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# LOCATION-BASED SERVICES USING WEB-GIS BY AN ANDROID PLATFORM TO IMPROVE STUDENTS' NAVIGATION DURING COVID-19

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**ABSTRACT**

Educational institutions seek to find optimal ways to provide educational services with the need for alternative solutions due to the requirements of the Covid-19 pandemic. The current study proposed a system that aims to identify the most critical new technologies built on Web-GIS for data analysis and associated information retrieval. It presents an algorithm to analyze the spatial information frequented by the user on the campus and determine the services that target the user based on predetermined spatial information. Provide a system based on integrating location-based services (LBS) using Web-GIS through the Android platform to help campus attendees take full advantage of services information granted to them in their whereabouts. The system employs the rule extraction algorithm to give a recommendations list (using extracted rules with confidence=100% and support= 0.7 to achieve high accuracy for the most points of interest (POI) based on the user's preferences. The proposed system evaluates the given recommendation and the application usage to produce satisfactory results. The average overall F-measure and accuracies are 94.8 % and 94.2, respectively.

**Keywords:** *Web-GIS, location-based services, android platform, points of interest (POI), location-based recommender systems*

## 1. INTRODUCTION

Higher education institutions were affected by Covid-19 during the last period. Based on the requirements of COVID-19 and the need for alternative solutions, educational countermeasures are being taken to continue educating students despite this crisis[1]. These requirements are not only at the level of the educational process but also the level of educational services provided to students on campus. Because of the student's growth and the diversity of institutions on campus, utilizing modern technologies to create a system that facilitates access to educational and administrative services is critical, especially in the circumstances of this pandemic. Furthermore, people are frequently confronted with several obstacles while discovering their exact locations. In this context, the use of Web-GIS for sharing information is rapidly growing[2]. Web-GIS is an interactive map and underlying database that can be viewed or studied with simply an internet connection and a web browser. Web-GIS also allows users to conduct simple activities like zooming, panning, identifying, and measuring. It also allows deep data analysis like producing density clusters or "hot spots" of the activity or locating the geographic center of a specific dataset.

Modern Web-GIS usually comprises mapping and database servers that can collaborate to give users highly scalable and performant maps and analysis[3]. On the other hand, traditional GIS tools and features must be rethought and redesigned to improve usability, particularly learnability, flexibility, and resilience[4]. Therefore, it is necessary to mention that a Geographic Information System is considered as a collection of computer software, hardware, and data, as well as humans, that enable users to enter, manipulate, analyze, and present data and information associated with a specific location on the Earth's surface to aid decision-making[5]. GIS offers numerous chances for educational authorities to improve all types of services to fulfill the needs of the era in which we live and cope with the large volume of information streaming from all over the world. Furthermore, the rapid increase in the use of GPS-enabled smartphones accelerates the development of location-based services[6]. A location-based service (LBS) can be defined as a mobile computing application linked to the user's current location. It gives consumers access to the most up-to-date information about their neighbourhood and provides clients with the most recent changes[7]. The location-based service (LBS) is adjusted by the user's present position and is retrieved from a spatial database located remotely on the LBS server[8].

Additionally, the Location-based Recommender System (LbRS) is one of the recommender systems in which the users demand recommendations for their location of interest[9]. LbRS helps users locate and assess their points of interest (POI) in situations with multiple choices. It also uses data mining techniques to create suggestions based on experience with user actions and attributes[10]. The most popular technique used for the recommendation problem is collaborative filtering. Methods based on collaborative filtering (CF) rely on a user's ratings, in addition to the ratings of other users in the system. The goal of employing CF-based is to find a subset of similar users with similar traits and preferences[11].

**CONTRIBUTIONs AND ORGANIZATION**

This paper addresses the integration of location-based services using Web-GIS through the android platform to improve student mobility during Covid-19. The main contributions of this work can be summarized as follows:

- The proposed application provides a comprehensive map of Mansoura University, with a new perspective on the most effective and up-to-date services, given to various beneficiaries, including students, employees, and visitors.
- The application presents the actual point of the user according to the values of the used device, which the user can access via the mobile application.
- The application alerts the user about any services near him that may be a point of interest. The application also provides a complete description of the recommended service and its favourite lists.
- The application contains a database used to analyze performance indicators and identify a list of recommended points of interest using a different data analysis method.
- A proposed Collaborative filtering (CF) algorithm is used to discover the user's interests' points. Then, these points are extracted based clustering algorithm to partition the locations into connected components (clusters) using a threshold value to filter poorly correlated components.
- Association Rule Mining is used to discover rules in transaction data by applying the extracted rules algorithm. The extracted rule assists in the recommended list, where the user requests any location, and the recommended list will appear on the home page.

