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A Deep Learning-Based Hybrid CNN-LSTM Model for Location-Aware Web Service Recommendation

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Abstract

Advertising is the most crucial part of all social networking sites. The phenomenal rise of social media has resulted in a general increase in the availability of customer tastes and preferences, which is a positive development. This information may be used to improve the service that is offered to users as well as target advertisements for customers who already utilize the service. It is essential while delivering relevant advertisements to consumers, to take into account the geographic location of the consumers. Customers will be ecstatic if the offerings displayed to them are merely available in their immediate vicinity. As the user's requirements will vary from place to place, location-based services are necessary for gathering this essential data. To get users to stop thinking about where they are and instead focus on an ad, location-based advertising (LBA) uses their mobile device's GPS to pinpoint nearby businesses and provide useful information. Due to the increased two-way communication between the marketer and the user, mobile consumers' privacy concerns and personalization issues are becoming more of a barrier. In this research, we developed a collaborative filtering-based hybrid CNN-LSTM model for recommending geographically relevant online services using deep neural networks. The proposed hybrid model is made using two neural networks, i.e., CNN and LSTM. Geographical information systems (GIS) are used to acquire initial location data to collect precise locational details. The proposed

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LBA for GIS is built in a Python simulation environment for evaluation. Hybrid CNN-LSTM recommendation performance beats existing location-aware service recommender systems in large simulations based on the WS dream dataset.

Keywords Location-based services · Recommendation system · Geographical information systems · Deep learning · CNN · LSTM

1 Introduction

To advertise an item or service in a particular region, a business may use LBA (location-based advertising) [1, 2]. The term "location-based advertising," or "LBA" for short, describes a specific category of location-based services that make use of geolocation data gathered from mobile devices like smartphones. LBA might potentially be utilized to hire seasonal or full-time staff for a neighbourhood company. LBA allows merchants to send location-specific, timely communications to consumers. Advertisers may target consumers with various messages based on their physical location by using their GPS coordinates. Allowing marketers to contact consumers while they are physically close to their stores has broken down formerly insurmountable barriers between marketplaces and consumers [3].

Recommendation systems (RSS) use a variety of filtering approaches, all of which are described here. Collaborative filtering is the approach that is most often used. A large number of online service recommendation systems are being developed based on collaborative filtering (CF). The analysis of the quality of service-aware web service suggestions and customized QoS-aware web service recommendations is discussed in detail [4]. Many of the most common customer-facing tactics are based on user-based or item-based approaches. The Matrix Factorization (MF) method stands out as one of the most effective approaches [5]. It leverages hidden vector attributes to represent individuals or items, initially mapping them into a shared latent space [6]. While MF has demonstrated considerable success, numerous adaptations and variations have emerged [7, 8]. However, despite its effectiveness, MF-based strategies continue to grapple with challenges like cold-start and data sparsity problems [9, 10], significantly limiting the efficacy of current methodologies.

It is important to include the geographical data that is often a part of the customer database when clustering the data to generate customer segments, including, in response, selecting where the channels of distribution need to be positioned. In recent years, geo-marketing has seen an uptick in the practice of clustering geo-referenced (or spatial) data, although conventional clustering approaches have shown certain limits in light of the industry's rising need for precision and consistency [11]. To maximize the effectiveness of customized targeting through the right channels, consumer segmentation must be both precise and homogeneous.

Current Challenges The existing environment of location-based advertising and recommendation systems is fraught with difficulties. The commonly used matrix factorization (MF) technique in recommendation systems encounters data sparsity and cold-start concerns. The drawbacks of this strategy impede system efficiency, particularly when dealing with sparse data or new user interactions. Furthermore, typical clustering algorithms [12, 13] are proven to have drawbacks in the realms of geo-marketing and clustering geo-referenced data for consumer segmentation. These difficulties come as a result of the industry's increased demand for precision and consistency, making precise consumer segmentation harder to attain using traditional clustering methods. Furthermore, analytic methodologies for independent consumer data encounter difficulties when dealing with vast and complicated geographic datasets, reducing the depth and accuracy of insights derived from exploratory data analysis.

Proposed Solutions Proposed Solutions: The proposed solutions outlined in this study aim to address challenges within recommendation systems and geo-marketing by exploring various methodologies. Firstly, alternatives to Matrix Factorization and strategies to mitigate data sparsity and enhance cold-start handling are investigated [14, 15]. Additionally, the development of hybrid models merging collaborative and content-based filtering or incorporating contextual information is suggested for more robust recommendations [16–18]. In the realm of geo-marketing, the study proposes exploring advanced clustering techniques, potentially integrating machine learning algorithms to manage large geographic datasets effectively. Furthermore, advocating for the utilization of complex analytic approaches, such as machine learning models or deep learning methods, to extract meaningful insights from multidimensional datasets for independent customer data analysis is emphasized. Successful implementation of these recommended solutions in real-world scenarios would require collaboration among data scientists, domain experts, and industry stakeholders. This research proposes, different deep learning-based approaches that are applied to perform the prediction, and the names of these are the LSTM and CNN, with the employ of these models, a hybrid model is built to implement this research, and the name of this hybrid model is hybrid CNN-LSTM model the location-aware web service recommendation.

Customers are independent whenever it comes to exploratory data analysis, even though most commercially available GIS provides for substantial storage, editing, and display of geo-referenced data [19]. Due to the extensive size and high complexity of geographic data, as well as the need for sophisticated data integration and mining tools, this strategy is impractical. When a dataset has a lot of dimensions, it might be difficult for analytic techniques to work properly. It is a common issue that not all of the variables will have a significant relationship with one another. Most analyses assume a very basic pattern, which may be adjusted according to several criteria, and so restrict or compress the field of possible hypotheses [20]. It is recommended that the many artificially enabled location-based services (LBS) in mobile ads make use of deep learning methods such as long short-term memory (LSTM), convolutional neural networks (CNN), recurrent neural networks (RNN), and artificial neural networks (ANN) [21].

The following article structures the remaining article as follows: The background and related work on location-based advertising have been discussed in Sect. 2. Section 3 talks about the proposed work, including location-based advertising and service methods for an identified problem. In Sect. 4, we discuss the experimental results of the suggested approaches and make comparisons to other current methods; in Sect. 5, we conclude and provide directions for future study.

