect patients with appropriate healthcare professionals. Patients frequently encounter difficulties when trying to select the appropriate healthcare professional due to the different available options [6]. A recommendation system updates this selection process by filtering and ranking physicians according to various factors, including specialty, patient ratings, and location, thereby preserving both time and effort [7]. By concerning patients with physicians who align with their favorites and needs, recommendation systems significantly enhance patient satisfaction. When patients observe that their individual requirements are recognized and met, they are more likely to view their healthcare experience positively. Online recommendation systems in the healthcare sector boost the patient experience by offering personalized,

efficient, and data-driven solutions for selecting healthcare providers. This ultimately results in improved health outcomes and greater patient satisfaction [8].

Specialized information filtering techniques are designed to forecast the recommendations of physicians. Information filtering systems typically start by emerging user profiles that capture individual preferences, behaviors, and historical interactions [9]. The effectiveness of recommendations is significantly dependent on the quality of the data gathered. Online ratings and reviews are subject to bias or manipulation, resulting in unreliable information. Users might provide feedback based on singular experiences rather than a thorough evaluation of a physician's qualifications. Patients frequently face an excessive amount of information while searching for physicians [10]. This abundance of options creates confusion and hinders their ability to make well-informed decisions, mainly when presented with numerous choices. Patients might be disinclined to reveal personal health information or preferences because of privacy concerns [11]. Safeguarding data and upgrading user trust are crucial for the effectiveness of any online recommendation system. Decrypting the specific attributes or experiences that contribute to a given rating is a challenging process. Patients might evaluate physicians based on a range of factors, which complicates the accurate interpretation of these ratings. To overcome these challenges, an innovative online physician recommendation using a machine learning model is developed.

The motivation behind this work:

- ✓ Conventional recommendation systems often face challenges with accuracy due to restrictions in data interpretation. Hence, the implementation of Cascaded Res-BiLSTM enables a more refined model based on user ratings and physician characteristics, resulting in more accurate recommendations.
- ✓ The Cascaded Res-BiLSTM architecture achieves high accuracy at processing sequential data, which is crucial for understanding the temporal dynamics of user interactions and ratings over time. This capability allows the system to identify trends and shifts in user predilections effectively.
- ✓ Many recommendation frameworks encounter issues related to data sparsity, mainly when new users or physicians are introduced. This proposed system addresses this challenge by successfully analyzing the user ratings.
- ✓ By designing relevant and precise recommendations, the system aims to boost user engagement and satisfaction. Patients are more liable to trust and utilize a system that consistently provides appropriate physician options linked to their preferences.
- ✓ The incorporation of state-of-the-art techniques, like Res-BiLSTM, enhances the overall performance of the recommendation system. This demonstrates a potential to utilize technological spreads within the healthcare sector.

Overall structure of the proposed model: This work is organized into several essential sections that mutually describe the operation of the recommendation system. It starts with an introduction that highlights the necessity for personalized healthcare solutions and the problems patients encounter when choosing suitable physicians. Section II, explains the review related to the physician recommendation system. The methodology in Section III expands the incorporation of advanced machine learning techniques, particularly the Cascaded Res-BiLSTM architecture. Next, the result in Section IV provides a performance evaluation of the system. This discussion explores the implications of the findings, highlighting how the system enhances user engagement and supports informed decision-making. Finally, the conclusion summarizes the research contributions and suggests potential future improvements in Section V.