The remainder of the paper is structured as follows; section 2 presents a brief literature review. Section 3 discusses the system architecture of the proposed location-based system. Section 4 presents the system design and implementation. Finally, the paper is concluded in Section 5.

## 2. LITERATURE REVIEW

This section will discuss many studies related to Web-GIS, location-based systems, and location-based recommender systems and their application. Web GISs have received wide attention and have been extensively developed and used in real-world applications recently. Kong et al.[12] pointed to that most academic libraries have expanded the volume of geographical information searching due to the emergence of web-based GIS tools. Users can search for geographic data, build customized maps, and perform simple geographical analysis. Jo et al. [13] explored the impact of using a web-based GIS in a world geography class on the development of students' spatial thinking abilities. Students' spatial thinking skills were considerably improved as a result of the Web-based GIS exercises used in this study. Farkas[14] underlines the impact of web browser capabilities and JavaScript's increasing usage on the development of GIS systems on the internet. Current geo-enabled JavaScript libraries have enhanced capabilities, making them capable of executing intensive tasks, such as complex geo-analytics. Kuria et al.[15] examined the structure of Web-GIS, evaluated several approaches used in the design, development, and implementation of Web-GIS systems, and proposed a technique for building a standard Web-GIS -based on evaluation criteria. Moreover, the current advances in Web-GIS are revolutionizing how geographic information can be used in the educational process. Intelligent mapping, mobile applications, editable feature services (EFS), and web map services (WMS) are increasingly more widely available[16, 17] .

In addition, choi et al. [18] evaluated the impact of two explanatory variables (personalization and simplicity of use) on the effectiveness of LbS in terms of economic advantages, perceived benefits, and intention to continue service usage. The empirical data support the substantial relationship between the explanatory and consequence variables. The services of Location-based Systems using mobile devices are addressed in [19, 20]. Huang et al.[21] emphasized that the services of LbS contain features that allow users to search for information about their physical location and locate routes to specific locations. So, mobile devices have reduced the limits connected with location destinations, allowing personalization in an appropriate way for users. Jha et al. [22] offered a methodological framework for integrating satellite and location-based data sources to evaluate extreme climate risk. This paper presents a methodology for identifying local consequences of global causes to assist policymakers in developing policies to reduce the risk of excessive rainfall-induced disasters. Gupta and U. Shanker [23] proposed a system to assist disabled persons with mild to moderate disability status in the early stages of cognitive development impairments. It includes a speculative calculation module that aids in routing by predicting user error and alerting them to ensure an actual travel direction based on the user's preferences. A person with a cognitive disability has a trajectory, a set of preceding GPS points in sequential order. The results reveal that the load is reduced more accurately than earlier track guidance systems.

Meanwhile, Mahmoud and Akkari [24] showed that the Haversine and Vincenty formulas are the two most essential formulas for determining distances on spheres and elliptic forms. Finding the shortest path between two points is critical because the Earth does not perfectly follow one of the geometric shapes. This research described and assessed the two formulas by applying them to location-based recommender systems and proved that Haversine is more appropriate in the realm of suggestion. However, Lian et al. [25] suggested a collaborative location recommendation framework to utilize the relationships between people, activities, and locations to give location-aware recommendations. Vijayakumar [26] offered a new travel RS that can be used on a mobile device to provide personalized travel planning with various points of interest (POI). A previously visited POI heat map will be generated to anticipate the recommended personalized list of trip locations. The highly relevant POIs will be selected for suggestions as destinations, based on the user-selected POIs, a tailored trip plan is recommended.

Schmidtke [27] showed that with the Covid-19 epidemic, there has been renewed interest in discussions about the LbS paradigm and underlined the political dimension, with certain countries utilizing citizen tracking tools. Shahriari-Mehr et al. [28] offered a list of recommended stores that suit the interests and preferences of the user when searching for online shopping sites. Users' online behaviours were extracted from an online shopping website. Then derive the similarities between users and stores and create a distance matrix between the user and the selected stores.

From previous studies, we can conclude that web-GIS architecture on the internet is constantly changing according to contemporary technologies and requirements and is used in many educational applications. Moreover, unlike previous studies, this research integrates many methods. It combines both the location-based system and the recommendation system with Web-GIS to create a mobile application to improve access to Mansoura University services. Several algorithms were also applied to analyze the data and develop recommendations for POIs. Thus, this is reflected in achieving users' wishes with high accuracy and less time and achieving distancing during Covid-19.

