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RESEARCH ARTICLE

DeePOF: A hybrid approach of deep convolutional neural network and friendship to Point-of-Interest (POI) recommendation system in location-based social networks

Sadaf Safavi[1] | **Mehrdad Jalali**[1,2]

[1]Department of Computer Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran

[2]Institute of Functional Interfaces (IFG), Karlsruhe Institute of Technology (KIT), Hermann-von Helmholtz-4 Platz 1, Eggenstein-Leopoldshafen, 76344, Germany

Correspondence
Mehrdad Jalali, Institute of Functional Interfaces, Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany.
Email: mehrdad.jalali@kit.edu

Abstract

Today, millions of active users spend a percentage of their time on location-based social networks like Yelp and Gowalla and share their rich information. They can easily learn about their friends' behaviors and where they are visiting and be influenced by their style. As a result, the existence of personalized recommendations and the investigation of meaningful features of users and Point of Interests (POIs), given the challenges of rich contents and data sparsity, is a substantial task to accurately recommend the POIs and interests of users in location-based social networks (LBSNs). This work proposes a novel pipeline of POI recommendations named DeePOF based on deep learning and the convolutional neural network. This approach only takes into consideration the influence of the most similar pattern of friendship instead of the friendship of all users. The mean-shift clustering technique is used to detect similarity. The most similar friends' spatial and temporal features are fed into our deep CNN technique. The output of several proposed layers can predict latitude and longitude and the ID of subsequent appropriate places, and then using the friendship interval of a similar pattern, the lowest distance venues are chosen. This combination method is estimated on two popular datasets of LBSNs. Experimental results demonstrate that analyzing similar friendships could make recommendations more accurate and the suggested model for recommending a sequence of top-k POIs outperforms state-of-the-art approaches.

KEYWORDS

Convolutional neural network (CNN), Deep learning, Friendship network, Location-based Social Networks (LBSN), Point-of-Interest (POI) recommendation

1 | INTRODUCTION

There are many advantages to incorporate social networks and recommender systems. As the location feature is added to social networks, a link is created between the real world and online social networks. These social entities are creating an account, connecting with friends, joining some communities, posting comments, videos, photos, tagging resources, and giving ratings. Location-based social networks collect data from users' check-in such as tips of the location and geographical information of the visited locations (latitude and longitude).[1] They share their experiences with their friends and psychologically engage their audience and influence their visual and emotional behaviors and strategies, share their check-in interests, make new friends, and convey their feelings.[2] For instance, by 2020, the number of Foursquare users has more than 55 million users per month and more than 3 billion monthly visits to various locations worldwide.

This rich information of LBSNs has a high ability to realize users. User's spatial records in the real world reflect his interests and behavior. Accordingly, users with similar spatial histories are more likely to share common feelings and behaviors. Estimating the degree of similarity between users leads to the introduction of innovative services and systems, one of the most important of which is the Recommendation Systems. These systems are intelligent filtering systems that analyze the user's behavior and needs, offer the most appropriate items and useful information. The main purpose of a recommendation systems is a personalized recommendation, user satisfaction, and long-time communication with users. So, POI can be defined as a specific point location that someone may find interesting or useful. The POI recommendation can be considered a critical task that permits users to acquire new places in high-demand areas in the LBSNs. Usually, POI recommendation systems investigate venue information and users' social relationships to categories them to recommend a list of POIs, where users intend to visit them with a high percentage that had been checked-in by their friends. These systems are an approach that is presented to deal with the problems caused by the large volume of information. POI recommendation systems not only amend a user's interest in LBSN service yet additionally benefits advertising agencies to planning, launching, and evaluating a prosperous marketing campaign according to psychological principles.[3–5]

The confronting some challenges are summarized as follows:

Heterogeneous data: LBSNs entail dissimilar types of information, comprising not only geographical information of places, site descriptions, and check-in records, but also media information (e.g., tweets and comments on users) and users' social relation information. The heterogeneous data represent the user moves from a diversity of perspectives, inspiring POI recommendation systems of dissimilar methods.[6,7] Vast scientific investigation demonstrates that the social relationship among users is a substantial part of the POI recommendation. In Reference [8], a hybrid random walk approach based on a graph with star structure has been proposed, which combined multiple heterogeneous link structures. In this method, frequency or the social check-in rating is regarded as a significant score to recommend.

Physical constraints: Compared to watching a movie on Netflix and shopping online from Amazon, physical limitations restrict check-in activity. Such restrictions make check-in activity in LBSN show considerable temporal and spatial properties. For instance, shops commonly provide services for some restricted time.

Complex relations: For online social network services, like Instagram, Twitter, and Facebook, a site is a new object, making the new relation between sites (locations), between places, and users. Moreover, the places where activities are shared change the relationships between clients who are willing to make new friends with geographical neighbors and psychologically influence each other. The geographical closeness considerably impacts the check-in of user behaviors on points-of-interest. On LBSNs, clients are physically interacting with POIs, which is a different event recognized than usual item suggestions. Zhang et al.[9] employed an iGSLR structure to draw out personalized geographical and social influence. They measured the interval distribution between each pair of sites by kernel density computing.

In earlier studies, have been demonstrated that POI recommendation algorithms are remarkably adjusted by three main factors: check-in correlation,[10] friend influence,[11] and user preference.[12] The common interests between users lead to the trust formation and a potential possibility to visit the same POI compared to using a single information source. Human behaviors show ubiquitous correlations in many aspects based on the social links, POIs, and check-in, and they can have the most psychological and behavioral influence on each other. For instance, individuals are inclined to travel several scenic spots or go to neighboring locations with short intervals. Their friends and users prominently control user check-in (location visit) activities commonly tend to travel shorter distances and use easier roads. Friends' important attitudes evaluate the friend's influence on the user to survey a location (mobility similarity within two individuals). User inclination implies the similarity between potential desire and users to the particular POIs in a region of interest.[13,14]

Over the last few years, applying the deep learning methods has been a constant rise in artificial intelligence tasks like natural language processing, computer vision, and POI recommendation, where main traits can be exploited deeply and successfully.[15–19] Deep learning outlines a representation-learning algorithm that is reliable to learn data representations with multiple simple components. Each component investigates high-level representations of input from the former module (from low-level feature extractor module).[10,20,21] Therefore, dissimilar deep learning pipelines reach very good results to extract the intrinsic high-level traits that can be useful for recommendation tasks.