2. Literature Survey

In 2023, Mani *et al*. [12] developed a hybrid Physician Recommender System (PRS) that merged different information filtering techniques, which helped patients identify appropriate physicians based on their individual preferences. In 2019, Wen *et al.* [13] presented a dynamic recommendation system that provided real-time, customized suggestions for each patient as they arrived. This system was designed effectively to tackle the complexities associated with various patient needs and constrained physician resources. In 2023, Chinnasamy *et al.* [14] introduced an innovative health recommendation system that employed filtering techniques. This system provided relevant and timely health-related information to promote better health outcomes. In 2020, Yan *et al.* [15] presented a new recommendation model, which improved the reliability of medical consultation recommendations. This model combines review

information with doctors' specialized data, which drastically boosts the accuracy of the recommendation. In 2019, Sahoo *et al.* [16] designed a recommendation system to enhance the precision and quality of healthcare recommendations. This system was customized to analyze various patient data. This system aimed to improve the decision-making processes in healthcare, thereby boosting patient outcomes and safety. In 2024, Kukalakunta *et al.* [17] have introduced an innovative model for personalized treatment recommendations. This method utilized patient-specific data to construct a detailed patient profile. The suggested model then analyzed this profile to predict the most effective treatment options for each individual. In 2024, Rajasekharan *et al.* [18] designed an innovative model, which provided recommendations that were specific to each consultation, enabling a high level of personalization in diagnosis suggestions. This model was essential across various clinical specialties. In 2020, Jones *et al*. [1] synthesized co-design practices for digital mental health strategies aimed at children and young people. The proposed model addressed the under-representation of certain groups, including younger kids and those with disabilities, which used more inclusive approaches in future developments.

3. Developing Cascaded Res-Bilstm-Based Online Physician Recommendation System

The objective of developing a Cascaded Res-BiLSTM-based online physician recommendation system in the healthcare sector is to progress the accuracy and efficiency of physician recommendations for patients. This system is employed to utilize advanced machine learning network Res-BiLSTM architecture, to effectively analyze intricate patient data and their preferences. Additionally, the proposed system is designed to tackle existing challenges like data scarcity, reliability of rating, and information overload. Thus, the proposed cascaded Res-Bi-LSTM-based online physician recommendation system aimed to overcome these challenges by employing a cascaded architecture that integrates residual connections and bidirectional LSTM networks, this model can capture the subtleties of patient preferences and physician characteristics. The designed cascaded Res-Bi-LSTM approach helps to reduce the influence of unreliable ratings by focusing on more consistent patterns in the data.

The cascaded Res-Bi-LSTM model is customized to analyze both patient-specific and physician attributes, enabling more customized recommendations with individual patient needs. This personalization helps to diminish information overload by providing the most relevant options to patients. The integration of the LSTM network, allows the cascaded Res-Bi-LSTM model to adjust new information and shifts in the healthcare landscape more effectively. This flexibility ensures that recommendations remain updated and pertinent over time. The feedback mechanism in cascaded Res-Bi-LSTM analyzes both patients' and physicians' feedback and facilitates a more comprehensive validation. This dual feedback mechanism helps to refine the recommendation process and enhances overall user satisfaction. The cascaded Res-Bi-LSTM system utilizes advanced performance metrics, including MAE, precision, recall, and F-measure, to assess the accuracy of its recommendations. Thus, the cascaded Res-Bi-LSTM-based online physician recommendation system effectively tackles the challenges faced by existing systems by improving their reliability and customized recommendations. The block diagram of the proposed physician recommendation system is provided in Fig. 1.

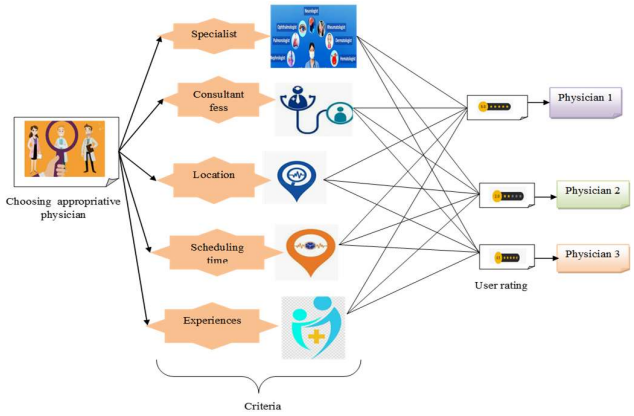


Fig 1. Block Diagram of Proposed Physician Recommendation System

3.1. Dataset Collection

Details regarding physicians, including their specialties, years of experience, educational qualifications, certifications, and patient ratings. This information is essential for assessing the qualifications and expertise of each doctor. This information is collected using the relevant data source from the link https://www.kaggle.com/datasets/ebrahimelgazar/doctor-specialist-recommendation-system accessed on 2024-11-06.