## 3. THE PROPOSED METHODOLOGY

The proposed system allows attendees to receive services to direct them geographically using their smartphones. It also employed information retrieval data analysis and built an algorithm to analyze and determine the services that target the user based on predetermined spatial information. It is decomposed of four subsequence stages: data collection, data preprocessing, collaborative filtering, and data analysis, as shown in Figure 1.

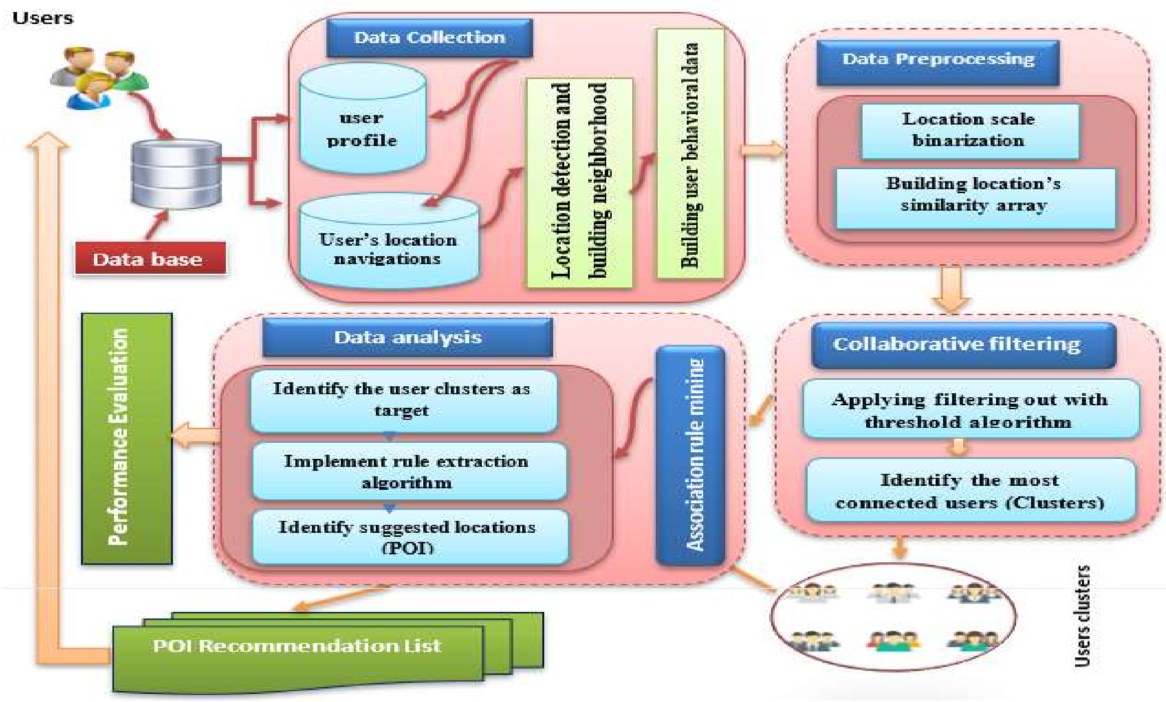


*Figure 1: The architecture of The Proposed Methodology*

### 3.1 Data Collection

Data collection is one of the most crucial steps of any research. It's the process of gathering and analyzing data on variables of interest. The purpose of any data collecting is to effectively analyze the data so that accurate results can be obtained[29, 30]. This stage contains a database system where the application users' data is stored during navigating between the different locations within the Mansoura University campus. This database stores user registration data such as (user_id, password, E-mail, specification, interests) and navigational behaviour data (server log file). It is based on the firebase service introduced by Google, storing data and analyzing performance indicators within the application. Locations could be detected from user's location navigations that can assist in building user behaviour data in terms of an array of user locations.

#### 3.1.1 Location detection and building neighbourhood services list

The starting point coordinates are given an initial value and then updated by access to the locator service on the device used. By comparing the updated coordinates of the user, the list of the nearest services is established according to distance calculating, as illustrated in Algorithm 1.

