PREDICTOUR PREDICTING MOBILITY PATTERNS OF TOURISTS BASED ON SOCIAL MEDIA USER'S PROFILES

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Abstract: This paper proposes PredicTour, an approach to process check-ins made by users of location-based social networks (LBSNs), and predict mobility patterns of tourists visiting new countries with or without previous visiting records. PredicTour is composed of three key parts: mobility modeling, profile extraction, and tourist mobility prediction. In the first part, sequences of check-ins within a time interval are associated with other user information to produce a new structure called ``mobility descriptor". In the profile extraction, self-organizing maps and fuzzy C-means work jointly to group users according to their mobility descriptors. PredicTour then identifies tourist profiles and estimates mobility patterns of tourists visiting new countries. When comparing the performance of PredicTour with three well-known machine learning-based models, the results indicate that PredicTour outperforms the baseline approaches. Therefore, it is a good alternative for predicting and understanding international tourists' mobility, which has an economic impact on the tourism industry when services and logistics across international borders should be provided. The proposed approach can be used in different applications, such as in recommender systems for tourists or in decision-making support for urban planners interested in improving tourists' experiences and attractiveness of venues through personalized services.

1. INTRODUCTION

The tourism industry is essential in several economies. According to the World Tourism Organization (WTO), the flux of tourists around the world generated revenues of more than one billion US dollars in 2019 [1], and it created millions of direct and indirect jobs [1]. In this context, it is relevant to understand patterns of tourists' behaviors to improve the attractiveness of venues with more efficient and personalized services. In particular, the study of tourist mobility is an under-explored aspect of tourism scholarship [2], [3]. Despite previous efforts, very few works have attempted to model the mobility patterns of tourists on large scale [4], [5]. One of the challenges involves finding the appropriate type of data. Location-based social networks (LBSNs) as Foursquare, Waze, Twitter, and Instagram,1 provide a new range of possibilities to obtain data on large scale, especially with a considerable increase of social media users. LBSNs have been successfully explored in large scale studies on users' behavioral patterns [6]. They range from identification of specific groups of people with the same interest [7] and study of socio-economic problems in different areas of a city [8], [9], to the understanding of cultural boundaries, and similarities between societies [10]_[12]. In addition, because LBSN data can be obtained from different places around the world, this type of data represents an alternative for studies interested in behavioral patterns of users acting as tourists [7], [13], [14]. The present work aims to predict international tourists' mobility patterns using LBSNS .We provide a novel approach called Predict Tour. First, it models the mobility of users from different perspectives to produce a *mobility descriptor* of each user. Next, it explores this structure to extract profiles of those users classified as tourists with similar characteristics. Finally, taking all the obtained information together, i.e., the model of tourists' previous nobilities associated with their identified profile, the proposed approach predicts the international tourists' mobility pattern in different countries. The experiments show that Predict Tour can be extended to cases with no prior information about the tourist's behavior in other countries In the present paper, we aim at answering three research questions: (i) what kind of intrinsic relationships can be observed when we group users? (ii) what kind of pattern can be observed in each profile? (iii) how does Predict Tour perform when compared with baselines under different difficulty levels? To comparatively evaluate the performance of Predict Tour, we consider well-known machine learning-based models _ Deep Auto Encoder, Multi-layer Perceptron, and Collaborative Filtering _ as comparison approaches. The results indicate that Predict Tour outperforms all the baseline approaches, improving the understanding and prediction of international tourists' mobility.

The main contributions of the study can therefore be summarized as follows:

The proposition and exploration of a new structure *mobility descriptor* that considers different data features ranging from straightforward information, such as users' origin and destination countries, to sophisticated information extracted from users' mobility in LBSNs. An approach to perform profile extraction which separates groups of tourists with similar mobility patterns and describes each group based on its profile. A novel methodology to predict mobility patterns of international tourists when visiting new countries with and without previous information. Based on these contributions, we believe that Predict Tour can be helpful for many applications in tourist planning. For instance, it can build recommender systems of new places for particular groups of international tourists. The remainder of the paper is organized as follows. Section II discusses related works. Section III detail Predict Tour. Section IV describes the methodology used in the experiments, with comparison approaches and metrics being discussed in Section V. Results are presented and analyzed in Section VI, with conclusion and future perspectives discuss in Section VII.