2 Related Work

Location-based services (LBS) is a broad and evolving field that encompasses various technologies and applications. In this section, we are giving a detailed survey on LBS. Related research on LBS is presented here.

Tan et al. [22] used a partial least squares structural method to analyze advertising on social media. In addition, an integrated framework based on interaction theory, individual variables, and the mobile technology acceptance model was used to comprehend customer preferences. Li and Xu [23] proposed a diversity-aware digital ad architecture to adequately meet their clients' needs (D-AdFeed). The knapsack problem, with several possible solutions, was used to frame this issue. Both greedy and genetic algorithms were used to find a solution. Goh et al. [24] used Logit and Poisson count models to analyse the search patterns and ad clickthrough rates. By developing a tailored mobile advertising system, Li and Du [25] were able to provide shoppers and businesses with contextually aware advertisements.

Utilising an ensemble-based approach, Haider et al. [26] investigated fraudulent practices in mobile ads. Consumers' familiarity with location-based advertising was measured using the persuasiveness needed for planning by Ryu and Park [27]. To examine why customers make repeat purchases, Lu et al. [28] introduced the theory of the planned model. Shin and Lin [29] studied consumer opinions and their propensity to ignore advertisements. Yang et al. [30] (2013) integrated an advertising model based on technological and emotional evaluations. Sharma et al. [31] used a neural network and partial least squares structure to increase consumers' receptivity to mobile marketing.

According to [32] analyse the LBSs's privacy-preserving strategies. They classify and provide an in-depth analysis of the current methods. They found the main ideas and most recent progress in several common works from each group and then analysed them in the past. For new study possibilities, we also talk about how privacy-preserving methods can be used in LBSs. This survey, which offers a current and thorough summary of previous research, may encourage further investigations into this promising field.

In [33] research examines the feasibility of using workers' smartphones as a legitimate tool for employers to do presence control. In addition, they suggest a mobile location-aware information system that satisfies universal access requirements, uses only reactive location technologies based on terminals and allows for non-intrusive presence control while keeping costs down. Encouraging workers to feel comfortable and in control of when their location data is collected while meeting the employer's control demands is the main emphasis. Using UAProf data processing at the origin server and A-GPS terminal-based/network-aided mobile positioning algorithms, the LAMS platform is a cutting-edge framework for synchronous mobile location-aware content personalisation.

This study [34] provides the creation of a set of fake query sequences to conceal mobile users' query locations and query characteristics and safeguard their privacy in LBS. First, they provide a framework that is centred on the client and aims to safeguard user privacy in LBS. This framework does not need any modifications to the LBS algorithm used on the server side, and it also ensures that the accuracy of an LBS query remains unaffected. Second, they propose a privacy model within the framework to establish the criteria that ideal dummy query sequences should adhere to. These criteria include: (1) maintaining a similar feature distribution, which assesses the ability of the dummy query sequences to conceal the true user query sequence, and (2) ensuring a high level of user privacy protection, which evaluates the effectiveness of the dummy query sequences in safeguarding the location and query privacy of a mobile user. Finally, they provide an implementation approach that meets the privacy model's requirements. Furthermore, both theoretical analysis and actual assessment reveal the usefulness of our proposed technique, demonstrating that the location and attribute privacy underlying LBS inquiries may be successfully safeguarded by the fake queries created by our approach.

The author [35] offers a wide range of scientific data for many study topics that are used by the associated scientific groups. Frequently, these websites' architecture or design does not match the way their customers think. Consequently, the desired data is not easily accessible. Scientific online information services may benefit from the methods developed by Usability Engineering and User Experience to better understand and meet the needs of their users. An easy-to-implement method for evaluating and improving scientific online information services is detailed in this article. Combining personas, usability inspections, online questionnaires, Kano models, and web analytics with other techniques that have previously been effectively used in reality makes up this approach.

In [36] the research suggests an Explainable Food Recommendation system to support its suggestions using the visual content of food. In particular, a new similarity score is created and included in the suggestion. This score is based on a propensity measure that quantifies the degree to which the user community favours a certain cuisine category. To improve the recommendation outcome's openness and interpretability, a rule-based explainability is finally added. Our results on a crawled dataset demonstrate that compared to other food recommendation methods, the suggested approach improves recommendation quality by 7.35%, 6.70%, 7.32%, and 14.38%, respectively, in terms of recall, precision, F1, and Normalised Dis-counted Cumulative Gain (NDCG). Additionally, they conduct ablation studies to prove that our recommendation system's components are technically sound.

In this study, [37] the author proposes to provide a novel strategy called Recommendation Based on Embedding Spectral Clustering in Heterogeneous Networks (RESCHet). This approach makes use of the embedding spectral clustering method, whose similarity matrix is produced using a heterogeneous embedding technique. Subsequently, they used the notions of submit-paths and atomic meta-paths to identify the connections among people and things relevant to every cluster. Finally, by calculating the Hadamard product between the pertinent vectors, they produced user suggestions. Tests conducted on three publicly available benchmark datasets have shown that RESCHet performs noticeably better than the current methods.

In this study [38], a recommender system that relies on Facebook user behaviour was created, and it provides consumers with the option to purchase their favourite things in two stages. The consumers' behaviour is examined in the first phase, and items are provided to them depending on their interests. In the second step, the recommender system uses data mining methods to provide consumers with offers that are related to their past purchases. The study's data are accurate, and the findings are reliable. Furthermore, the findings show that the developed recommender system is quite accurate in presenting offers to consumers (Table 1).