**Algorithm 1.** Building neighbourhood services list algorithm.

***Input:*** *Services coordinates list(**Scl**), User coordinates array(**Uc**), **counter** for service coordinated in the list(**S1**), the calculated distance **(Dis)***
***Output:*** *neighbourhood services list ordered with distance (**Nsl**)*
***Begin***
*Read Uc [] //user_ coordinates array*
*Let Nsl= zeros (r, r)*
***For** each coordinate in Services Coordinates list S1= 1 to Scl.size*
*Dis =0: Calculate distance*
*Dis = result*
*Nsl.add (Scl[s1], Dis)*
*Next S1*
***End for***
*Nsl.Order()*
*Return Nsl*
***End***

Since the calculation is done geographically on a spherical surface with its topography, it was necessary to use the haversine equation. The haversine formula is crucial for the navigation system since it calculates the shortest distance between two points. This formula determines the distance between coordinates and other coordinates

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in a straight line, disregarding any hills or valleys on the surface. This formula is entirely accurate for most calculations [31, 32].
Haversine is written with the following equations

$$x = (lon2 - lon1) * \cos\left(\frac{lat1 + lat2}{2}\right) \quad (1)$$

$$y = lat2 - lat1 \quad (2)$$

$$d = sqrt(x^2 + y^2) * R \quad (3)$$

Where X is Longitude, Y is Latitude, d is Distance, and R = Earth Radius = 6371 km, (1 degree = 0.0174532925 radian). The distance between two GPS coordinate locations will be calculated using this algorithm. Figure2 shows a spherical triangle with the Haversine Formula law.

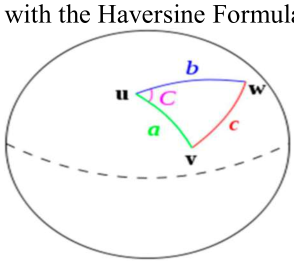


*Figure 2: The ball Triangle with the Haversine Formula Law*

If the three sides' lengths are a (from t v), b (from u t), and c (from v to w), and the opposing angle c is C, the law of the haversine formula is as follows:

$$\text{Haversine (c)} = haversine(a - b) + sin\,(a) sin\,(b) haversine\,(c) \quad (4)$$

### 3.1.2 Building user behavioural data

The behaviour data collected from user entry to the application, such as checked-in locations with coordinates (user-identification during the application workflow), favourite locations and data provided with the ability to import data stored in different formats as a JavaScript Object Notation (JSON). Table 1 shows a list of locations that the user has been joined in the database where the locations IDs are encoded. We calculated the frequencies of each user for each location across all the sessions to generate a locations array of size m × n. For each user visit, the application creates a new session defined by a unique id for the locations that the user will navigate through.

*Table 1: A sample of User's Location Navigations*

| User_ID | Locations |
|---|---|
| U1 | L7, L1, L6, L5, L2, L3 |
| U2 | L5, L8 |
| U3 | L9, L8 |
| U4 | L16, L10, L12, L3, L7, L13 |
| …… | …… |
| UM | L15, L1, L4 |

## 3.2 Data Processing

Data processing is manipulating and translating the collected data into a usable and appropriate form[33]. Our system maps data into binarization format. Locations stored in binary form (1,0) where (1) indicates that the user accessed the location and (0) indicates they did not access. The locations array is then identified from the data which the system mapped in the binary form.

### 3.2.1 Measuring location's similarity array

Users who have a similar history of visiting the exact locations prioritize having similar preferences and interests. Furthermore, the distance between users and locations refers to the probability of the user's attraction to the specified location [34]. The pre-identified locations array is used for measuring users' similarity array according to Algorithm 2. Each similarity of ($U_i$, $U_j$) is computed according to the following equation:

$$Similarity(U_i, U_j) = \frac{\sum_{m=1}^{n_1} Sim(L_m)}{Max(\sum_{m=1}^{n_1} L(U_i), \sum_{m=1}^{n_1} L_m(U_j))} \quad (5)$$

Where *m* is the number of locations in the application, $U_i$ *and* $U_j$ are items of the users, and $L_m$ is an item of location.

$$Sim = \begin{cases} 1, & L_m(U_i) = L_m(U_j) = 1 \\ 0, & Otherwise \end{cases}$$

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**Algorithm 2.** User's similarity array algorithm.

```
Input:: Locations_array matrix(LM)
        variable to store the summation of
        locations(LSM)
        counter for every row in the matrix(Rc1)
        counter for every column in the
        matrix(Cc2)
Output: User_ similarity matrix(SM)

Begin
Read LM // Locations _ array matrix
 Let SM= zeros(r,r)
 [r c] =size // the size of array L, r: the row, c: the
column
   For each location in the array, x = 1 to r
     For each user in the array, y = 1 to r
         LSM=0
         For each user location, I = 1 to c
          if (Rc1(i)==1 & Cc2(i)==1)
   //similarity variable if user (1,2) =1
          Let SM=1
          Else //similarity variable if user(1or2)
   =0
          Let SM=0
           End if
           Let LSM=LSM+SM
          End for
          Calculate the similarity between users.
   SM(x,y)=LSM / max(sum(Rc1), sum(Cc2))
       End for
   End for
   Return User_ Similarity matrix.
End
```