2. LITERATURE SURVEY

The current related literature is described in this chapter. Several works on tourist be havior use data obtained from traditional approaches such as surveys and interviews. For ex ample, by exploring questionnaire data, Zieba (ZIEBA, 2017) studied how individual features of Austrian tourists can influence their travel motivation. Additionally, the author investigated if tourists' habits are different in other countries. Scuderi and Chiara (SCUDERI; NOGARE, 2018) analyzed expense patterns using a tourist card (which provides discounts in the city of Trentino). Given the vast amount of data available from LBSN, there is a broad spectrum of pos sibilities for carrying on studies about urban societies on an unprecedented scale (SILVA et al., 2019), including those focused on cultural aspects. Some recent research focuses part of the studies on comparing the behavior of users on social media with the behavior extracted from tra ditional data (BAGHAL; WENZ; SLOAN, 2021), (CHEN et al., 2022), (SKORA et al., 2022), and (BELYI et al., 2017). In this way, we organized this chapter into three subgroups to sum marize the main related topics. We consider the aspects of human mobility using user-generated data (Section 3.1), prediction of trends from LBSN data (Section 3.2), and characterization of tourist activity patterns (Section 3.3). Finally, we highlight and discuss the main gaps explored in our work (Section 3.4).

2.1 CHARACTERIZATION OF HUMAN MOBILITY

This type of study focuses on the computational aspect of the research on the behavior and mobility of users. Different studies are explored, contributing to stating that using technol ogy is a promising approach to understanding the users' behavior. Amoretti et al. (AMORETTI; BELLI; ZANICHELLI, 2017) developed a study about users' behavior to construct a smart mobility application that recommends point of interest (POI). Aiming to build individual and group behavior profiles, the authors work with user ac tions, for instance, through check-ins and preferences. Their experimental evaluation demon strates that the system recommendations have a satisfactory precision when considering users' profiles in the methodology. The idea of working with profiles is interesting because it reinforces our hypothesis to have better performance with specialized systems. Luceri et al. (LUCERI; BRAUN; GIORDANO, 2018) investigate the social influence and how it impacts human behavior from event-based social network (EBSN) data. They study how influence propagates among subjects in a social network. The authors employ a deep learn ing approach to learn the subjects' interplay to model social influence and predict their behavior. Their results highlight the importance of (i) the interplay among the subject's friends in terms of dependent influence probabilities and (ii) the negative samples to detect influential friends and learn influence strengths. Their deep neural network (DNN) framework can model social influ ence, taking into account these aspects, and predicting human behavior, achieving remarkable results. In a similar direction, Roy et al. (ROY; CEBRIAN; HASAN, 2019) quantify the impacts of an extreme event on human mobility. From geo-located social media data, the authors mea sure the ability of a mobility system to manage shocks and return to normality after an extreme event. Results show that geo-located social media data allow studying socio-economic impacts and help to guide policies toward developing disaster strategies.

2.2 PREDICTION FROM LBSN DATA

Zheng et al. (ZHENG et al., 2014) state that urban computing can help to understand the nature of urban phenomena and contribute to predict the future of cities. There are UC prediction research developed to help solving problems in different areas. One example is the estimation of better routes considering the location, popularity, visiting order, visiting time, transit time and other features. Hsieh et al. (HSIEH; LI; LIN, 2012) proposed a sequence of locations with associated timestamps, based on the knowledge extracted from large-scale check-in data to recommend time-sensitive trip routes. In that work, the authors designed a goodness function based on some special features and used a greedy algorithm to construct the time-sensitive routes for a given query. Their experiments confirm that it is possible to extract knowledge from check-in data, especially to predict a time-sensitive trip route with a higher potential of satisfaction for the users. In the same direction, Gu et al. (GU et al., 2014) developed a routing system in LBSN leveraging check-in data. The authors designed a system that can accomplish fast routing in LBSN, leveraging geographical knowledge predicted from check-in data. The experiments showed that their approach performed accurate predictions in geography and accomplished fast routing compared to traditional techniques. Zion and Lerner (ZION; LERNER, 2018) use an unsupervised neural network to in corporate the most used trajectories among POI with social lifestyles. Using these lifestyles as labels, they trained a CNN to extract mobility patterns from the routes. Results show evidence that by using cellular data, it is possible to identify social lifestyles and extract mobility patterns to predict the trajectory of users successfully.