This dataset is commonly used to train machine learning models that predict the most suitable specialty for a patient based on their needs. In this dataset, a total of 250 physician data are included for the analysis. Using this dataset, researchers build more effective recommendation systems, which enhance the patient experience by guiding them to the appropriate healthcare providers, ultimately leading to progressed healthcare outcomes.

3.2. BiLSTM: Basic Theoretical Description

Bi-LSTM network [19] utilizes two LSTM layers to process input sequences in both forward and backward directions. This dual processing helps to capture contextual information, which significantly enhances its ability to learn from sequential data. LSTM cells consist of three primary gates.

Input gate: Regulates the amount of new information to be stored in the cell. It is indicated as Tr, and the mathematical form is given in Eq. (1).

$$Tr = \gamma\left(E_g \cdot \left[j_{p-1}, pr\right] + kr\right) \tag{1}$$

Forget gate (Rb): It determines how much of the existing cell state is retained and the mathematical expression is provided in Eq. (2).

$$Rb = \gamma\left(E_b \cdot \left[j_{b-1}, pb\right] + kb\right) \tag{2}$$

Output gate (Gm): Control how much of the cell state is obtained as output and the statistical form is provided in Eq. (3).

$$Gm = \gamma\left(E_m \cdot \left[j_{m-1}, pm\right] + km\right) \tag{3}$$

Here, the weighted matrix term is indicated as E_g, E_b, and E_m. The bias terms are represented as kr, kb, and km. The sigmoid activation function is specified as γ. Bi-LSTM networks tackle the vanishing gradient issue by utilizing a memory cell capable of retaining information over extended periods.

3.3. Cascaded Res-BiLSTM-based Recommendation system

Designed Cascaded Res-BiLSTM-based recommendation system combines the benefits of residual network and Bi-LSTM networks to progress the effectiveness of recommendation systems. This architecture helps in organizing sequential data and identifying intricate patterns in user-item interactions. Bi-LSTM processes input sequences in both forward and backward directions, effectively capturing temporal dependencies. This potential is necessary for recommendation systems, as user ratings will change over time. In this Cascaded Res-BiLSTM system, residual blocks are incorporated into the BiLSTM layers with a series of convolutional layers. These convolutional layers are followed by a skip connection that adds the block's input to its output. This design enables the Cascaded Res-BiLSTM system to learn

both the residual mapping and the original input, which enhances the feature extraction. A residual block in Cascaded Res-BiLSTM addresses the vanishing gradient problem, facilitating the training of deeper networks. They allow the Cascaded Res-BiLSTM to perform individuality mappings, which is essential when the user demand is close to the input. The cascaded architecture stacks multiple layers of Res-BiLSTM blocks. Each layer processes the output from the previous layer, allowing for deeper feature extraction and more complex representations. The output from the final BiLSTM layer is directed and fed to a fully connected layer to produce the final recommendations.

The benefits of the designed Cascaded Res-BiLSTM-based framework are provided in the below points.

- ✓ By integrating the strengths of BiLSTM and residual connections, the system effectively learns from sequential data, boosting recommendation accuracy.
- ✓ Residual connections allow for the training of deeper networks without the risk of overfitting, enhancing the flexibility of the proposed model.
- ✓ The Bi-LSTM architecture captures the temporal dynamics of user rating, resulting in more relevant recommendations.