### 3.3 Collaborative Filtering

Collaborative filtering is one of the most commonly investigated and used recommendation algorithms. It is a method for filtering vast amounts of data based on the interactions of a large number of users in the past. It also recommends an item to a user based on the interests of a similar user[35, 36]. In this stage, the required user's interests' points are discovered. These points are extracted based on a clustering algorithm to partition the locations into connected components (clusters) using a threshold value to filter poorly correlated components. The discovered clusters are based on the correlation among locations, where similar clustering objects are allocated to the same cluster and objects that differ are put in different clusters. After filtering the similarity based on the specified threshold, the clustering algorithm is applied to similar group data as illustrated in Algorithm 3.

**Algorithm 3.** Clustering algorithm.

```
Input:  User Similarity Matrix (SM)
         each row in the matrix Filt_SM (R)
         each column in the matrix Filt_SM(C)
Output: The Similarity Matrix after filtering the
threshold (Filt_SM)
        : the extracted clusters (Clu)

Begin
   Read SM
     Let Filt_SM =SM
    Let threshold=ts
       For each R in the matrix Filt_SM
           For each C column in the matrix Filt_SM
              If Filt_SM (R, C) <= threshold
              Let Filt_SM (R, C) =0
           End for
       End for
Return Filt_SM
Read the similarity matrix after filtering threshold
(Filt_SM)
 search the matrix Filt_SM that have a value not zero
Let Filt_SM=find (Filt_SM)
   calculate the connected component matrix (clusters)
Con_Clu = [ ]
   [x, y] =size (Filt_SM)
   Let I=1 // the first row of the matrix Clu
   Let Con_Clu (I)= Filt_SM (x, :) // consider first row
in Filt_SM is the first cluster
 L: For each row in Filt_SM
   If Filt_SM (x, :)= Con_Clu (i) then goto L: // to
compare the first cluster with next row
   Else Filt_SM (x, :) ≠ Con_Clu (i) then let I=I+1 //
add anew cluster
   Else If Filt_SM (x, :) ∈ Con_Clu (I) then Con_Clu
(I)=union (Con_Clu (I), Filt_SM (x, :))
End for
   Return Con_Clu (I)
End
```

### 3.4 Association Rule Mining

Association rule mining aims to find association rules that meet a set minimum level of support and confidence from a given database [37]. The extracted user clusters are added in the user location array table as a target. The rule extraction algorithm introduces a novel methodology for treating a conditional probability for all possible values in the database. The database is divided into *N* predictive attributes and many target clusters. According to algorithm 4, each attribute is denoted by *Li(i=1,2,.....N)*. The target attribute has *C* clusters. Each cluster is donated by *clusters (C=1,2,.......C)*. The search depth level is labelled as $level_L$ $(1 \le Lv \le N-1)$.

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**Algorithm 4.** Rule extraction algorithm

***Input:*** *Modified User locations database*
***Output****: rules to recommend the points of interest*
***Begin***
*01 C = 1,2, ....... C,*
*02 i = 1,2, ....... N*
*03 Lv=1, Ts=Li*
*04 Calculate L (Ts clusters)*
*05 If L (Ts clusterc) =1, then Translate the value(s) of Ts into rule belongs to cluster c*
*06 Do not extend the value(s) Of Ts with other values*
*06 Else Lv=Lv+1*
*07 If Lv>N-1, then Go to End*
*08 Else Add another value of remaining attributes to test set, Ts*
*09 Go to 04*
*10 If all remaining values are in conjunction with set Ts, let i=i+1*
*11 Goto 03*
*12 C=C+1: Go to 02*
***End***

The evaluation component extracts the value(s) which satisfy the $L_c = 1$. It begins with an empty test_set. Then, the individual value (Li) is inserted into each time, and the corresponding conditional probability, *L (S clusters),* is calculated. If $L$ *(Ts cluster*$_c$*)* $=1$, then a rule contains the value belonging to cluster$_c$ and does not conjunction with the other remaining values. The algorithm's search time will be reduced as a result of this process. If $L$ *(Ts cluster*$_c$*)* $\neq 1$, then modify by adding another value of the remaining attributes and checking their conditional probability. The addition of a new value is constrained by the number of antecedents in rule $\leq N\text{-}1$, as explained in Algorithm 4.

## 4. THE EXPERIMENTAL RESULTS

### 4.1 Data Processing

We applied both algorithm 1 and equation 1 to calculate the distance between the scientific computing system centre and other services like the national bank ATM and many other points, as shown in Figure 4.