A deep neural network (DNN) to combine several features has been implemented by Reference [3] in location-based social networks. In this network, it has learned their importance of user behavior. Also, to diminish the sparsity of data in POI recommendation systems, the effects of categorical, temporal, geographical, and co-visiting have been investigated. Doan et al.[6] have employed a novel demonstrating location visit behavior (user check-in) using emphasizing area attraction and neighborhood competition. He et al.[15] have designed a POI recommendation structure to integrate factors, time factors, geographical and social factors. Their strategy is used the linear weighting and cascading combination. In Reference [18] have employed a Spatial-Aware Hierarchical Collaborative Deep Learning technique (SH-CDL) to overcome the user preferences' spatial dynamics challenges of hierarchically increasable representation learning and dissimilar traits for spatial-aware user decisions. A novel POI recommendation algorithm is implemented by Reference [13] to mine data in real-time. For mining text-based POIs information and learn from their inherent demonstration, a Convolutional Neural Networks (CNN) has been exerted.

Hence, according to the mentioned challenges and rich contents and data sparsity, the following questions are raised. How can friends most similar to the user's behavior be selected from all his friends? What impact will the utilization of deep learning methods have on POI recommendations?

This research proposed the new deep learning structure named DeePOF to recommend top-k POIs to any client due to the importance of recommending POI in LBSNs and predicting the user's next potential places with higher accuracy, and suggesting locations that are of interest to the user. DeePOF is a combination of convolutional neural network and mean-shift clustering technique, which classifies the most similar friendship relying on the check-in behavioral pattern of user friends then CNN's proposed model based on six input specifications including user Identification, month, day, hour, minute, and second predicts the next POI locations to visit, depending on the current position and time of the user. Also, the shortest time distance is measured with a similar friendship check-in pattern to increase the proposed POI accuracy, and the next suitable location is recommended to the user. The following are the major contributions of this article:

- We propose a good performance deep learning method named DeePOF to obtain an accurate sequence of top-k POIs to users. This method is a combination of a convolutional neural network, mean-shift clustering, and friendship,
- In the process of similarity computation, we consider similar pattern's friendship utilize the mean-shift clustering method and classifies several users into a group with the same user preferences to the current user that having similar past preferences,
- To improve the accuracy of a recommendation's result, the shortest time distance was investigated between this predicted location and all possible areas in the vicinity range based on top-related friendship.

The structure of our DeePOF is represented as follows. The clustering algorithm and similarity computation are outlined in Section 2.1. In Section 2.2, the convolutional neural network model is depicted. Section 2.3 indicates our proposed CNN model. Final remarks and outcomes are explained in Section 3.

2 | MATERIAL AND METHODS

In this part, we describe the proposed method in details. The proposed framework for recommending POIs according to the importance of friendship is indicated in Figure 1.

2.1 | Clustering the POI's

The clustering approach is an unsupervised algorithm used for dividing data, where each cluster has the most similar features.[17] The mean-shift technique denotes a nonparametric approach that can measure all locations' density in a map region. It means for each region; this method does the same manner. This strategy categorizes the locations together iteratively in an unsupervised method to guarantee that each cluster's locations gain the greatest similarity in locations. Furthermore, the user has to define the number of clusters for a particular problem or estimated based on different usable data like the number of clusters estimated or previous information. The mean-shift technique proposes benefits like competence and reasonable freedom to specifying a predicted amount of sections.[22,23] This freedom outlines the form of the window (kernel), size, and bandwidth that is utilized to choose the best possible number of the locations (data).[24] As the Mean Shift is a simple clustering approach that performs wonderfully on spherical-shaped data and is able to select the number of clusters automatically (unlike the other clustering approaches like KMeans), it is a good option for partitioning all users in an area. Moreover, the outcome of this clustering strategy is not dependent on the initial point.

The mean-shift technique firstly analyses the gradient of the density about alike locations in the limited region, which is utilized inside of a loop involving iteration to discover the maximum density in any segment (limited region). The mean-shift technique utilized in our work comprises of two phases. The first phase requires selecting the correct shape of kernel and size (bandwidth), which outlines the distance between the locations. Although the window's shape and size can be specified using an experimental approach producing acceptable results for numerous applications, the mean-shift strategy has a key constraint. Approximation of the most suitable bandwidths in the whole region is challenging when data features in the limited area are diverse across the area. There are some unwanted locations in the ultimate fragmented map, while numerous exact locations can be recognized. In deciding the kernel's most appropriate size and shape, we used the trial and error approach.[24]

An initial estimation needs to be updated iteratively until the finest place with the highest density function is evaluated to attain the primary point with a maximum gradient of the density function. Consequently, other locations in the same kernel for completing a single-section begin moving towards this primary point.[23,25,26]

Employing a Gaussian kernel yielded with $K(l_i - l) = e^{-c\|l_i - l\|^2}$ for controlling the shortest distance between locations, an average of weight about the local density in the window is determined with:

$$m(l) = \frac{\sum_{l_i \epsilon N(l)} K(l_i - l)\, l_i}{\sum_{l_i \epsilon N(l)} K(l_i - l)} \tag{1}$$

where $N(l)$ represent the neighboring point of l. The mean-shift is the difference between $m(l)$ and l which provided by Fukunaga and Hostetler.[27]