Thus, the Cascaded Res-BiLSTM system achieves high capability to analyze complex patient data enabling it to provide highly personalized recommendations customized to individual patient needs, preferences, and medical histories, beyond the performance of simpler recommendation systems. The diagrammatic illustration of the proposed Cascaded Res-BiLSTM-based recommendation system is provided in Fig. 2.

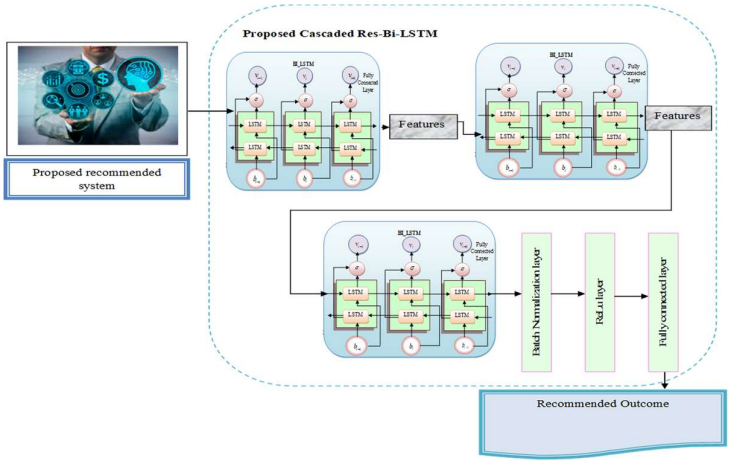


Fig 2. Proposed Cascaded Res-BiLSTM-based Recommendation System

4. Assessments Made On Online Physician Recommendation System

The experimental setup for gathering data from the "Doctor's Specialty Recommendation" dataset is structured to assurance the relevance and generality of the data while systematically assessing the performance of the system. By adjusting the step per epoch count and evaluating performance metrics, this setup helps to improve the accuracy and reliability of the recommendations offered to patients, ultimately contributing to progress the of healthcare outcomes. To validate the success rate of the proposed model, the experimental outcome of the proposed model was compared with the existing models like "The recommendation models like CS [20], MF [21], TM [22], and KBS [23]" were also employed for the validation of proposed recommendation model. The performance of the recommendation system was assessed using several key metrics described in the below equations.

Precision: This metric evaluates the accuracy of the recommended system using the formula in Eq. (4).

$$K_p = \frac{Fc}{Fc + Jp} \tag{4}$$

The system's ability to identify the better recommendation system is recall R_c, using Eq. (5).

$$R_c = \frac{Fc}{Fc + Jn} \tag{5}$$

The harmonic mean of both precision and recall values is the F1 score, which is assessed using the formula in Eq. (6).

$$R_c = \frac{2 * Kp * R_c}{K_p + R_c} \tag{6}$$

The average error between the actual rating and predicted rating is measured in terms of MAE, mathematical formula is provided in Eq. (7).

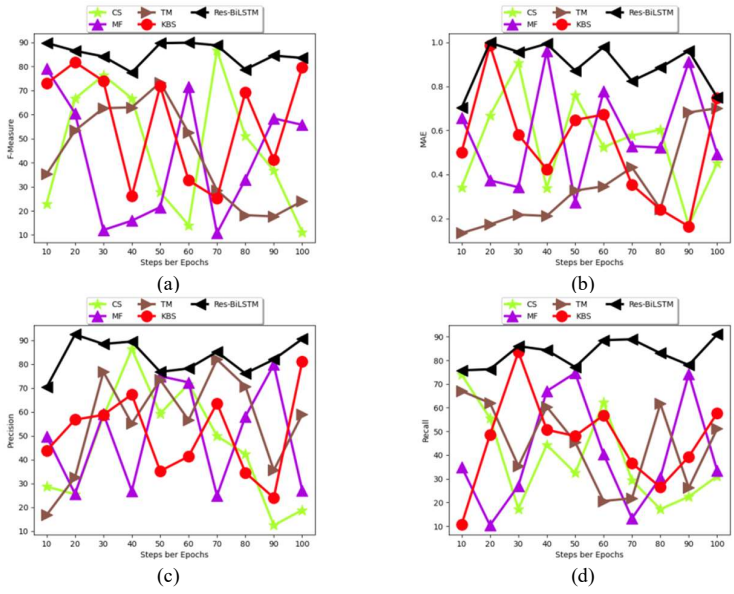
$$MAE = \frac{1}{f} \sum_{Qw} v - \bar{v} \tag{7}$$