2.1 Research Gap

Certain gaps become apparent within the current corpus of research concerning location-based services and advertising. To begin with, although research has examined digital advertising architectures and customer preferences, more extensive inquiries are required to determine the efficacy and consequences of location-based advertising interventions for consumers. Present models predominantly concentrate on concerns about advertising, customer preferences, and recommendation systems. Consequently, there exists a knowledge vacuum concerning the complexities linked to location-based mobile advertisements, including the need to minimise intrusiveness while optimising openness. Furthermore, the investigation into energy-efficient and secure routing protocols for wireless sensor networks highlights the criticality of further research into the intersection of energy efficiency and security in location-based services. Moreover, a comprehensive examination of the integration of user-generated text and geographical data for spatial market segmentation is lacking. Finally, although recent research has examined privacy concerns in location-based advertising, there remains a dearth of knowledge regarding the continual creation of strategies for successfully addressing these concerns in light of the growing relationship between advertisers and

Table 1 Review of existing models for location aware-base services

References	Title/year	Problem	Methods	Result
[11]	Deep learning-based feature extraction and a bidirectional hybrid optimized model for location-based advertising, 2022	There is a growing privacy difficulty among mobile users and personalization worries as a result of the increased connection between the advertiser and the consumer	To provide precise location details, GIS gathers relevant location data. Information about a word's geographical context is fed into the embedding process. A vector and a matrix are assigned to each word. Then, a deep sparse autoencoder (DSAE) is used to gather those characteristics	Accuracy (99.97%), precision (99.5%), F-measure (99.5%), computational time (99.8 ms), the area under the curve (82.23%), and recall (99.52%) are only some of the metrics used to evaluate the suggested approach over a range of document volumes
[39]	"Uplift modeling for location based online advertising, 2019	The efficacy of location-based targeting is unknown at this time because of the challenges inherent in determining the net impact of advertising interventions on consumers	Many studies have shown the usefulness of uplift modeling for estimating the ITE of various interventions, which include but are not limited to prescription direct marketing and online advertising	Two distance characteristics, five kinds of activity time, eleven types of census data, and the number of trips to 47 POI categories including sports goods and clothing stores remain after the advertiser's store frequency is subtracted. This allows for the generation of an uplift curve
[40]	Identifying machine learning techniques for classification of target advertising, 2020	To solve the issues associated with contextual advertising, the suggested method employs multiple instant learning (MIL) boost	The findings indicate that 23 unique user- centric and content-centric strategies for delivering tailored online advertisements may be created with the use of machine learning	We highlight the typical research effort and provide a brief overview of the aims and contributions of every system in each area
[41]	Opening location-based mobile ads: How openness and location congruency of location-based ads weaken negative effects of intrusiveness on brand choice, 2018	explored how location-based mobile communications may be optimized for maximum impact while minimizing distractions like unwanted feelings of intrusion	In this research, a virtual supermarket was utilized in conjunction with a location-based smartphone app to recreate conditions that were similar to those seen in a real supermarket without leaving the safety of the lab	switch from logistic regression to PROCESS because LR can't foresee non-linear conditional effects

Table 1 continued

References	Title/year	Problem	Methods	Result
[42]	Recommendations in Location based Social Networks: A Survey, 2015	It is a challenging task to infer users social beliefs based on their knowledge of various geographical areas	They begin by classifying recommender systems according to their intended recommendation target, which may be a specific place, person, activity, or social network. Then divide recommender systems into three distinct categories depending on their underlying technology	Introduced a multi-tenant, multi-user, multi-layer collaborative LBS platform. Location estimation hardware employed inside smart buildings makes up the first of these levels
[43]	Deep Learning for User Interest and Response Prediction in Online Display Advertising, 2019	Multiclass classification, in addition to binary classification (for predicting user clicks) (for user interest prediction)	Generative modeling is used in the corporate world. The CTR for a fresh impression is calculated using historical data and shown as a tree model. Examples of generational models are CTR hierarchy trees and hierarchical Bayesian networks	Predicting user Ad responses and user Ad clicks for individual campaigns is enhanced by considering patterns and temporal variation of user requests, according to experiments and comparisons with actual data
[44]	Smart Profiling of City Areas Based on Web Data, 2018	Distinct areas of the city are marked off using a computerized grid of square cells	Selecting relevant data sources, preprocessing them, extracting important characteristics, running a clustering algorithm to generate city area profiles, and finally visualizing the results on a city map are all steps taken by the system	They used k-means clustering and varying cell sizes to group city areas. We show how clustered areas in different city zones have similar traits
[45]	TDP: A Novel Secure and Energy Aware Routing Protocol for Wireless Sensor Networks, 2017	The suggested protocol routes in four steps. Topology management begins with k-means. LQA evaluates every network node in the second stage	Grading, based on LQA value, assigns grade points to each network node in the third stage. At the last stage, grade points determine the routing's safest path	The NS2 is used to test the proposed protocol in a significant class of SONs, such as a WSN. The effectiveness is measured by the current LEACH procedure

Table 1 continued

References	Title/year	Problem	Methods	Result
[46]	False advertising or slander? Using location-based tweets to assess online rating- reliability, 2017	The system utilizes amazon product reviews and Twitter message corpora to forecast item classes, after which they employ these ratings to discover geographic clusters. The models use transformers as an attention mechanism and BERT-based data augmentation	This research elucidates the causes of bias in online rating systems and gives a quantitative assessment of such prejudice. The authors compute a happiness score for a venue using location-aware tweets from companies and compare it to Yelp reviews to see whether the venue is overrated or underrated	Using the Affective Norms for English Terms lexicon, we can mine Foursquare and Twitter to determine the sentiment of location-aware tweets (ANEW)
[47]	Geo-Spatial Market Segmentation & Characterization Exploiting User Generated Text Through Transformers & Density-Based Clustering, 2021"	In this paper, we present a study of spatial market segmentation, which we believe to be a novel approach to integrating and combining geographical data with user-generated text content to discover geographic clusters of textual occurrences and infer links between each cluster and a set of retail product categories	Using Amazon customer reviews and Twitter message corpora, several machine learning models predict product classes, and those scores are then utilized to group the collected geographic clusters	Effectively producing maps of regions along with evaluations for how pertinent they are to a group of classes is the goal of this method. Our product document classifier achieved an F1-Score of 86% for product reviews and 76% for tweets after we manually annotated data from 10 product categories

mobile users. By recognising and rectifying these deficiencies, one can enhance the overall comprehension of the complexities and potentialities that lie within the dynamic domain of location-based advertising and services. In contrast to prior investigations, the present study employs GIS to acquire accurate location data by integrating geographical context into the word embedding procedure. Innovating the application of advanced deep learning techniques to location-based advertising is exemplified by the creation of a Bidirectional Optimised Hybrid Model (BLSTM-DNN-ASOA) and the implementation of a deep sparse autoencoder (DSAE) for feature extraction. The efficacy of a proposed model is demonstrated by a comprehensive set of evaluation metrics, which comprise F-measure, precision, accuracy, computational time, AUC, and recall. Through the attainment of enhanced performance compared to prior approaches, this article makes a significant contribution to the advancement of knowledge and implementation of deep learning in the domain of location-based advertising. As a result, it provides industry practitioners and academics with invaluable insights.