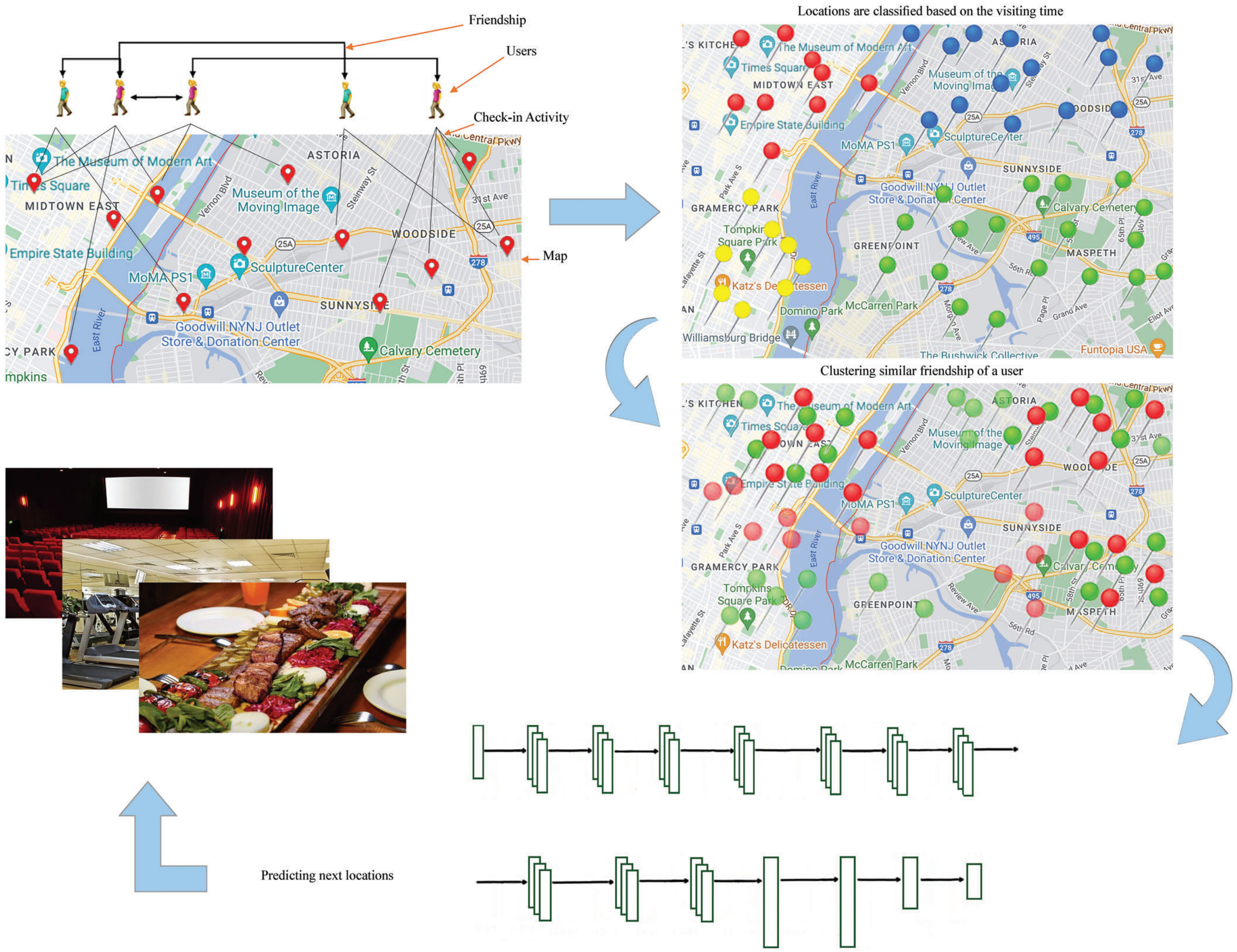


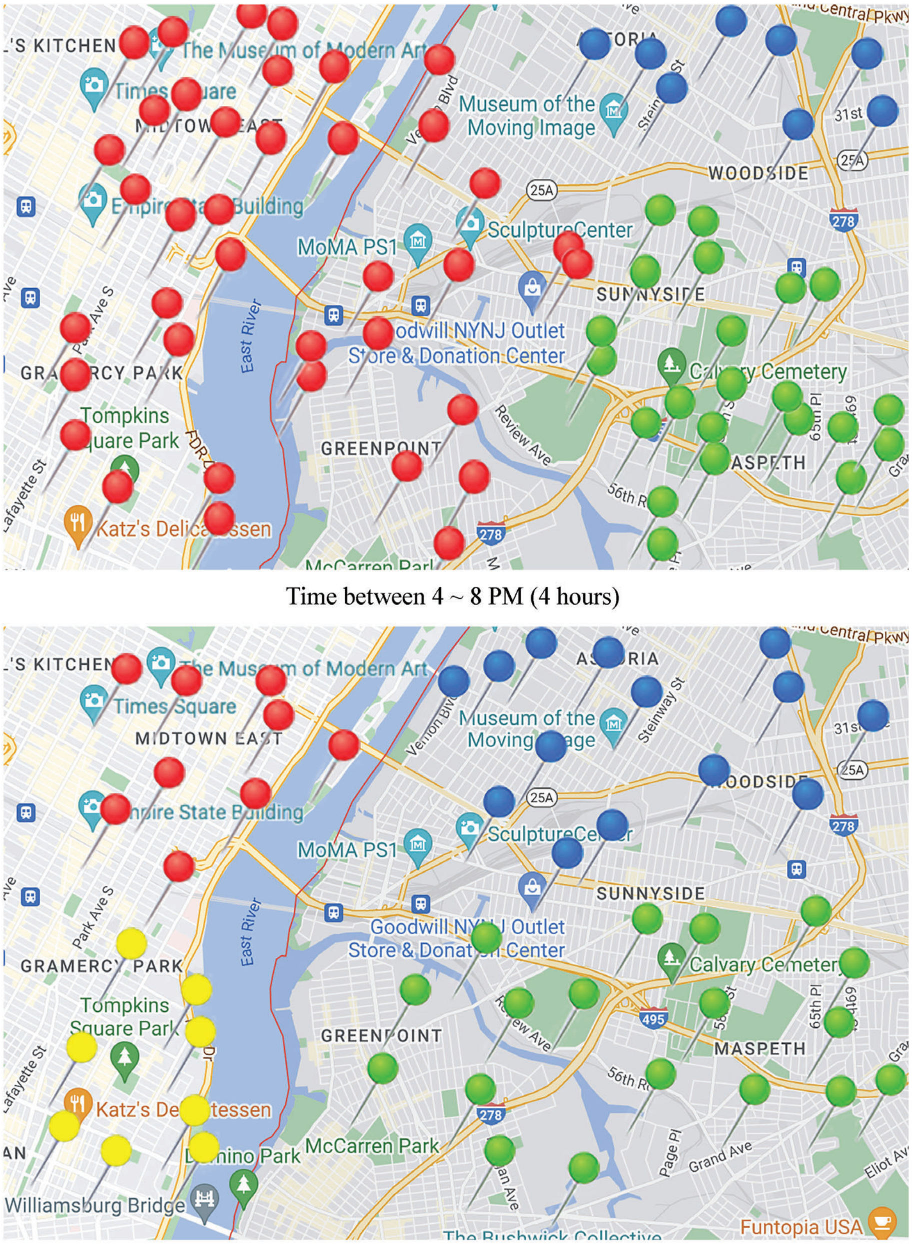
FIGURE 1 DeePOF framework for recommending POIs according to the importance of friendship

In this work, at the first step, the time span is divided into six spans (00 ~ 04, 04:01 ~ 8, 08:01 ~ 12, 12:01 ~ 16, 16:01 ~ 20, 20:01 ~ 24), and based on each span, the visited location of each user and its corresponding friendship is selected. It means all of the visited locations are categorized based on the visiting time (Figure 2). Due to using such discrimination of the visited locations by the time among all of the user friendship, a rise to the forecast of the appropriate location in the ultimate result can be gained. In the next step, as is shown in Figure 3, the whole visited sites of each user in each span are segmented using the mean-shift method. It needs to be noticed that contrary to other clustering approaches like fuzzy c-means and K-means, mean-shift does not need to specify the number of clusters by users. This causes when we are dividing visited area in a specific time span, we encounter the different number of clusters for each user.

The proportion of the overlapping between the friendship's clusters and user's clusters has been computed for each user. In other words, to overcome the mentioned problem about the number of the cluster, we consider those overlapping clusters to more exploration, which have the most overlapping areas. Finally, only 15% of the most overlapping locations inside of all clusters are selected. By doing this technique and other following strategies, we are trying to obtain more correctness of prediction of the final preferred locations.