#### 4.1.1 Measuring location's similarity array

As we mentioned before, the data extracted from the server log file is stored in a user location array. Locations are represented in binary form (1,0). After identifying the user location array, it is used to create the user's similarity array, as shown in Table 2.

*Table 2: User's Similarity Array*

| User | U1 | U2 | U3 | U4 | U5 | U6 | U7 |
|---|---|---|---|---|---|---|---|
| U1 | 1 | 0.71 | 0.86 | 0.428 | 0.29 | 0.57 | 0.71 |
| U2 | 0.71 | 1 | 0.86 | 0.5 | 0.33 | 0.33 | 0.83 |
| U3 | 0.86 | 0.85 | 1 | 0.429 | 0.29 | 0.43 | 0.71 |
| U4 | 0.43 | 0.5 | 0.43 | 1 | 0.83 | 0.83 | 0.5 |
| U5 | 0.29 | 0.33 | 0.29 | 0.833 | 1 | 0.67 | 0.33 |
| U6 | 0.57 | 0.33 | 0.43 | 0.833 | 0.67 | 1 | 0.5 |
| U7 | 0.71 | 0.83 | 0.71 | 0.5 | 0.33 | 0.5 | 1 |

### 4.2 Collaborative Filtering

First, the clustering algorithm filters out the mutual similarity values according to a specified threshold, as shown in Table 3. Secondly, it finds the correlation between users and each other to discover clusters (the most connected users) are shown in Figure3**.**