Normalized Discounted Cumulative Gain (NDCG) is a ranking quality metric used for the validation of the success rate of the proposed model.

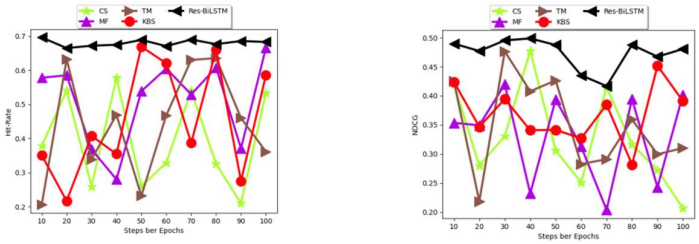
Here, a true positive value is indicated as Fc , and a true negative value is indicated as Fn . The false positive value is indicated as Jp and the false negative value Jn . The actual value is indicated as v , and the predicted value is specified as $\bar{v}$. These experimental measures are essential for evaluating the reliability of the proposed recommendation model.

4.1. Performance Analysis

Performance analysis in online physician recommendation systems is essential for ensuring that the system effectively addresses the needs of both patients and healthcare providers. It analyzes how effectively the system recommends physicians based on user rating. By examining metrics such as precision, recall, and F-measure, developers can upgrade algorithms to boost the accuracy of recommendations, ensuring that patients receive suitable options. High-performing recommendation system adopts trust among users. When patients notice that the system reliably distributes accurate and relevant references, their self-reliance in this platform grows, potentially leading to increased appointments. The precision rate of the proposed Cascaded Res-BiLSTM-based recommendation system is enhanced with 28.8%, 27.3%, 19.4%, and 7.6% than the existing models like CS, MF, TM, and KBS. High precision signifies that the system successfully recommends physicians who closely match patient needs, thereby lessening the chances of irrelevant suggestions and boosting user confidence in the system, which is essential for patients with specific preferences. This metric plays a vital role in reducing missed chances for patients to find suitable healthcare providers. Thus, analyzing precision, recall, and F-measure is crucial for boosting the performance of online physician recommendation models, which ultimately results in improved patient outcomes and greater satisfaction. The graphical representation of performance measures among existing techniques is provided in below Fig. 3.



(a) (b) (c) (d)



(e) (f)

Fig 3. Proposed Cascaded Res-BiLSTM-based Recommendation System regarding (a) F1-measure, (b) MAE, (c) Precision, (d) Recall, (e) Hit-rate, and (f) NDCG

4.2. Numerical Analysis of the proposed model

Numerical analysis facilitates the assessment of the system among accuracy, precision, recall, and MAE. It enables comparisons with other recommendation techniques and identifies the strengths of the Cascaded Res-BiLSTM model among other traditional methods. Through numerical analysis, optimal parameters for the model are identified, resulting in enhanced performance and reliability. Numerical analysis helps in evaluating how well the recommendation system adapts to increasing data sizes or user counts. If the count of physicians varies from 51-100, the proposed Res-BiLSTM-based recommendation model achieved a precision rate of 93.1%, which is better than existing techniques used for recommendation. It allows for the validation of the model's robustness across various scenarios, based on differing user ratings. Thus, by presenting numerical results, the Cascaded Res-BiLSTM model system is validated for practical applications, thereby progressing its credibility and potential in the recommendation system. The numerical values of performance metrics using the proposed Res-BiLSTM model among existing recommendation techniques are provided in Table I.