2.2 | Convolutional neural network

The ability to detect arrangements of data or characteristics is called pattern recognition. In other words, Pattern recognition can be categorized as a classification method based on knowledge already obtained or on statistical information mined from patterns or their representation and is implemented in the domain of computer vision for countless applications like recommendation systems, data mining, and biological imaging.[28–31]



Time between 4 ~ 8 PM (4 hours)

Time between 00 ~ 04 AM (4 hours)

FIGURE 2 A graphical demonstration of utilizing clustering method to two various time span for a user

In today's pattern recognition strategies and their applications in many fields, the convolutional neural network (CNN) structures illustrate a massive breakthrough in data analyzing and processing. The CNN models principally deduce the relation between some key details, textural content and are utilized at the core of every model from data mining to the prediction of visiting new sites by people.[32,33]

Just like Artificial Neural Networks (ANNs), the CNN structures are based on neurons and have a grid-like topology. These models qualify us to exploit key information and characteristics from the POIs and friendships efficiently using a series of convolution layers with the user-defined size of kernels. This neuron-based architecture involves many trainable weights and biases that can be used for classification, feature extraction, and prediction applications. All using trainable weights and biases are randomly applied at the begging of the training phase. The main building block of any convolutional neural network is considered as the convolutional layer that responsible for computing the dot product between the filters (kernels) and input data (such as friendships and POIs).[34–37] Commonly, the first layer of CNN begins with a convolution layer is to make the input convolve and play an essential task in exploring the key features of an input data.[32,38]

Additionally, in the convolutional layers, the spatial and temporal dependencies can be obtained successfully. The algebraic operation in these layers that accomplishes a dot product between the kernel and related input data is demonstrated as a convolutional operation.[32,34,39] Also, it should

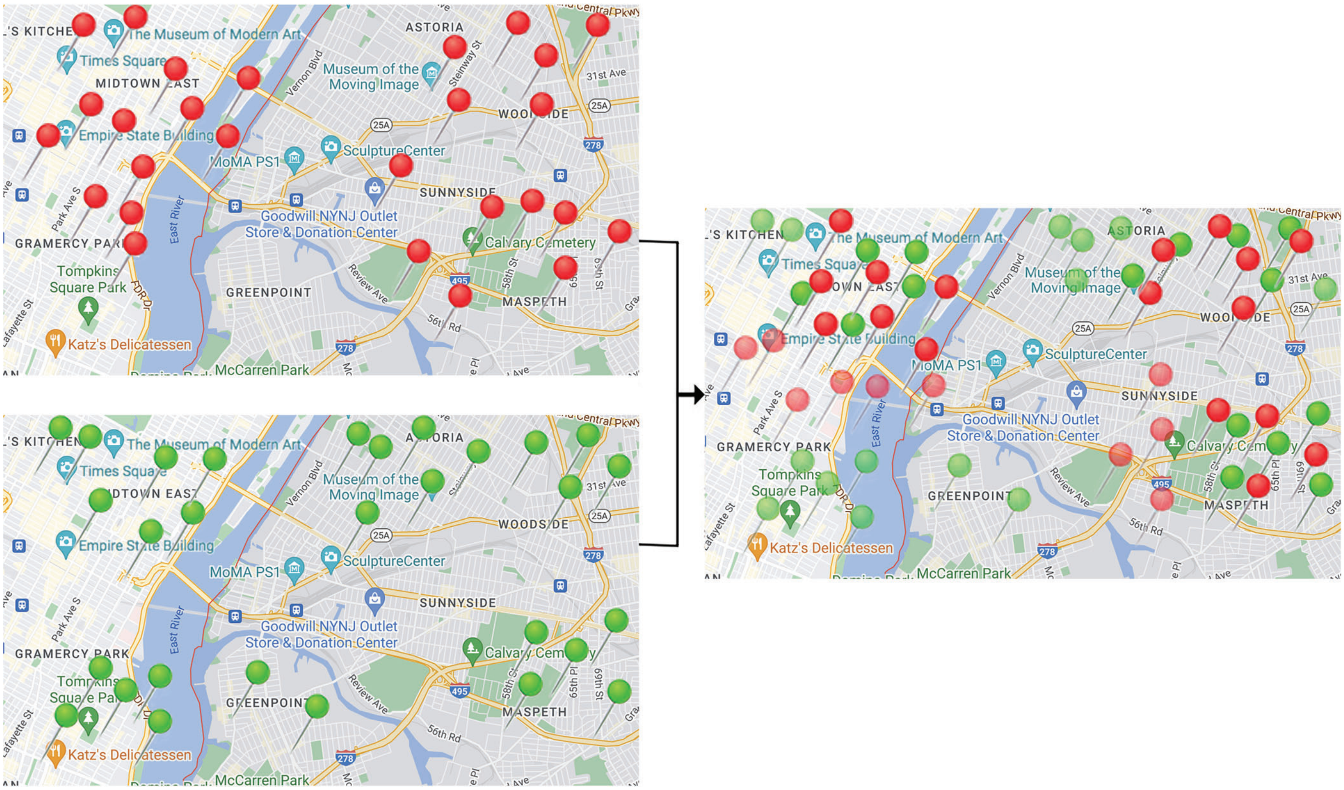


FIGURE 3 Scheme to determine overlapping clusters for a user

be noticed that the deeper convolutional layer detects the higher-level features, whereas the first convolutional layers are responsible for the extraction of the low-level features.[35]

Another beneficial layer used when we are working with a deep layer model is the batch normalization layer. A batch normalization scheme is scaling and standardizes the method used for the output of each layer before feeding it at the input of the next layer for each mini-batch.

As sparsity leads to the vanishing gradient and is causing difficulty in extracting proper features, an arbitrary activation function is employed based on the input data for each feature map that diminish the sparsity and improves the computational efficiency.[36,40,41]

The ReLU activation function based on the backpropagation of errors has been employed to alter the non-positive values to zero values in our work. The Equation (2) shows the ReLU activation function.[36]

$$y = max(0, x) \tag{2}$$

where x outlines the ReLU layers input and y demonstrates the output of it.