3 Methodology

3.1 Convolutional Neural Network (CNN)

Among the various applications for deep neural networks, image and video processing are among the most common. This is especially true with convolutional neural networks (CNNs). There has been a rise in the use of convolutional neural networks (CNNs) to analyze numerical data, including time series and sensor data, in recent years [48]. The main idea behind CNNs for numeric data is to apply the convolution operation to local temporal windows of the input data, allowing the network to learn temporal patterns and dependencies in the data. CNNs are effective at capturing both local and global patterns in time series data, making them suitable for various applications such as time series forecasting, anomaly detection, and signal processing. Despite their effectiveness, CNNs for numeric data still face some challenges, such as dealing with missing data and handling long-term dependencies. Recent advances in research have focused on developing more robust and efficient CNN architectures, such as the WaveNet and Temporal Convolutional Network (TCN) models, which have shown promising results in various applications. In addition to numeric data, CNNs have also been used for other types of data, such as text and graphs, demonstrating their versatility and potential to advance the field of deep learning. Overall, CNNs represent a powerful tool for processing various types of data, and their continued development and optimization have the potential to advance the field of artificial intelligence and its applications in various domains [49]. In Fig. 1, we see the basic structure of a convolutional neural network (CNN) that may be used to classify images.

A typical CNN will include the following layers: input, convolution, ReLU, pooling, and completely connected

- *Input* The raw pixel values are stored in this layer, as the name implies. The original data for a photograph may be seen in its "raw" pixel values.
- *Convolution* Being the primary processing node, this layer is an essential component of convolutional neural networks.
- *ReLU* Activation-function-using layer: a layer that takes the output of the previous layer and utilizes it to activate its output (also called a rectified linear unit layer). RELU's addition to the network's non-linearity would take another form.

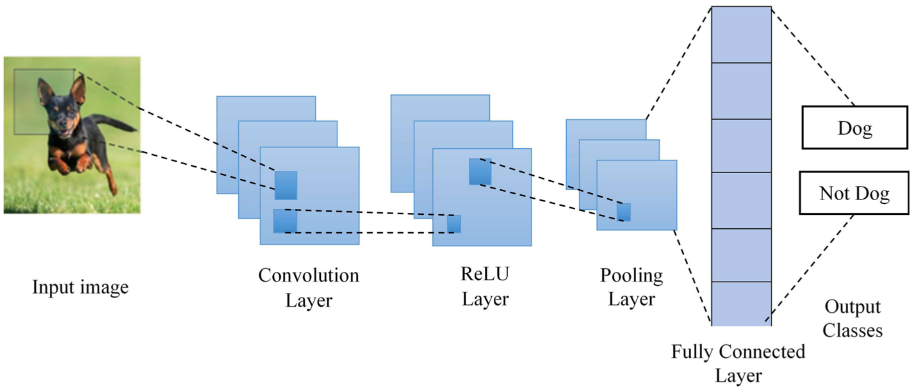

Fig. 1 Convolutional neural network (CNN)

- *Pooling* The pooling layer is another part of convolutional neural networks. Pooling operations refer to the act of combining the values of neighbouring features into a single one by using either an average or a histogram operator. The incorporation of pooling into the model has several goals, the primary ones being to make the model immune to local distortions and to reduce the total number of features [50].
- *Fully Connected* Moreover, this layer might be referred to as the "output" layer or the fully linked layer. It is used in the determination of class score output, the outcome of which is a voluminous 1*1*L array, where L is the integer representing the class score.

3.2 Long Short Term Memory (LSTM)

LSTMs, like RNNs, are composed of many interconnected layers, but the interactions between these four levels occur differently. There are memory cells in the LSTM model, and gates control them. There are three distinct types of entrance gates (input gate, output gate, and forget gate). These gates, which control the flow of data like dials, are responsible for mixing the data. To alter the data in an LSTM, these gates are used. A fixed quantity of training data may be stored in the memory module. Cell state memory is the memory unit that gives LSTM the ability to recall long-term dependencies. There are three primary varieties of gates: the forget gate, the I/P gate, and the O/P gate [51]. Short-term and long-term memories are stored in different types of memory cells. It reminds me of a conveyor belt in certain ways. It permeates the whole sequence and has only minimal pointwise operations with the gates. LSTM is an excellent tool for classifying processes and making predictions based on time series over a given amount of time [52].

- *Hidden State* An LSTM layer's output, known as the hidden state, is used as input in the layer that follows it. To indicate how much of each piece should be sent, the sigmoid layer produces values between 0 and 1. The Tanh layer produces new state-enhancing vectors.

$$h_t = o_t \cdot \tanh(c_t) \tag{1}$$

- *Forget Gate* The data stored in a memory cell may be removed using the forget gate. If the situation changes, the forget gate will produce zeros, which the memory cell will pointwise multiply, erasing the associated data. The sigmoid layer then generates a vector

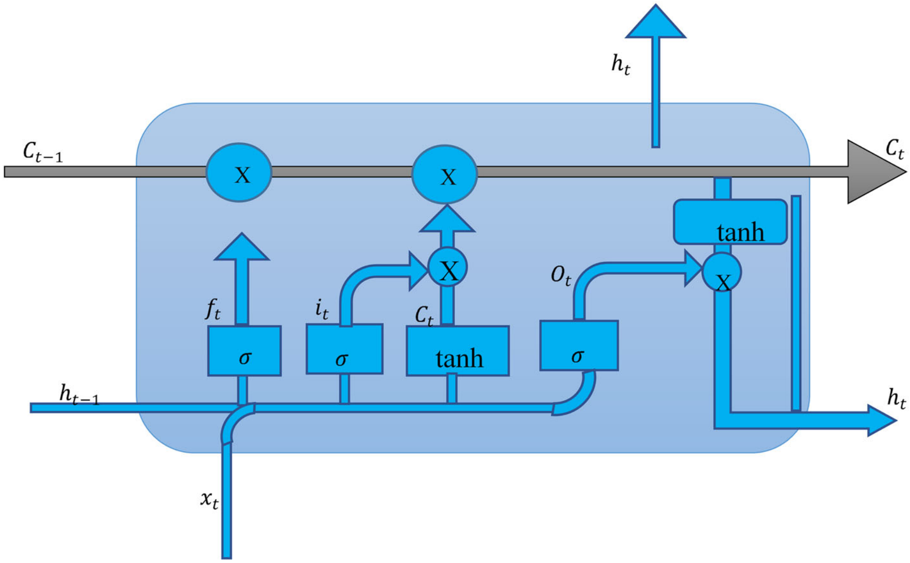

Fig. 2 Long Short Term Memory (LSTM)

with values between 0 and 1.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$