2.3 TOURISTS' ACTIVITY PATTERNS

Vu et al. (VU; LI; LAW, 2020) present an approach to tourist cross-country activities analysis. The authors called this approach venue-referenced social media data (VR-SMD). The idea is to determine various tourist activities and the temporal preferences for each activity at different destinations. Their experiments focus on Malaysian outbound travelers, and the results allowed activity preferences to be analyzed from the temporal perspective to obtain detailed insights. Porras-Bernardez and Gartner (PORRAS-BERNARDEZ; GARTNER, 2021) propose a framework to improve the analysis and visualization of tourist behavior. The proposed approach uses Flickr data to classify users by their origin country. Natural language processing techniques are applied to better understand the semantics of the social media platform. Additionally, their approach also provides a visualization of the preferences between points of interest by each nationality. Although there are some limitations, such as the fact it is based only on the origin country information, the results demonstrate that it is a promising approach. Grinberger and Shoval (GRINBERGER; SHOVAL, 2019) explore smartphone data to study tourists' activity patterns and the time-space resource allocation decisions they reflect. They identified three distinct behavioral patterns and evaluated personal and external factors in each group member. Their approach consists of transforming movement trajectories in sta tionary and mobile behavior episodes, computing network-based time-space measures for each trajectory, clustering them with the K-means algorithm, and performing a multinomial logistic regression to analyze the relationship of variables in each different behavioral pattern. Their results suggest that activity patterns emerge from a time-space decision in which effects are uncertain upon each other across scales and behavioral dimensions.

3. EXISTING SYSTEM

According to Barbosa et al. [15], the study of human mobility is especially important for applications such as estimating migratory flows, traffic forecasting, urban planning, and epidemic modeling. As the authors show, there are several initiatives in this direction. For instance, Pappalardo et al. [16] use mobile phone and GPS data to explore patterns of human mobility. They discovered the existence of two distinct classes of individuals: returners and explorers. Lima et al. [17] use mobile network data records (from call detail record data) to analyze the behavior of a large number of individuals. According to the authors, human mobility and social structure are important characteristics to understand the diseases spreading. Mourchi et al. [18] build a set of features that capture spatial, temporal, and similarity characteristics of user mobility and combine these features for future location prediction. In the study of Amoretti et al. [19], a smart mobility application that recommends points of interest (POI) is proposed based on users' behavior. Aiming to build individual and group behavior profiles, the authors consider user actions, for instance, through check-ins and preferences. Luceri et al. [20] investigate the social influence and how it impacts human behavior from event-based social network data. They study how influence propagates among subjects in a social network. In a similar direction, Roy et al. [21] quantify the impacts of an extreme event on human mobility, showing that geolocated social media data allow studying socio-economic impacts and help to guide policies toward developing disaster strategies. The study developed by Rajashekar et al. [22] shows that the behavioral models proposed by the authors are capable of uniquely identifying each user under a one-class learning constraint. They used smartphone data such as those provided by specific applications, cell towers, and websites to construct a user specific behavioral model.

DISADVANTAGES OF EXISTING SYSTEM

- The system is not implemented modeling mobility with foursquare check-ins.
- The system is not for predicting mobility patterns for different difficult levels.

4. PROPOSED SYSTEM

In the present paper, we aim at answering three research questions: (i) what kind of intrinsic relationships can be observed when we group users? (ii) what kind of pattern can be observed in each prole? (iii) How does PredicTour perform when compared with baselines under different difficulty levels? To comparatively evaluate the performance of PredicTour, we consider well-known machine learning-based models Deep Auto Encoder, Multi-layer Perception, and Collaborative Filtering as comparison approaches. The results indicate that PredicTour outperforms all the baseline approaches, improving the understanding and prediction of international tourists' mobility. The main contributions of the study can therefore be summarized as follows:

The proposition and exploration of a new structure mobility descriptor that considers different data features ranging from straightforward information, such as users' origin and destination countries, to sophisticated information extracted from users' mobility in LBSNs.

An approach to perform prole extraction which separates groups of tourists with similar mobility patterns and describes each group based on its profile.

A novel methodology to predict mobility patterns of international tourists when visiting new countries with and without previous information.