In the Fully-Connected layer (FC) layer, each node along with its corresponding learnable weight multiplies to each input vector to attain more robust high-level features.[34,42,43] The next layer in the CNN architecture for prediction is the regression layer. This layer is responsible for modeling the relationship between a truth target and the input data.[40,42]

Our CNN model can be learned proper weights and biases in each layer using a gradient descent technique to minimize a certain cost function.[41]

2.3 Proposed CNN model

As mentioned before, CNN pipelines can extract key information from the input and store and analyze this data, leading to more accurate decisions that can improve the final goal. A new CNN framework in this work has been employed based on all visited sites and related time. The main idea behind selecting a CNN model is its ability to find some complex pattern inside the data whereas it is easy to implement and is much faster compared to other hand-crafted feature extraction models. The proposed method employs six input feature maps comprising the user ID, month, day, hour, minute, and second of each user's visits. As is obviously indicated in Figure 4, 10 convolutional layers with different kernels have been implemented. We used three convolution layers at the beginning of the model with using three kernels (3@2 × 1 filters) in each layer, which means there are three

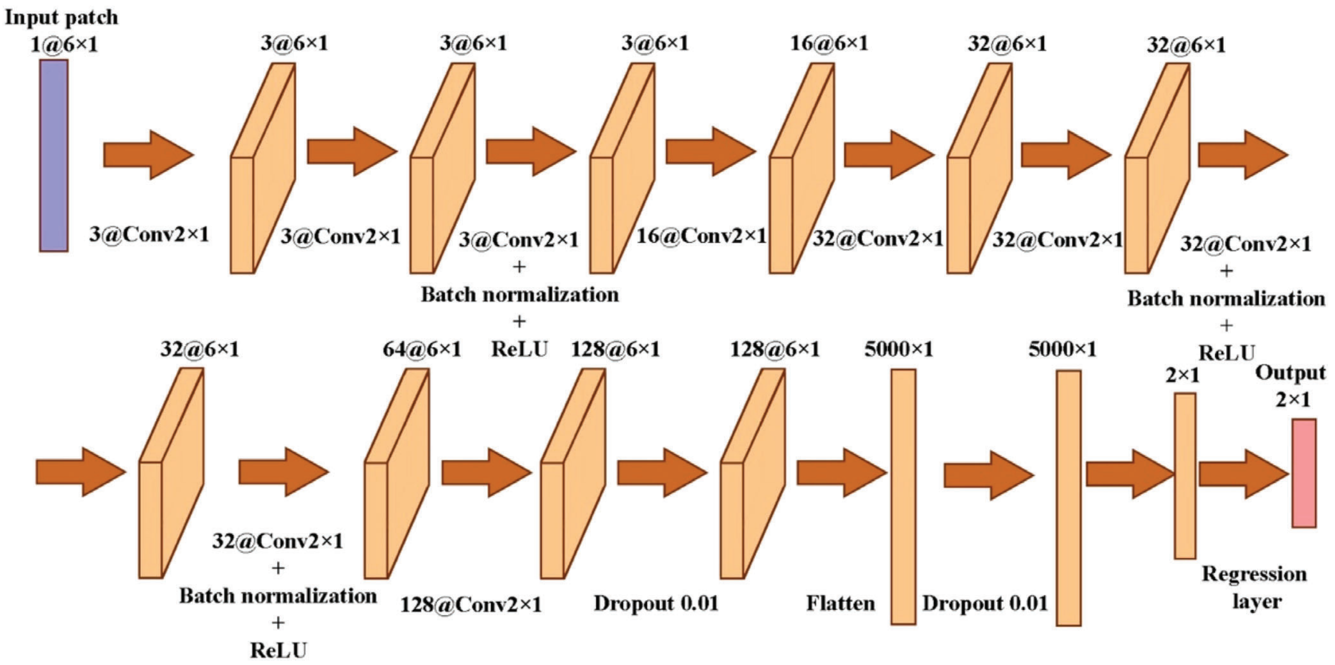


FIGURE 4 Proposed CNN structure

filter banks with dimension of 2 × 1. This 2 × 1 size filter bank is used in all convolutional layers. Our experiments prove that using three convolutional layers with small number of kernels is much efficient than using only one convolutional layer with 8, 16, or 32 kernels. In the next layer, 16 filters have been used, followed in the next three layers with 32 filter banks. These four sequential convolution layers are responsible for exploring the middle-level features and are crucial parts of the model when the number of POIs recommended for a user increases.

The last three convolutional layers are used to extract high-level feature extraction using one layer of 64 filter banks and two layers of 128 filter banks. These three layers play a crucial role when the number of PIOs recommended for a user is small, especially smaller than 20. The batch normalization layer and ReLU function are used to keep the normal range's output values and improve training. Furthermore, to the reduction of the overfitting effect and control the fitting process, two dropout layers[43] with a 0.01% dropout probability, was employed in our CNN structure to make neurons independently trained and less dependent on other neurons. Two flattened layers follow the final two convolution layers. Finally, the regression layer undertakes the accountability of generating two values that specify the predicted location of the recommended locations according to the training data. The training process has 800 epochs, and the learning rate is 0.01. Algorithm 1 provides a detailed summary of the steps of the DeePOF algorithm.

Algorithm 1. DeePOF algorithm

Input: user U, *social relation G*, check-in matrix R, DateTime T (month, day, hour, minute, and second), location L (ID, latitude & longitude)
Output: top-K POIs for each user *u* based on friendship
Epochs = 800
Learning rate = 0.01
Dropout probability = 0.01%

1. Identify each user's friends
2. Divide the time span into 6 spans (00 ~ 04, 04:01 ~ 8, 08:01 ~ 12, 12:01 ~ 16, 16:01 ~ 20, 20:01 ~ 24)
3. part_time = (00 ~ 04, 04:01 ~ 8, 08:01 ~ 12, 12:01 ~ 16, 16:01 ~ 20, 20:01 ~ 24)
4. **for** i = 1: size(part_time)
5. clustering users and their friendship based on the mean-shift algorithm
6. selecting 15% of the most overlapping between the user's clusters and friendship clusters
7. **end**

8. Utilized proposed CNN architecture
9. return *predicted locations*
10. error = calculate the distance between predicted location and the user's friendship locations
11. **if** error = 0 **then**
12. return *top-k POIs*
13. **else**
14. Measure the shortest time distance using a similar friendly check-in pattern
15. return top-*k POIs*
16. **end**

In our proposed model, due to the network layers and their parameters, there is no need for the data to be in a sequence. The user's current position is considered, and it is unnecessary to know where he was a few minutes ago. In the training phase, it received the essential training, and the data were randomly arranged.

Due to small differences in the output values, which are likely to propose a different location, the exact location is not generated in the CNN prediction model's output. So, we have to compute the distance between the predicted location and all possible locations in the vicinity region based on top-related friendship extracted in the 2.1 steps. To calculate this distance, we consider those top locations related to the same user and other selected users based on a friendship.

The proposed CNN architecture used the RMSE approach[42] for minimizing the loss in Equation (3), which computes the discrepancy between true and predicted locations.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{predicted} - \mathrm{True})^2} \tag{3}$$

where n describes the number of estimated or real values (location).