- *Input Gate* The I/P gate of the state cell decides if the input needs to be looked at more closely to see if data needs to be entered (or changed). For example, the output from the previous iteration ot-1, the I/P tx, and the initial condition of iteration ct-1 are all examples of inputs that may need to be looked at more closely. This is put point-first into the memory cell.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

- *Output Gate* The final product will be an abstracted version of the current state of memory. The amount of information sent from the visible state of the cell to the hidden state is managed by the output gate. Then, we choose which features of the cell will go to the hidden layer, which is the sigmoid layer (Fig. 2). The cellular state is multiplied by the sigmoid gate's output after a tanh-tanh transformation, producing values between -1 and 1.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{4}$$

4 Proposed Model

An in-depth description of the suggested model and its accompanying algorithm are presented here, together with a discussion of the research process used to develop it.

4.1 Problem Identification

Establishing a measure of service quality is the primary obstacle to service recommendation (QoS). Location-based advertising is a popular advertising strategy that targets users based on their geographical location. However, existing location-based advertising methods have limited accuracy and effectiveness due to several factors, such as inaccurate location data, a limited understanding of user behaviour, and a lack of personalized targeting. Deep learning techniques can provide a solution to these problems by leveraging complex models to analyze and interpret user data, which can be used to generate personalized and effective location-based advertising.

Therefore, the problem for location-based advertising using deep learning is to develop accurate and effective models that can leverage user data to generate personalized advertising recommendations based on their geographical location. This requires addressing the following challenges: data quality, user behaviour modeling, personalization, and privacy concerns. In solving these challenges, developing deep learning models is required to effectively analyse and interpret location data to generate personalized advertising recommendations that are relevant and effective for individual users while also addressing privacy concerns.

4.2 Research Methodology

In this study, we mix conventional and deep learning techniques to create a hybrid model for predicting the popularity of location-based services based on user recommendations. Python is used for the actual implementation. This is accomplished by using the freely available WS-Dream dataset. There are a total of 5,825 services and 19,74,675 QoS values from 339 users. Then the collected dataset was preprocessed using different data preprocessing techniques. In the data preprocessing, handling and filling in the missing values, and also using the Z-score normalization technique for data normalization. In addition, the min-max method is used for data scaling. In this work, features are identified and extracted in the feature extraction, and the Pearson correlation coefficient is also calculated in the correlation analysis. Then, split the dataset into two sets: train sets and test sets, and the ratio of training and testing is 80 and 20. After this process, different deep learning approaches are applied to perform the prediction, and the names of these are LSTM and CNN. With the use of these models, a hybrid model is built to implement this research, and the name of this hybrid model is the hybrid CNN-LSTM model. The correctness of the proposed model was evaluated using several statistical metrics, including the average absolute error, root mean squared error, coefficient of determination, etc. Finally, the proposed hybrid CNN-LSTM model may be used to forecast the QoS values of online services at indicated locations.

4.3 Hyperparameter Tunning

The design of the hybrid CNN-LSTM model for predicting location-based service popularity in this research included the use of many crucial hyperparameters. The architecture of the model was determined by setting the amount of LSTM units and CNN filters to 64, which influenced its ability to collect both temporal and spatial data efficiently. The learning rate of 0.001, an important hyperparameter, was carefully chosen to manage the step size of the optimization process, which influences the model's convergence pace. Another critical parameter, the dropout rate of 0.3, was used to prevent overfitting, with its value controlling the proportion of neurons randomly destroyed during training. To balance training speed and memory limitations, the batch size of 64, which represents several samples processed in every iteration, was determined. A number of epochs, which represents iterations throughout the full training dataset, was a critical hyperparameter influencing training length and model convergence. Non-linearity was introduced by carefully selecting activation functions in the layers, such as ReLU for CNN and sigmoid or tanh for LSTM. The optimizer (Adam) and the loss function (typically Mean Squared Error (MSE) or others adapted to the prediction task) further influenced the model's performance. These hyperparameters worked together to fine-tune the model's prediction capabilities, with optimization carried out through extensive experimentation and validation on training and validation datasets.

4.4 Dataset Collection and Description

For this research, the WS-Dream dataset is utilized to assess how well the suggested method works. QoS values from several users across multiple services may be found in the WS-Dream dataset, a massive web services dataset. To evaluate the efficacy of our proposed algorithm, the dataset's inclusion of location data for both users and services makes it a particularly suitable candidate. The WS-Dream dataset includes 19,74,675 quality of service metrics, collected from 339 users over 5,825 services. There is a wide range of possible quality of service metrics, including throughput, response time, reliability, and availability. QoS data was shown as a user-service matrix, with people in the rows and services in the columns, to make it easier to analyze (Table 2).

4.5 Data Preprocessing

The suggested method would benefit from the addition of the Autonomous System Number (ASN). The utilized dataset included customers from 30 countries and 136 ASNs and services from 73 countries and 990 ASNs. To guarantee the algorithm's success, we preprocessed the data in question. It included dealing with missing values, which may arise from some causes, including improper data input or inadequate data gathering. Imputation was used to manage missing values, which entails replacing them with approximated values based on the existing data. In this research, we imputed missing values using the attribute's mean value using a process called mean imputation. Including CN and ASN attributes into the algorithm required using Sklearn's category encoding transforms the labeled features into numerical embeddings. This allowed us to express each classified attribute as a nation code, which can be used to generate personalized ads for each user based on their location. Furthermore, we also performed data normalization to ensure that all the attributes had the same scale, which is important for many machine learning algorithms to function correctly. Z-score normalization, whereby the numbers of every feature are adjusted precisely to have a mean of zero and a standard deviation of one, was also utilized. Finally, we also performed feature scaling to ensure that all the features had similar ranges, which is necessary for some algorithms to function properly. All features are also scaled to fall inside the range [0, 1] using the Min-Max scaler approach. Overall, these pre-processing steps helped us to ensure that the data was in a suitable format for machine learning algorithms to be applied and improved the accuracy and effectiveness of the proposed model.