ADVANTAGES

- Predic-Tour that considers relevant features extracted from LBSN data beyond the trivial tourist origin and destination countries. An overview of the proposed approach is depicted in Figure 1, which includes three main parts: (i) Mobility Modeling, (ii) Profile Extraction, and (iii) Tourists' Mobility Prediction.
- The proposed system also implements (i) spatial organization of mobility descriptors using a Self-Organizing Map (SOM) [39]; (ii) clustering of outputs provided by SOM into different proles with the Fuzzy C-means (FCM) algorithm

SYSTEM ARCHITECTURE

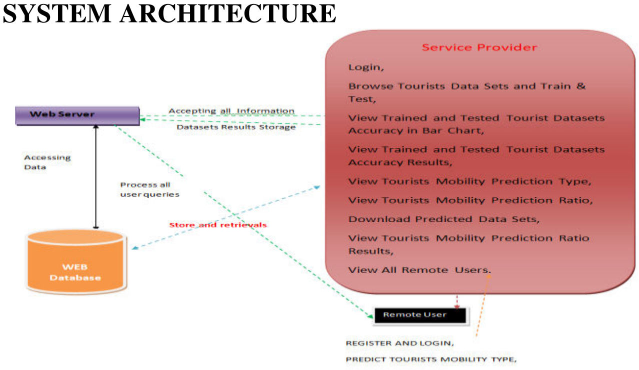

Fig 1: System Architecture

5. DATASET:

We can collect the dataset from the kaggle.com site and placed into our project folder used for predicting the user tour.

1	gender	age	name	Followers	counts_PlacesVisits	Origin_country	Current_Tourist_Country	last_mobility_date_Time	ProfileId	Label
2	M	53	daeni	1894	8279	China	South Korea	2021-04-53T20:43:26Z	172.217.12.142-10.42.0.42-443-46523-6	0
3	M	22	italiana 92	192	663	Germany	Kazakhstan	2021-04-26T09:47:35Z	10.42.0.211-31.13.71.3-54495-443-6	1
4	M	21	Lauraaa	96	1369	Taiwan	Kazakhstan	2021-04-06T14:24:07Z	10.42.0.151-10.42.0.1-15331-53-17	0
5	F	20	Qqkwmdowlo	96	22187	United States	Kazakhstan	2021-04-07T11:21:01Z	10.42.0.211-23.219.23.167-36347-80-6	1
6	M	21	schaessie (3	96	35262	France	United States	2021-04-06T14:53:20Z	216.58.219.227-10.42.0.151-443-34288-6	1
7	M	24	Baby dee	298	7339	United States	United States	2021-04-08T14:37:51Z	10.42.0.211-10.42.0.1-21120-53-17	0
8	F	24	Anna	120	18672	China	United States	2021-04-27T47:29:58Z	10.42.0.151-10.42.0.1-17040-53-17	1
9	M	23	Feelinchen	773	47091	China	United States	2021-04-08T14:18:11Z	10.42.0.211-10.42.0.1-2943-53-17	0
10	M	20	chantal	120	29984	China	India	2021-04-07T20:01:55Z	220.243.219.55-10.42.0.42-80-40093-6	0
11	M	24	rina4790	96	5979	China	China	2021-04-06T16:10:49Z	10.42.0.211-104.193.88.109-38510-80-6	1
12	M	22	anniwhat	96	10450	United States	United States	2021-04-26T11:23:41Z	10.42.0.151-108.168.176.199-57691-5222-6	1
13	both	20	Pierrette	2801	2612	China	Turkey	2021-04-08T14:34:53Z	180.149.136.194-10.42.0.151-443-33755-6	1
14	M	22	Nathalie	60	31736	South Korea	China	2021-04-06T14:52:17Z	10.42.0.151-36.110.213.49-47170-443-6	0
15	M	20	brava ragazza	254	32450	South Korea	China	2021-04-26T10:04:30Z	10.42.0.42-123.125.115.164-42103-443-6	0
16	M	22	Madeline	96	1710	South Korea	Germany	2021-04-08T14:49:55Z	10.42.0.211-23.208.168.108-35587-80-6	1
17	M	53	Lia	100	26842	South Korea	China	2021-04-26T17:47:17Z	172.217.10.78-10.42.0.211-443-49136-6	0
18	M	21	Vanessa	374	31020	South Korea	Japan	2021-04-06T14:57:34Z	10.42.0.151-31.13.80.37-40986-443-6	1
19	M	22	Je** ðŸŒ¸	88	20266	South Korea	Japan	2021-04-53T04:36:43Z	172.217.12.170-10.42.0.42-443-46006-6	0
20	M	20	Jey	240	16683	United States	China	2021-04-26T10:26:08Z	10.42.0.211-64.71.142.120-33206-443-6	1
21	M	53	tina	474	3413	China	Germany	2021-04-53T18:11:13Z	10.42.0.151-14.17.42.57-53099-80-6	0
22	M	47	mel	96	8310	China	Taiwan	2021-04-26T08:07:07Z	10.42.0.1-10.42.0.42-53-37181-17	1
23	M	21	debora	1436	53903	United States	United States	2021-04-08T15:09:47Z	172.217.10.10-10.42.0.151-443-40017-6	0
24	M	21	MISHEffect	1495	33018	Malaysia	Spain	2021-04-53T21:35:40Z	10.42.0.211-77.234.44.199-47467-80-6	0
25	M	22	rebekka4792	96	5302	Russia	Spain	2021-04-06T18:52:15Z	220.243.219.55-10.42.0.211-80-54501-6	1
26	M	24	ðŸ'SweeT_CherryðŸ'	348	22847	Tunisia	France	2021-04-07T20:21:17Z	10.42.0.151-114.134.80.163-50927-80-6	0
27	F	21	Jaylay	120	7407	Tunisia	China	2021-04-53T13:18:14Z	10.42.0.1-10.42.0.42-53-37517-17	1
28	both	47	à¥ Mish Ganja-Girl à¥	96	16096	Japan	Canada	2021-04-26T11:50:47Z	10.42.0.42-63.251.88.56-37725-443-6	0
29	M	22	I_love_soccer	53	15457	Japan	China	2021-04-06T11:59:59Z	203.205.147.229-10.42.0.151-80-36648-6	1
30	M	20	ðŸ'šNadine Jennifer ðŸ'š	90	6962	China	United States	2021-04-26T08:18:01Z	131.253.61.98-10.42.0.211-443-55152-6	1
31	both	22	ðŸŒ¸Joya TiffanyðŸŒ¸	386	30863	United States	China	2021-04-08T15:09:04Z	172.217.10.3-10.42.0.151-443-50724-6	1