3 | EXPERIMENTS

3.1 | Datasets

Many spatial investigations have been implemented on real datasets Yelp and Gowalla (more information about datasets is illustrated in Table 1 that involves various geographical check-in information denoted by the longitude and latitude. Therefore, the probability of Point-Of-Interest co-occurrence of a user to find a meaningful relationship can be discovered by exploring the distance among pairs of check-ins. Check-in records have a key relationship to user implicit preference relation (IPR) of a user and can be considered common interests between all users. We are capable of investigating the correlation of check-ins by geographical closeness.

The following two main existing challenges in POI recommendation is described:

1. Rich contexts

Miscellaneous context information on location-based social networks, like a social relationship, user proximity, and also POI geographical coordinate, can be observed. Context information is inadequate and unclear, which makes it difficult for point of interest recommendation. For instance,

TABLE 1 Data description

	Users	POIs	Records	Social relations	Sparsity (%)
Yelp	30,887	18,995	265,533	860,888	99.860
Gowalla	18,737	32,510	86,985	1,278,274	99.865

POI geographical distance can completely impact the user behavior trajectory. Users could occasionally visit some sites, such as a satisfactory cinema nearby workplace or home, and then, users will introduce particular POI to their friends.

1. Data sparsity

The main problem in the POI recommendation system is data sparsity. As soon as a client appears and checks-in a site, the location and the time are stored with a check-in label, and propose it to other persons to visit the site. The repetition of visiting different locations for each individual is an item in the user-location sheet (matrix). As not all users can visit all POIs, it can be observed a considerable sparsity inside the matrix.

Yelp is a company in San Francisco that operates a social networking, and its website was founded in 2004 and is a well-known review website with over 184 million people access by 2020. This website covers plentiful merchants, such as cinemas, shopping malls, and restaurants. The Yelp dataset challenge round 7 (access date: February 2016) encompasses of 860,888 reviews, 265,533 social relations, 30,887 users and 18,995 POIs.[44] Gowalla, the first mobile application that allowed people to check into locations and its dataset is a location-based system. Gowalla enables clients to share experiences about what they hear and see with relatives and friends. Gowalla dataset (access date: February 2009–October 2010), encompasses of 18,737 users, 1,278,274 reviews, 86,985 social relations and 32,510POIs.[45] An overview of these datasets are provided in Table 1.

3.2 | Performance metrics

The following three measures were calculated by matching each anticipated site's outcome with its corresponding true sites to achieve the correct order of top-K POIs for a user. The remarkable correctness of the DeePOF technique was estimated using Precision and Recall. These criteria are outlined as follows[46]:

$$\begin{cases} \text{Precision}@k = \frac{1}{|P|} \times \sum_{i=j}^{U} \frac{\left|TopK\left(P_j\right) \cap L_j\right|}{\left|TopK\left(U_j\right)\right|} \\ \text{Recall}@k = \frac{1}{|P|} \times \sum_{j=1}^{U} \frac{\left|TopK\left(U_j\right) \cap L_j\right|}{\left|L_j\right|} \end{cases} \tag{4}$$

where $TopK\left(U_j\right)$ depicts the highest K suggested POIs in the test samples pursuant to distinct techniques, L_j determines the POIs that the jth client has seen in the training samples and K indicates the various range (5–50) of suggested POIs to investigate the potency of models. *Recall@K* means that fraction of seen point of interests by the goal client that is rewardingly suggested, whereas *Precision@K* means a fraction from top-K suggested POIs to the intended user.

In addition to precision and recall, the k-fold cross-validation method is also used.[47] In K-fold cross-validation, the data is randomly distributed into k groups and the criteria are repeated K times. At any given time, one subset of K is used as the test dataset and other groups are employed as a training data set. By moving the training and test data set, the efficiency of the model can be increased. To achieve full model efficiency, an error is estimated according to all K reviews.

3.3 | Experimental results

DeePOF is implemented in Matlab 2019b, and the investigations were run on a computer equipped with GTX 1060 6GB with i5-4570. In this work, three state-of-art models are chosen to validate the performance of the recommended DeePOF.

UFC[46]: UFC demonstrates a grouping strategy that uses friend importance, user preference, and check-in correlation. This method incorporates three essential aspects, and with the collaboration filtering technique, user preference is personalized.

LORE[48]: For investigating the impact of the successive influence for venue recommendations, the dynamic location–location transition graph by additive Markov chain is created by LORE[48] for incrementally mining sequential form of person check-in sequences.

LFBCA[49]: LFBCA technique explores for each user the impact of social relations to suggest POIs. To characterize the check-in relation, locations and users are joined in the diagram. The expectancy of an individual to a place is outlined using a graph-based strategy.

HGMAP[50]: To overcome challenges like in traditional recommender systems, such as cold-start and data sparsity, a Hybrid Graph convolutional networks with Multi-Head Attention for POI recommendation (HGMAP) was proposed. This model creates a spatial graph using the geographical distance among leverages Graph Convolutional Networks (GCNs) and pairs of POIs to indicate the high-order connectivity between POIs.

APOIR[51]: is the earliest adversarial learning-based POI recommendation pipeline. It entails of two portions, a discriminator and a recommender, which are mutually trained to learn user inclination by playing a minimax game. This game considers social relation and geographical influence as rewards in a reinforcement learning model.

The goal of our examination in this work is to achieve the correct sequence of top-K point-of-interests for each client. According to the number K from the recommended point-of-interests, we investigate the performance of diverse techniques over both datasets Yelp and Gowalla by the utmost suggestion value. The results of the proposed prediction pipeline on Yelp datasets are reported in Figure 5.

The DeePOF evaluation results with other approaches to the Gowalla dataset are reviewed in Figure 6.

3.4 Discussion on performance

According to Figures 5 and 6, DeePOF reliably outperforms UFC, LFBCA, LORE, HGMAP, and APOIR vividly on all datasets in terms of two criteria, Recall@K and Precision@K. Among these methods, UFC, LFBCA, and LORE obtain the worst results in all measures. For instance, in Yelp, the proposed DeePOF method achieves 0.059, 0.044, and 0.035 in Precision@5, Precision@15, and Precision@25, respectively. Although there is a small difference between the values obtained by HGMAP and APOIR strategies but HGMAP outperforms the APOIR method. Moreover, HGMAP and APOIR strategies gain much better results compared to other three mentioned techniques in all measures but still lower than the proposed pipeline.