Table 2 Data description

Metric	Value
Dataset	WS-Dream
Metrics	Quality of Service (QoS), Size
Size	19,74,675 QoS metrics
Users	339
Services	5825
Data Format	User-Service Matrix
QoS Metrics	Throughput, Response Time, Reliability, Availability, etc
Data Collection	Massive web services dataset
Additional Features	Includes location data for both users and services
Purpose	To assess the efficacy of the proposed algorithm in the context of location-based services

4.6 Feature Extraction

What we mean by "feature extraction" is the transformation of unstructured data into discrete characteristics that may be used in subsequent analyses without losing any of the original data's context. In this study, we use feature extraction methods to zero in on the data points that will be most useful to our model. We employed a method called correlation analysis, which entails determining how closely each characteristic is linked to the desired outcome (here, the user's choice for a certain service). The model places a premium on features that have a strong correlation with the dependent variable. The Pearson correlation coefficient between each characteristic and the outcome variable was determined for examination of correlation. The Pearson correlation coefficient, which may also take on ranges around -1 and 1, is used to measure the linear connection between two variables. There is a perfect positive correlation when the value is 1, no connection at all when the value is 0, and a perfect negative correlation when the value is -1.

Based on the correlation analysis, we identified the most relevant features for this proposed model. These features were then used as input variables for our algorithm, and with careful feature selection, we were able to boost the model's accuracy and performance. Overall, feature extraction techniques such as correlation analysis can be useful in identifying the most important features of a machine learning model, which can improve its accuracy and efficiency.

4.7 Data Splitting

Machine learning often makes use of data splitting to separate data into distinct groups. There should ideally be three distinct sets of information: "train," "validation," and "test.". Dividing data is advised to improve the amount of training data in each dataset. In training and testing, data is often divided 80:20 or 70:30. For moderate-sized datasets, dividing the data into three equal parts–70% training, 20% validation, and 10% testing–is suggested. For this study, we created a training set with 80% of the data and a testing set with 20%. (20% of total information).

4.8 Proposed Hybrid CNN-LSTM Model

Here, we present a hybrid approach that utilizes LSTM and CNNs, and we evaluate it using the WS-Dream dataset. Quality of Service (QoS) measurements from many users across multiple providers may be found in the WS-Dream dataset. Due to the inclusion of user and service locations, this dataset is ideal for testing the efficacy of the suggested approach. The proposed CNN-LSTM model takes in user ratings of web service quality from the WS-Dream dataset. Quality-of-service (QoS) indicators are used to train a convolutional neural network (CNN) to extract high-level spatial features from an input dataset. The LSTM receives the CNN's output and learns to successively process the features while capturing their temporal relationships. For the LSTM part, we employed cells that can remember and pass along information about their surroundings over very long periods. The WS-Dream dataset was used to teach the hybrid model, which has 19,74,675 QoS values across 339 users and 5,825 services. Response time, throughput, availability, and dependability are just a few examples of the many QoS variables that may be measured. This article describes the deep learning models and their architectures that were utilized to produce this hybrid model (Fig. 3).

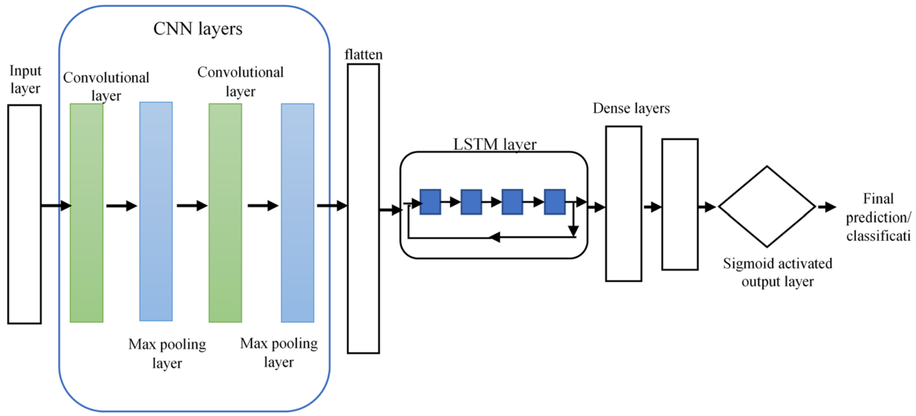

Fig. 3 Structure of Proposed Hybrid CNN-LSTM model

5 Experimental Results and Analysis

Here, we report on our experiments with Python-based location-based services applied to the WS-Dream dataset. The success of the proposed method may be measured in two ways.

5.1 Evaluation Metrics

RMSE and MAE are common statistical assessment metrics used to determine how well the provided method performs.

1. *Mean Absolute Error (MAE)* While calculating the mean absolute error, the errors are not squared. The absolute value of the mistakes is determined and then averaged.
   We only care about the magnitude of the difference between the estimated and real target values; hence, the MAE uses the absolute value. This prevents the MAE from being inaccurately calculated due to mistakes cancelling each other out. The formula for RMSE is as follows Eq. 5.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i| \tag{5}$$

   In this formula: MAE represents the Mean Absolute Error. n: is the number of data points or observations. y_i: represents the actual or observed values. x_i: represents the predicted or estimated values for the corresponding observations.
2. *Root Mean Squared Error (RMSE)* The Root Mean Squared Error (RMSE) is calculated by averaging the squared errors over all samples and then squaring the result. This is similar to the Mean Squared Error (MSE) but with a square root instead of a plus sign. This allows RMSE to produce an error metric that is consistent with the target variable's measurement system. If next year's sales are our objective y, then the RMSE will offer the error in dollars, whereas the MSE will give the error in dollars squared, which is considerably less comprehensible. The formula for RMSE is as follows Eq. 6.