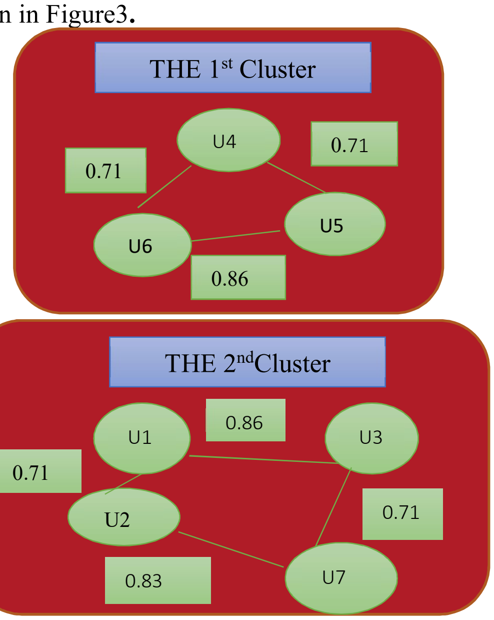


*Figure 3: Discovered Clusters*

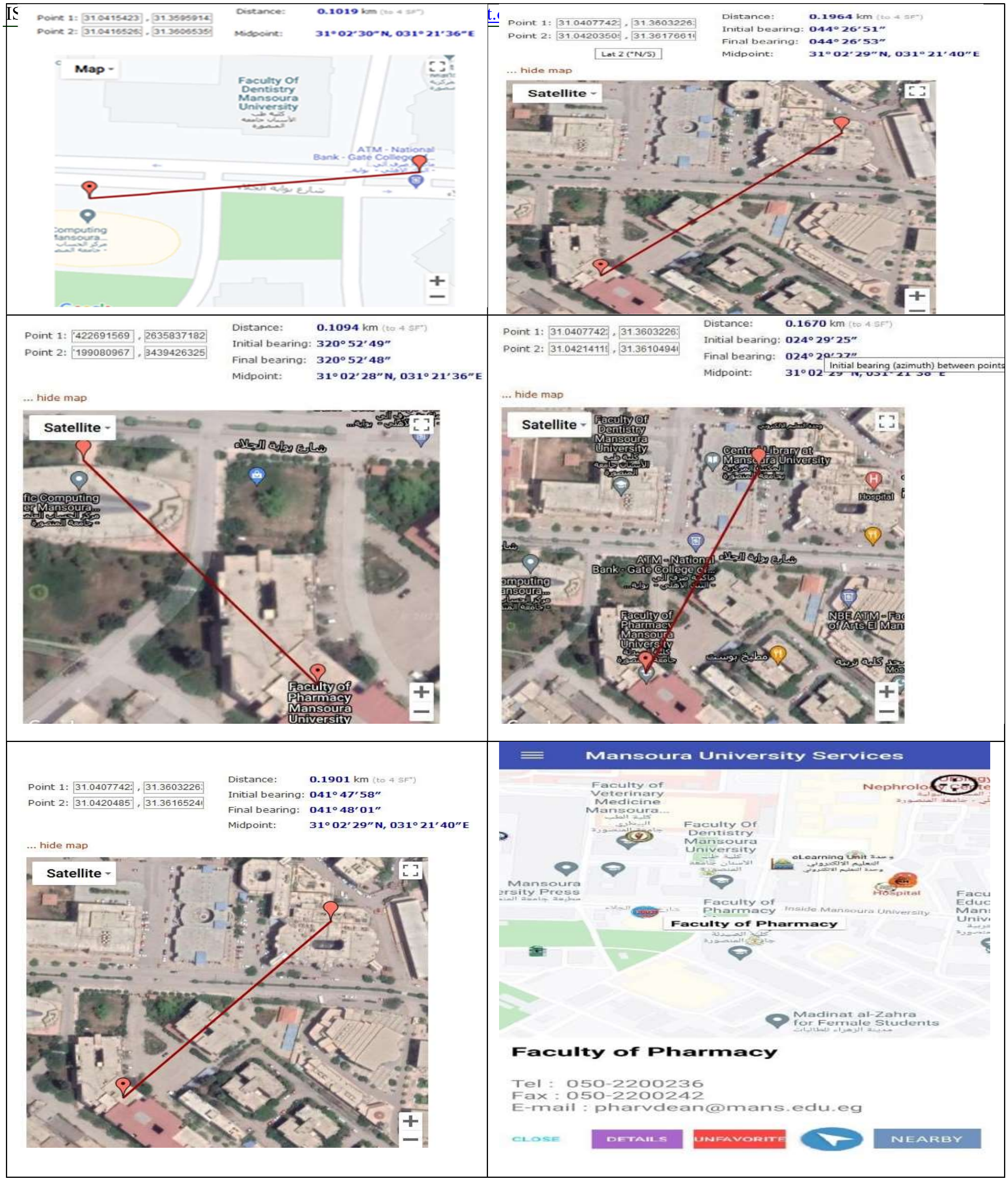


*Figure 4: Map Distance Calculation*

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### 4.3 Association Rule Mining

The rule extraction begins with Table 1 by adding the session clusters as a target, as shown in Table 4. Then the proposed rule extraction algorithm is applied to this database. The application maintains a list of locations within the same cluster, starting from a requested location. The rule extraction algorithm contains a refinement component. This component refines the extracted rules according to three levels: the first level removes redundant rules, and the second level summarizes rules with exact attributes but different values. The third level neglects the rule, with a supporting level less than a specific threshold. Finally, the extracted rules algorithm is applied at L (U cluster $_c$) =100% and support >= 0.7. The set of extracted rules is shown in Table 3.

*Table 3: Examples of Extracted Rules with Confidence 100%*

| ***Combination*** | ***Rule*** |
|---|---|
| L1, L3 | If L1=1 and L3=1, then cluster1 |
| L1, L4 | If L1=1 and L4=1, then cluster1 |
| L1, L6 | If L1=1 and L6=1, then cluster1 |
| L2, L3, l6 | If L2=1 and L3=1 and L6=1, then cluster2 |
| L2, L5 | If L2=1 and L5=1, then cluster2 |
| L2, L6 | If L2=1 and L6=1, then cluster2 |

The rule extracted assist in predicting the recommended list where the user requests any location. The system introduces the correlated locations upon the extracted rule with a confidence of 100%. After applying the extracted rule algorithm, the recommended list will appear on the home page at the locations of the further readings, as shown in Figure 5.


*Figure 5: A recommended List of POIs*
*Evaluation Criteria*

## 5. THE PROPOSED SYSTEM EVALUATION

### 5.1 Evaluation Criteria

To analyze the quality of the recommendations, they must be evaluated using evaluation metrics[38]. Precision, Recall, and F1 and accuracy are the most used recommendation metrics for quality measurement. Precision is defined as the proportion of relevant recommendations among all recommendations. The number of relevant recommendations from relevant places is referred to as Recall. F1 is the product of Recall and Precision [39, 40]. F1 is typically utilized since it considers Precision and Recall values and returns only positive outcomes. Accuracy is a ratio of accurately predicted results to the total outcomes that tell us how often the classifier is correct. Suppose *rule* on the recommendations to the user, $N_u$ is the set of $n$ recommendations to $u$. The relevancy threshold is the evaluation Recall, Precision and F1 measures for acquired recommendations $b$ taking $n$ test recommendations to user $u$, assuming all the users take $n$ test recommendations, then Precision, Recall and F1 can be calculated by the following equations:

$$precision = \frac{1}{|U|} \sum_{u \in U} \frac{|\{ i \in N_u \,|\, r_{u,i} \geq \theta \}|}{n} \quad (6)$$