In other words, our DeePOF well employed the combination of the friendship relations and clustering approach to recommending point-of-interests. As depicted in Figures 5 and 6, this is interesting that K is not small; the proposed model is still proficient to gain high

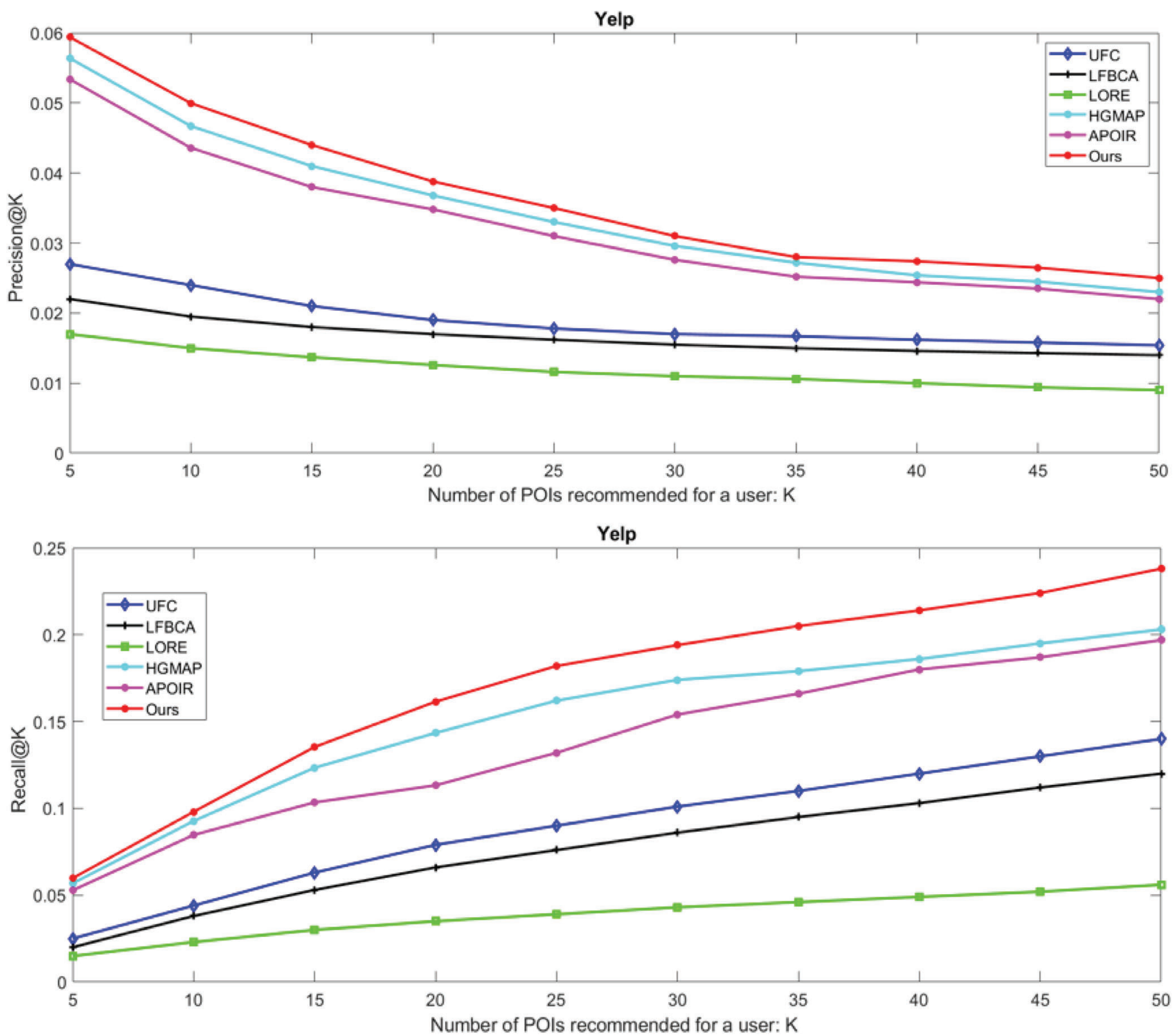


FIGURE 5 Comparison between DeePOF and five other models

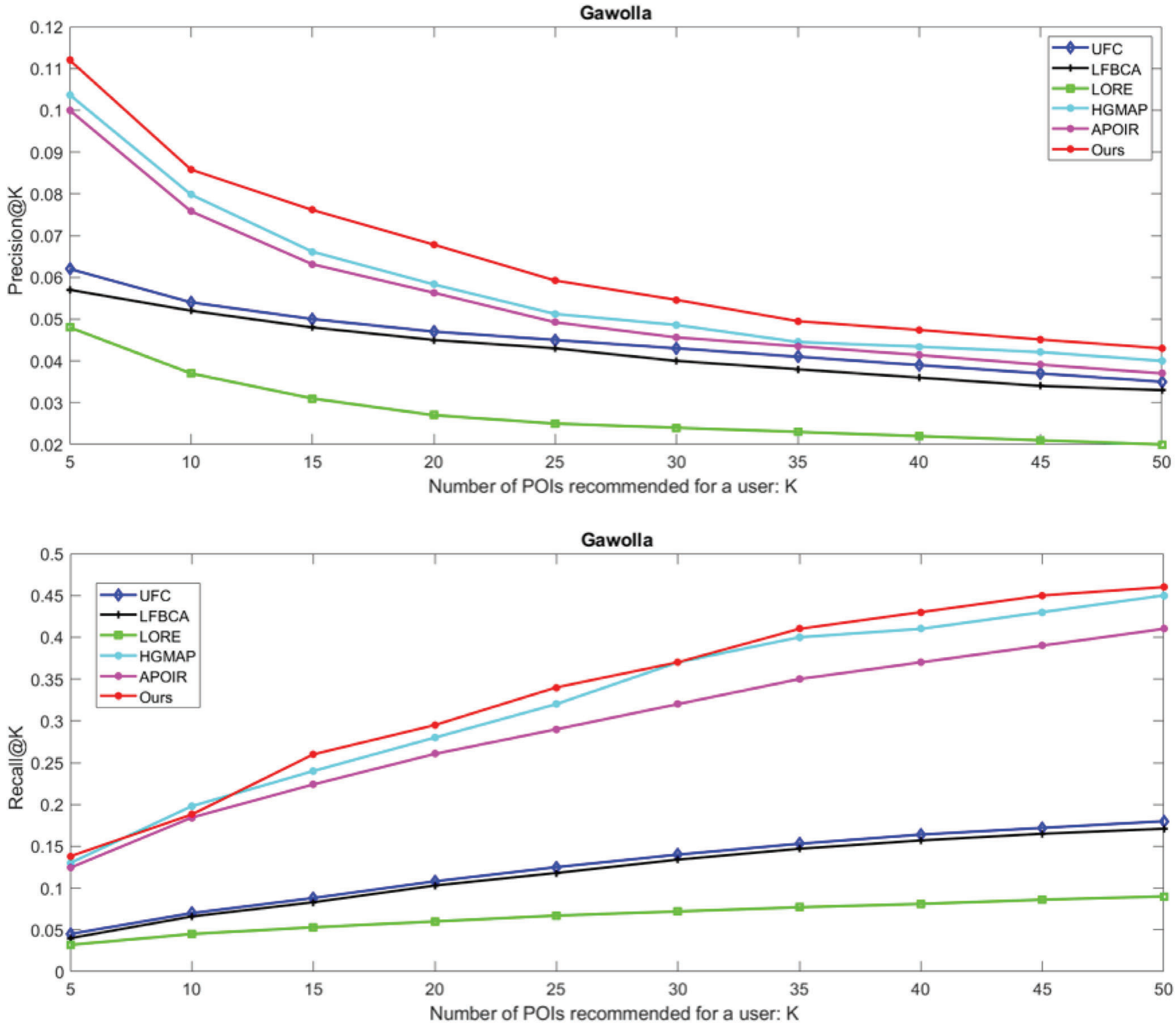


FIGURE 6 Comparison between DeePOF and five other models

recommendation outcomes. Particularly in Figure 5, Recall@5 is smaller than Recall@10, verifying the success of the suggested strategy. LFBCA model does not accomplish better than our structure but outperforms LORE consistently in all criteria for evaluation. LORE approach does not achieve good results in all evaluation criteria in both datasets. This outcome supports that the top-relation based on the attained clusters' overlapping is a chief factor in POI recommendation.

The estimate of the SD and mean of the data sets represents the computation results. Tables 2 and 3 provide a quantitative comparison between the outcomes of our proposed method with the other three techniques in both the Yelp and Gowalla datasets. The proposed method of POI recommendation of this study estimates a better mean and SD in the measurements. The mean of UFC method is somewhat similar to our methodology. According to the mentioned information, the LORE strategy has the weakest performance of the other techniques.

The two datasets evaluated have differences in data sparsity. The evaluation results indicate that DeePOF works better on Gowalla's dataset than on Yelp, and Gowalla has a greater significance of friends than Yelp. It means there are more valuable social relationships in Gowalla, and friends' check-ins are an item that can influence users.

In addition to the above, to measure the achievement of the proposed strategy, the K-fold cross-validation method was also computed. For this study, k is considered as 5. The details are shown in Figure 7.

To further analyze the results, we conducted a paired *t*-test to compare the differences between DeePOF and the other techniques. We found that our method's improvement is statistically significant on all datasets (p-value < 0.01).

TABLE 2 Results from the Yelp dataset quantitative comparison

	K = 5		*K* = 10		*K* = 15	
Technique	**Precision**	**Recall**	**Precision**	**Recall**	**Precision**	**Recall**
UFC	0.027 ± 0.03	0.027 ± 0.005	0.024 ± 0.03	0.042 ± 0.004	0.022 ± 0.01	0.060 ± 0.003
LFBCA	0.022 ± 0.02	0.020 ± 0.004	0.020 ± 0.01	0.037 ± 0.004	0.019 ± 0.02	0.047 ± 0.004
LORE	0.017 ± 0.01	0.017 ± 0.002	0.015 ± 0.02	0.020 ± 0.003	0.014 ± 0.01	0.026 ± 0.006
HGMAP	0.056 ± 0.01	0.0568 ± 0.002	0.046 ± 0.02	0.0927 ± 0.006	0.0411 ± 0.01	0.124 ± 0.004
APOIR	0.053 ± 0.01	0.052 ± 0.002	0.043 ± 0.02	0.0845 ± 0.003	0.038 ± 0.01	0.103 ± 0.006
Proposed	**0.059 ± 0.01**	**0.0598 ± 0.002**	**0.049 ± 0.01**	**0.098 ± 0.01**	**0.044 ± 0.01**	**0.135 ± 0.005**

TABLE 3 Results from the Gowalla dataset quantitative comparison

	K = 5		K = 10		K = 15	