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{6}$$

In this formula: RMSE represents the Root Mean Square Error. n: is the number of data points or observations. y_i: represents the actual or observed values. x_i: represents the predicted or estimated values for the corresponding observations.

The selection of RMSE and MAE as evaluation metrics for this research is driven by their interpretability, sensitivity to outliers, and suitability for model optimisation. The measures used provide a fair assessment of both the average magnitude of mistakes and the consequences of bigger deviations. The combination of RMSE and MAE allows for a comprehensive evaluation that aligns with specific characteristics and priorities of a dataset and a recommendation system in the domain of location-aware recommendations, where the goal is to provide accurate and meaningful suggestions to users.

5.2 Result

This section provides visual representations of the different WS-Dream dataset-based trial results. The output for the WS-Dream dataset utilized is presented in the form of graphs and tables below.

Table 3, showcases a performance result of a proposed Hybrid CNN-LSTM model, evaluated employing the WS-Dream dataset. For the metric of Response Time, the MAE and RMSE exhibit a decreasing trend as the density increases from 0.5 to 0.25, with the lowest MAE and RMSE observed at a density of 0.25. Specifically, at a density of 0.25, the MAE is 0.359 and the RMSE is 0.1388. Similarly, for Throughput, both MAE and RMSE decrease as density increases, with the lowest values again observed at a density of 0.25. At this density, the MAE is 12.764, and the RMSE is 37.874. These results suggest that increasing density leads to improved performance of the Hybrid CNN-LSTM model in predicting both RT and Throughput metrics for location-aware web service recommendation tasks.

Table 4, showcases a performance result of a proposed Hybrid CNN-LSTM model, evaluated employing the WS-Dream dataset. For the metric of Response Time, the MAE and RMSE exhibit a decreasing trend as the density increases from 0.5 to 0.25, with the lowest MAE and RMSE observed at a density of 0.25. Specifically, at a density of 0.25, the MAE is 0.359 and the RMSE is 0.1388. Similarly, for Throughput, both MAE and RMSE decrease as density increases, with the lowest values again observed at a density of 0.25. At this density, the MAE is 12.764, and the RMSE is 37.874. These results suggest that increasing density leads to improved performance of the Hybrid CNN-LSTM model in predicting both RT and Throughput metrics for location-aware web service recommendation tasks.

Table 5 presents a comprehensive comparison of experimental results for Response Time in Location-Aware Web Service Recommendation across various models and densities. The performance metrics, like MAE and RMSE, are depicted for densities ranging from 0.5 to 0.25. Among the models evaluated, Hybrid CNN-LSTM demonstrates competitive performance with decreasing MAE and RMSE values as density increases. Notably, at a density of 0.25, the Hybrid CNN-LSTM model achieves an MAE of 0.359 and an RMSE of 0.1388. For RLSD, at the same density, the MAE is 0.5214, and the RMSE is 0.1583. Comparison with other models reveals varying levels of effectiveness, with UMEAN, IMEAN, UPCC, and IPCC demonstrating relatively higher errors across different densities. Models like LDCF and NCF exhibit lower errors compared to others, while RLSD displays consistent performance across densities. Overall, the results underscore the effectiveness of the Hybrid CNN-LSTM model in accurately predicting Response Time, particularly at higher densities, showcasing its potential for enhancing location-aware web service recommendation systems.

Figures 4 and 5 show the results of an MAE and RMSE comparison of a proposed hybrid

Table 3 Performance results of the proposed hybrid CNN-LSTM model

Hybrid CNN- LSTM Model	Density									
	0.5		0.10		0.15		0.20		0.25	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Response Time	0.5275	0.1683	0.4066	0.1388	0.359	0.1683	0.5214	0.1583	0.4588	0.1244
Throughput	18.534	52.566	13.566	45.687	12.784	40.533	12.654	45.656	12.764	37.874

Table 4 Response time experimental results

Approaches	Density 0.5		0.10		0.15		0.20		0.25	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
UMEAN	0.876	0.853	0.873	1.857	0.874	1.857	0.873	1.858	0.874	1.858
IMEAN	0.703	0.567	0.686	1.542	0.684	1.533	0.681	1.529	0.68	1.525
UPCC	0.634	0.377	0.553	1.311	0.511	1.258	0.483	1.22	0.467	1.189
IPCC	0.633	1.397	0.591	1.341	0.507	1.258	0.454	1.208	0.431	1.175
UIPCC	0.624	1.386	0.579	1.328	0.498	1.247	0.448	1.197	0.425	1.165
RegionKNN	0.594	1.641	0.577	1.637	0.569	1.627	0.569	1.617	0.562	1.619
LACF	0.682	1.5	0.65	1.468	0.61	1.416	0.582	1.381	0.562	1.357
PMF	0.568	1.537	0.487	1.321	0.451	1.221	0.43	1.171	0.416	1.139
NCF	0.44	1.325	0.385	1.283	0.372	1.253	0.362	1.205	0.349	1.138
LDCF	0.246	0.7398	0.2787	0.895	0.2291	0.7573	0.237	0.8004	0.2585	0.8819
RLSD	0.5643	0.1765	0.4977	0.1699	0.53	0.1892	0.6155	0.1831	0.5977	0.171
Hybrid CNN- LSTM Model	**0.5275**	**0.1683**	**0.4066**	**0.1388**	**0.359**	**0.1683**	**0.5214**	**0.1583**	**0.4588**	**0.1244**

Bold indicates the result of proposed model

Table 5 Throughput experimental results

Approaches	Density									
	0.5		0.10		0.15		0.20		0.25	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
UMEAN	54.333	110.296	53.947	110.345	53.971	110.201	53.906	110.19	53.862	110.194
IMEAN	27.342	65.844	26.962	64.843	26.757	64.266	26.669	64.069	26.595	63.873
UPCC	27.559	60.757	22.687	54.598	20.525	50.906	19.243	48.834	18.253	47.135
IPCC	27.102	62.665	26.27	60.479	25.487	57.561	23.726	54.564	22.286	52.293
UIPCC	27.07	60.51	22.44	54.506	20.256	50.585	18.888	48.238	17.863	46.392
RegionKNN	26.857	69.614	25.352	68.015	24.947	67.365	24.687	66.923	24.746	66.831
LACF	27.419	65.77	24.847	62.057	22.943	58.816	21.562	56.507	20.587	54.785
PMF	18.943	57.02	16.004	47.933	14.668	43.642	13.988	41.652	13.398	40.025
NCF	15.468	49.703	13.616	46.034	12.284	42.317	11.833	41.263	11.312	39.534
LDCF	17.629	57.746	14.711	50.73	13.952	48.871	13.199	47.323	12.332	45.142
RLSD	19.517	61.822	16.154	53.344	14.958	50.681	14.388	49.393	14.332	49.195
Hybrid CNN- LSTM Model	**18.534**	**52.566**	**13.566**	**45.687**	**12.784**	**40.533**	**12.654**	**45.656**	**12.764**	**37.874**