Table 5.1: PredicTour dataset

6. RANDOM FOREST ALGORITHM

- The supervised learning method includes the well-known Random Forest machine learning algorithm. In ML, it can be utilized for both regression and classification issues. It is based on the idea of ensemble learning, in which multiple classifiers are combined to solve a complex problem and boost the model's performance.
- "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset," as the name suggests, "Random Forest is a classifier." The random forest predicts the final result based on the majority of predictions from each tree rather than relying on a single decision tree.
- The powerful machine learning algorithm Random Forest is a member of the ensemble learning family. It is frequently utilized for regression and classification tasks. A reliable and accurate model is created by combining multiple decision trees using the algorithm.
- The most important aspects of Random Forest are as follows:
- Ensemble Instruction: The idea of ensemble learning, in which multiple models are combined to make predictions, is used in Random Forest. Decision trees are the models utilized in Random Forest. Random Forest has the potential to enhance the model's generalizability and overall accuracy by combining the predictions of multiple decision trees.
- Trees of Choice: Predictions are made using a set of hierarchical decision rules in decision trees, a straightforward but effective model. Every choice tree in an Irregular Woodland is prepared on an arbitrary subset of the information and an irregular subset of the elements.

This arbitrariness assists with decreasing over fitting and work on the model's exhibition.

- Sub sampling at random: To generate multiple subsets of the training data, Random Forest makes use of a method known as random sub sampling, also known as bootstrapping. A decision tree is trained from each subset, which is referred to as a bootstrap sample. Arbitrary sub sampling guarantees variety in the information utilized for preparing each tree and assists with decreasing the relationship between's singular trees.

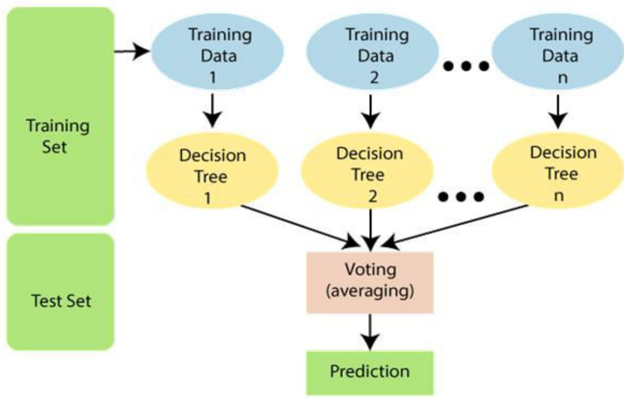

Fig 6.1: Random Forest Prediction

7. UML DIAGRAMS

7.1. CLASS DIAGRAM

The cornerstone of event-driven data exploration is the class outline. Both broad practical verification of the application's precision and fine-grained demonstration of the model translation into software code rely on its availability. Class graphs are another data visualisation option.