Technique	**Precision**	**Recall**	**Precision**	**Recall**	**Precision**	**Recall**
UFC	0.062 ± 0.05	0.043 ± 0.006	0.055 ± 0.04	0.071 ± 0.005	0.051 ± 0.02	0.086 ± 0.006
LFBCA	0.057 ± 0.07	0.040 ± 0.004	0.053 ± 0.03	0.062 ± 0.003	0.049 ± 0.03	0.078 ± 0.004
LORE	0.048 ± 0.06	0.029 ± 0.003	0.037 ± 0.06	0.042 ± 0.002	0.031 ± 0.01	0.050 ± 0.007
HGMAP	0.104 ± 0.03	0.130 ± 0.003	0.080 ± 0.03	0.198 ± 0.002	0.066 ± 0.01	0.241 ± 0.007
APOIR	0.101 ± 0.04	0.124 ± 0.003	0.075 ± 0.03	0.184 ± 0.002	0.631 ± 0.01	0.224 ± 0.007
Proposed	**0.112 ± 0.03**	**0.138 ± 0.004**	**0.085 ± 0.04**	**0.188 ± 0.002**	**0.076 ± 0.03**	**0.262 ± 0.005**

FIGURE 7 Evaluation of k-fold cross validation

To summarize, this research's contributions provide a novel method of deep learning to suggest an accurate sequence of top-k POIs for users regarding a similar pattern's friendship. The proposed DeePOF improved the accuracy of the POI recommendations compared with other state-of-the-art methods.

4 | CONCLUSION AND FUTURE WORK

This study design the novel and useful personalized POI recommendation structure named DeePOF by incorporating friend importance, check-in correlation, and user preference. A mean-shift clustering strategy has been employed to investigate the key and important friendship to apply a dominant relationship to discover user psychological preference. The analyses clarify that contrasted with procedures dependent on the simple location, the proposed CNN structure, which employs other people's experiences, can give progressively appropriate POI recommendations. We also indicate that only those user's experiences with the utmost equivalent pattern in visiting sites (using clustering approach) can be effective to amend the predictive performance. A comprehensive experiment is performed on Gowalla and Yelp datasets. Exploratory outcomes uncover that the DeePOF structure outperforms other state-of-art structures. This research's limits can be limitations within clusters; the algorithm may mistake and put all too close POIs in one cluster. Also, there may be constraints in the amount of data necessary to network learning. We plan for our future work to Consider reinforcement learning instead of convolutional networking because there is a benefit to learning with less data. We also intend to work with other data sets.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization: Sadaf Safavi and Mehrdad Jalali. *Methodology*: Sadaf Safavi and Mehrdad Jalali. *Formal analysis*: Sadaf Safavi and Mehrdad Jalali. *Data curation*: Sadaf Safavi and Mehrdad Jalali. *Writing—original draft preparation*: Sadaf Safavi and Mehrdad Jalali. *Writing—review and editing*: Sadaf Safavi and Mehrdad Jalali. All authors have read and agreed to the published version of the manuscript.

DATA AVAILABILITY STATEMENT

All datasets used in the empirical evaluation are publicly available. The code will be made public upon acceptance of the manuscript.

ORCID

Sadaf Safavi https://orcid.org/0000-0003-4852-7138
Mehrdad Jalali https://orcid.org/0000-0003-2465-4933

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