Bold indicates the result of proposed model

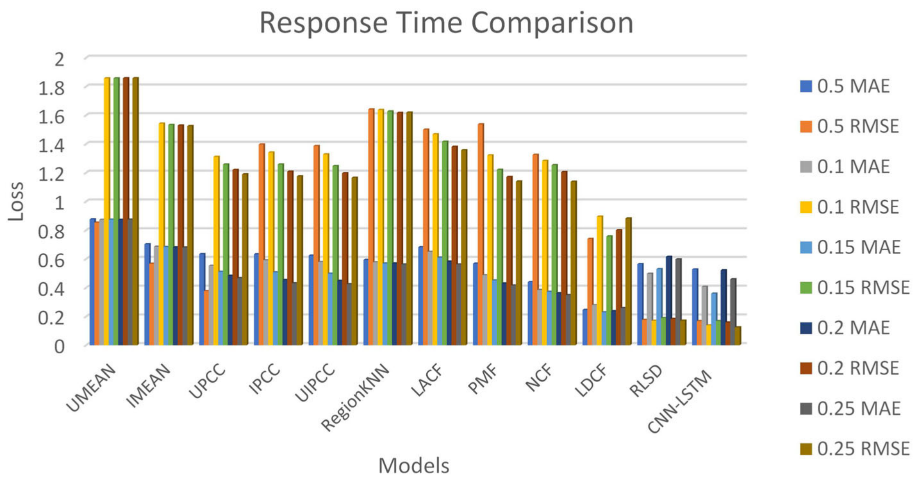

Fig. 4 Loss values comparison of response time

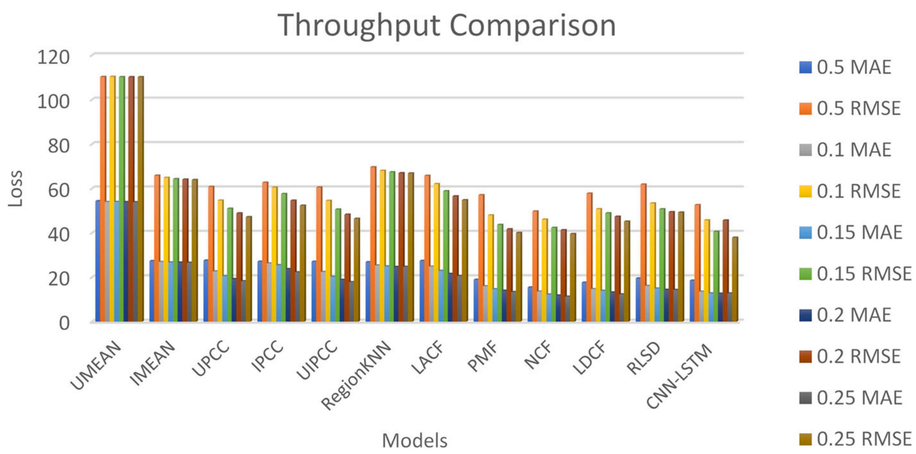

Fig. 5 Loss values comparison of throughput

CNN-LSTM model with those of current models in terms of reaction time and throughput at varying densities (0.05 to 0.25). A more precise model could be possible with less loss (except if the model was overfitting to the data in the training set). During both training and testing, the loss value may be calculated to evaluate the model's efficacy on the two datasets. Similar to accuracy, the loss does not have a proportional representation. It's the sum of all the blunders in a sample's training and testing data. In terms of reaction time and throughput, the suggested hybrid CNN-LSTM model was demonstrably superior to modern methods.

Figures 4 and 5 shows the results of comparing the proposed hybrid CNN-LSTM model with current models in terms of reaction time and throughput at different densities (0.05 to 0.25) using the mean absolute error (MAE) and root mean squared error (RMSE). A more precise model could be possible with less loss (except if the model was overfitting to the data in the training set). During both training and testing, the loss value may be calculated to evaluate the model's efficacy on the two datasets. Similar to accuracy, the loss does not have a proportional representation. It's the sum of all the blunders in a sample's training and testing data. In terms of reaction time and throughput, the suggested hybrid CNN-LSTM model was demonstrably superior to state-of-the-art methods.

6 Conclusion

This research offers a unique deep neural network-based Location-aware services recommendation model, in particular the Hybrid CNN-LSTM model, which has been suggested as an approach for location-aware web service recommendation, exhibits outstanding accuracy in the WS-Dream dataset at different densities. The assessment, illustrated through the utilization of tables and figures, demonstrates that the model's precision in forecasting reaction time and throughput enhances as the density level decreases. Notably, the minimum values of MAE and RMSE are detected at density 0.25. As illustrated in Tables 3 and 4, the reduced MAE and RMSE values for reaction time and throughput indicate that a model consistently outperforms modern approaches. The model's precision is further underscored by loss value comparisons in Figs. 4 and 5, which demonstrate reduced losses throughout the training and testing phases in comparison to existing models. The combined evidence highlights the effectiveness of the Hybrid CNN-LSTM model that has been proposed for improving the precision of location-aware web service recommendations, with a particular emphasis on its performance at lower density levels. Despite this, it does what we need it to do; nonetheless, more research and improvement in QoS prediction are required. We hope to modify the hyperparameters of the deep learning model used for location service recommendations shortly. This study presents an application survey and research scope to encourage researchers to solve service recommendation difficulties and to aid them in picking a more effective algorithm strategy for a suggestion based on the system's requirements and input sets. This work will continue to progress in the area of recommendation systems and improve their ability to fulfil user requirements.

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Data Availability Statement The data used in this study will be made available upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no Conflict of interest.

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