The core components, application involvement, and class changes are all represented by comparable classes in the class diagram. Classes with three-participant boxes are referred to be "incorporated into the framework," and each class has three different locations:

• The techniques or actions that the class may use or reject are depicted at the bottom.

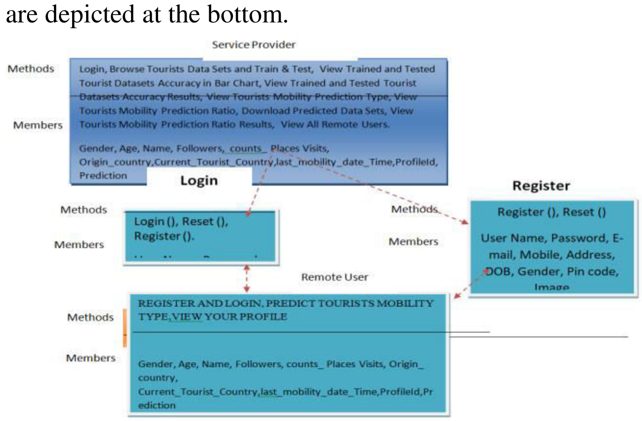

Fig 7.1 shows the class diagram of the project

7.2. USECASE DIAGRAM:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

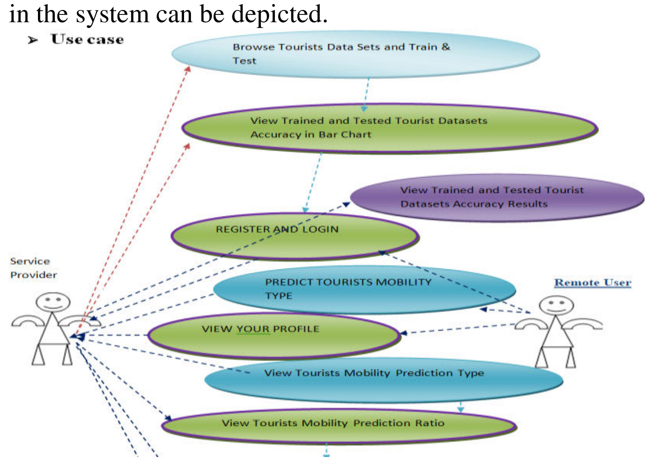

Fig 7.2 Shows the Use case Diagram

7.3. SEQUENCE DIAGRAM:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

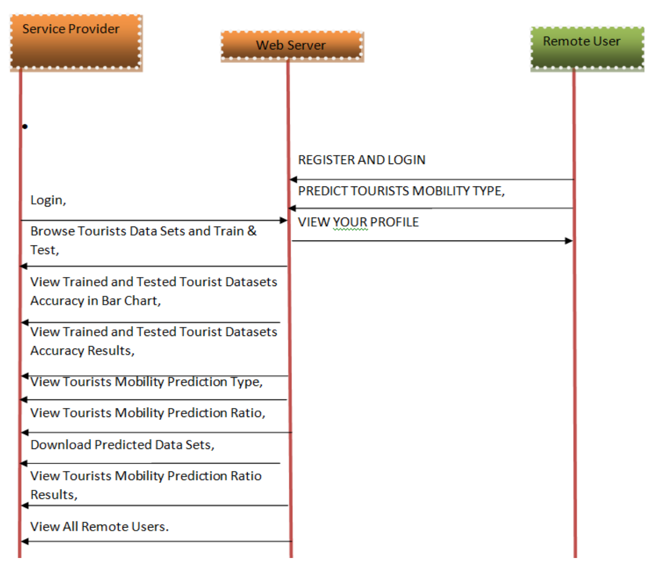

Fig 7.3 Shows the Sequence Diagram