Table 1. Numerical Analysis of Proposed Cascaded Res-BiLSTM-based Recommendation System

Precision					
Counts of Physician	CS [20]	MF [21]	TM[22]	KBS[23]	Res-BiLSTM
1-50	54.20982	10.77145	66.19976	18.86789	72.12702
51-100	90.11624	63.67058	14.86181	44.12804	93.16937
101-151	51.45782	77.27791	49.00166	59.91926	80.0408
151-200	68.76085	83.37227	23.64092	57.32654	87.60662
200-250	92.84773	87.27947	75.11497	84.65232	92.82873
Recall					
1-50	17.87098	67.52215	32.10462	42.63333	76.72867
51-100	11.99483	65.84283	61.76902	53.3401	71.51543
101-151	57.25731	37.99984	50.76362	55.62087	63.45986
151-200	49.89796	14.28113	56.1165	51.70157	64.73454
200-250	88.19187	76.69406	67.30239	85.69286	89.80742
F-measure					
1-50	54.79696	59.35035	30.55091	53.76145	65.7583
51-100	47.03422	52.37144	24.88932	30.24348	59.37904
101-151	78.66004	44.73561	12.80511	37.94934	79.66823
151-200	41.56893	38.58929	15.86116	28.41917	43.7521
200-250	87.11507	82.35734	84.09853	89.75851	90.56376
MAE					
1-50	29.5832	37.9414	70.7473	79.066	19.8839
51-100	15.6502	87.3615	11.7217	23.4717	6.921
101-151	20.2738	56.2081	44.686	39.8739	14.4462
151-200	18.1803	75.5222	88.7536	64.7812	11.1184
200-250	34.7303	91.6946	91.5836	99.0486	24.8404
Hit-rate					
1-50	65.0393	30.3203	58.4469	34.3566	73.5979
51-100	22.6524	23.6534	24.6934	47.0523	59.4491
101-151	63.0054	28.1796	48.4229	46.4922	78.2993
151-200	47.3001	25.9783	28.548	21.8742	50.2183
200-250	65.5682	33.1995	64.146	63.0434	72.7839
NDCG					
1-50	43.3666	31.3162	38.0441	38.4458	52.7044
51-100	23.1164	30.9934	43.9955	34.4211	51.5956
101-151	48.1571	39.737	25.3532	40.1964	54.8937
151-200	25.1084	35.8415	40.7069	48.0508	50.1875
200-250	48.6136	49.8488	46.4767	49.1626	79.5328

5. Conclusion

Designed Cascaded Res-BiLSTM model effectively improved the accuracy and relevance of physician recommendations. By utilizing user ratings and sophisticated machine learning techniques, the Cascaded Res-BiLSTM model delivers personalized recommendations that closely align with patient preferences. By prioritizing user ratings and preferences, this model identifies the specific needs of patients, thereby boosting their overall experience in choosing healthcare providers. The proposed model showcased enhancements in various evaluation metrics, including precision, recall, and F-measure, when compared to traditional recommendation systems. This demonstrated that the Cascaded Res-BiLSTM model not only identifies appropriate physicians but also performs with greater reliability.

Limitations and potential future directions: This recommendation system faces challenges with new users or physicians who lack sufficient ratings. In such scenarios, the proposed model struggles to provide accurate recommendations, as it trusts historical data for generating suggestions. Patient preferences are often complex and influenced by multiple factors, including personal experiences, backgrounds, and specific health needs. The proposed framework will not fully capture these intricacies, resulting in less personalized recommendations. Considering these limitations, future research will focus on integrating a wider range of data sources, such as social media feedback electronic health records, and patient demographics to boost the model's understanding of user preferences and improve the accuracy of recommendations. Implementing real-time user feedback mechanisms will allow continuous alteration of the proposed model.

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