8. RESULTS

8.1 Output Screens

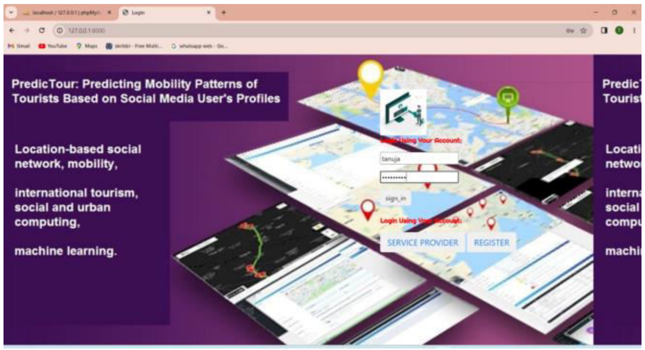

Fig 8.1 User Login page

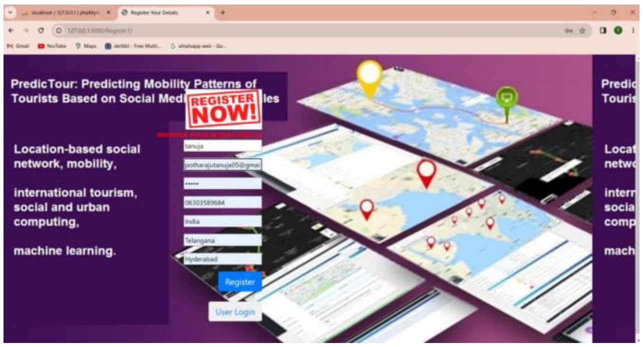

Fig 8.2 User Registration Page

In the above screen to fill the details of the remote users.

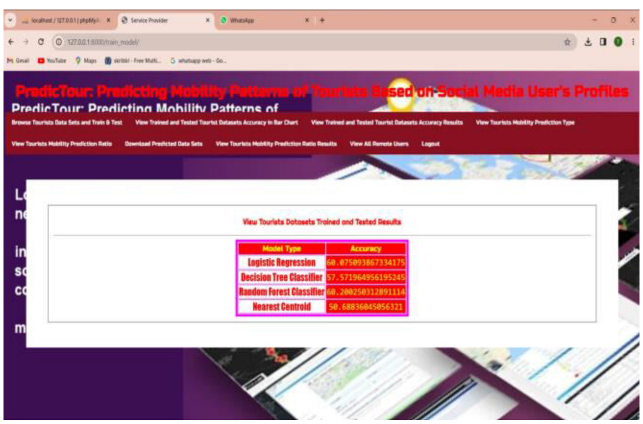

Fig 8.3 Load Data Set

In order to the further process firstly we need to load the dataset and run the algorithms

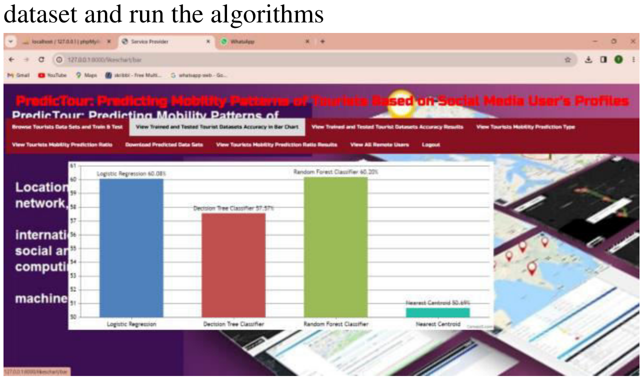

Fig 8.4 Accuracy Comparison Graph

The dataset is processed through the algorithms where the accuracy is measured and display the graph.

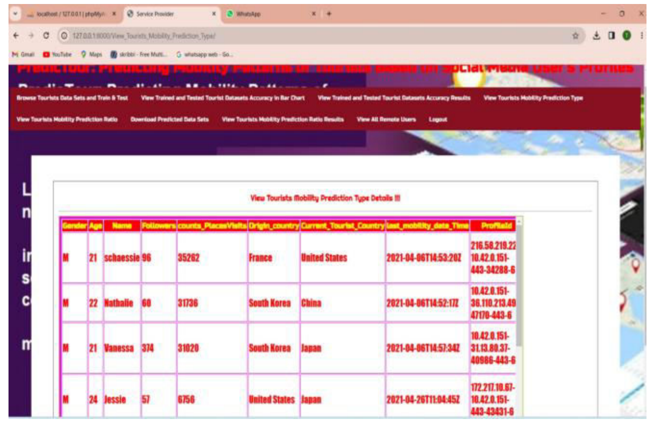

Fig 8.5 Tourists Mobility Prediction Results

In the above screen displays tourists mobility prediction results.

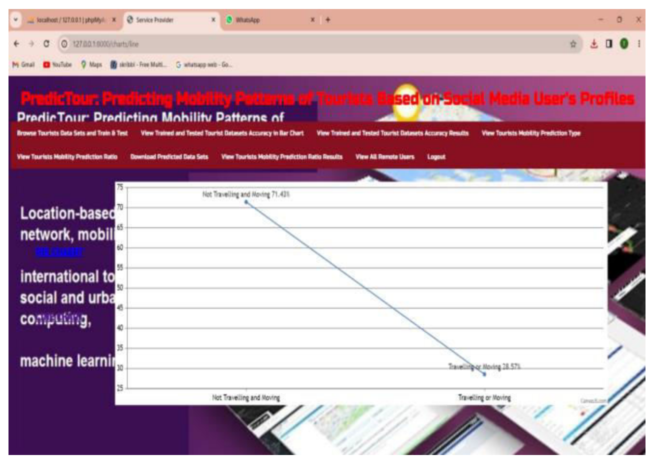

Fig 8.6 Prediction Result Ratio Graph

In the above screen display the tourists mobility prediction results ratio in graph.

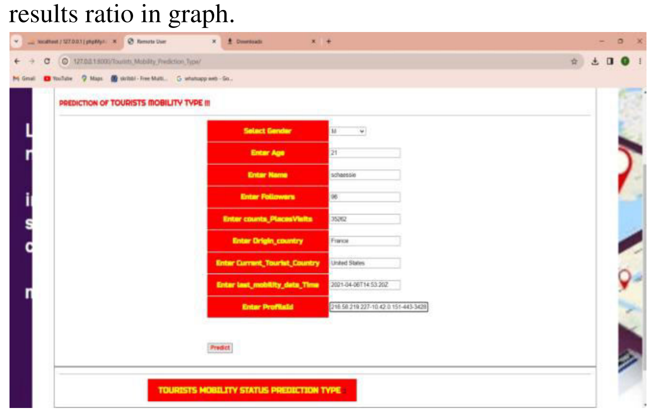

Fig 8.7 Mobility Prediction Type

In the above screen shows the prediction of the user is in travelling state or not travelling state.

9. CONCLUSION

This study aimed to extract and explore patterns available on LBSN data to improve the understanding of users' behavior and use this information to predict international tourists' mobility patterns in different countries. In the present paper, the proposed approach, Predict Tour, explored LBSN data to construct a mobility descriptor necessary to express nontrivial information regarding international tourists' mobility. Predict Tour is then capable of predicting the mobility of tourists at unvisited countries based on the tourists' profiles extracted from Self Organizing Maps (SOMs) and Fuzzy C-means clustering. We showed evidence that Predict Tour can extract important characteristics of each user profile, which can be further explored in a tourism context. In this paper, we evaluated the performance of Predict Tour in different scenarios and against relevant baselines. The results showed that our approach could achieve satisfactory performance, providing smaller RMSE than the addressed baselines, especially for non-pessimistic scenarios. Furthermore, if we focus on the performance for the top 5 and top 10 features, the most important ones, Predict Tour outperformed the baselines in virtually all test cases, except on the extreme ones expected to occur less in practice. Our approach can be helpful in different kinds of applications for tourists. For instance, in the construction of specialized place recommendation systems, the suggestion of attractive services and products, and improvement of transport and attractions strategies. The map of intrinsic relationships provided by SOM could also be useful to show (in a visual tool for tourism planning, for example tourists with similar behaviors, which could be grouped into the same activities. Although this paper has focused on international tourism, we believe that Predict Tour could also provide results for intern tourism with slight adaptations in home and destination locations.

FUTURE SCOPE

This study can be expanded in numerous ways. In future works, we intend to address larger datasets to evaluate the impact on the prediction performance of all the considered approaches. We can also pay more attention to outliers, i.e., tourists whose behavior is far from the behavior represented by the profile centroid. Another possible expansion is the idea of grouping users by geographic proximity, considering spatial distances of places. In the same way, the availability of places that are part of tourists' routine should also be studied in the future. These factors can influence their choices. For example, a tourist from Indonesia may have difficulty finding Indonesian cultural preferences in a western country due to religious or gastronomic differences. However, it is the opposite when visiting a country with a similar culture to the tourist's home.

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