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$$recall = \frac{1}{|U|}\sum_{u\in U}\frac{|\{\, i\in N_u \,|r_{u,i}\geq\theta\}|}{|\{\, i\in N_u \,|r_{u,i}\geq\theta\}|+|\{\, i\in N_u^C \,|r_{u,i}\geq\theta\}|} \quad (7)$$

$$F1 = \frac{2\ \times precision\ \times recall}{precision + recall} \quad (8)$$

$$Accuracy = \frac{TN+TP}{TN+FP+FN+TP} \quad (9)$$

Support and confidence are also important concepts in the association rules mining technique. These criteria are used to assess the quality of rules that have been developed. The support of the association rule is the transaction rate in *D*, which contains both *X* and *Y*. In other words, the probability *P (Y U X)* of a rule's support is described by the equation below.

$$Support(X \rightarrow Y) = |X \cup Y|/n \quad (10)$$

Where $X \cup Y$ : is the number of transactions that contain *X*, *Y*, and *n:* represents the total number of transactions in the database. Then, the confidence of the association rule is the rate of transactions in *D* containing *X* that also includes *Y*. The conditional probability *P (Y U X)* is the measure of a rule's confidence, and it's defined by the following equation.

$$Confidence(X \rightarrow Y) = \frac{|X \cup Y|}{|X|} \quad (11)$$

Where *X*, *Y* are item sets and (Y |X) is a conditional probability between x and y.

### 5.2 The System Performance Evaluation

Table 4 and Figure 6 show the result after applying each of the three performance measures against the test set. The learning materials generated by our system were evaluated by trying to determine the efficiency of results, using the performance measures, Precision, Recall and F-measures using a test set of queries and results—human judges label results as (relevant or not relevant). Regarding the size of the test set, the performance measures resulted in approximate values. These values show that the learning materials are reasonably efficient to a user query.

*Table 4: Performance Evaluation*

| ***Locations*** | ***Precision*** | ***Recall*** | ***F-measure*** | ***Accuracy*** |
|---|---|---|---|---|
| ***L1*** | 0.962 | 0.974 | 0.967 | 0.950 |
| ***L2*** | 0.924 | 0.951 | 0.937 | 0.935 |
| ***L3*** | 0.903 | 0.939 | 0.920 | 0.920 |
| ***L4*** | 0.94 | 0.955 | 0.947 | 0.930 |
| ***L5*** | 0.971 | 0.953 | 0.961 | 0.960 |
| ***L6*** | 0.961 | 0.952 | 0.956 | 0.955 |
| ***L7*** | 0.942 | 0.951 | 0.946 | 0.945 |

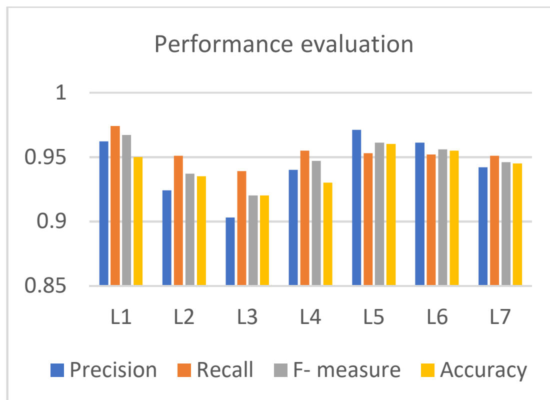


*Figure 6: The evaluation Results with Precision, Recall, F-measures, and Accuracy.*

## 6. LOCATION-BASED SERVICES MOBILE PLATFORM

The mobile application of the proposed system provides a complete map of Mansoura University with a new vision for the most important and latest services provided to the various beneficiaries, including students, employees, and visitors. In addition, the mobile recommendation system and navigation pages provide paths that the user can use through the mobile application, Figure 7. It gives a complete description of the mobile application.

The proposed mobile application is based on the open-source Android system provided by Google. through its platform Android Studio built on object-oriented programming with Java. Maps based on Google Maps data were added to our application using the Google Maps Android API. Access to Google Maps servers, data download, map display, and response to map motions are all handled automatically by the API. Furthermore, it enables us to add graphics to the map like icons for university services points Educational, medical, food and technical services. It also permits us to add :

- Line segments in groups (Polylines).
- Segments that are enclosed (Polygons).
- Bitmap graphics tied to certain map locations (Ground Overlays) .

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- Image sets that appear on top of the base map tiles (Tile Overlays).

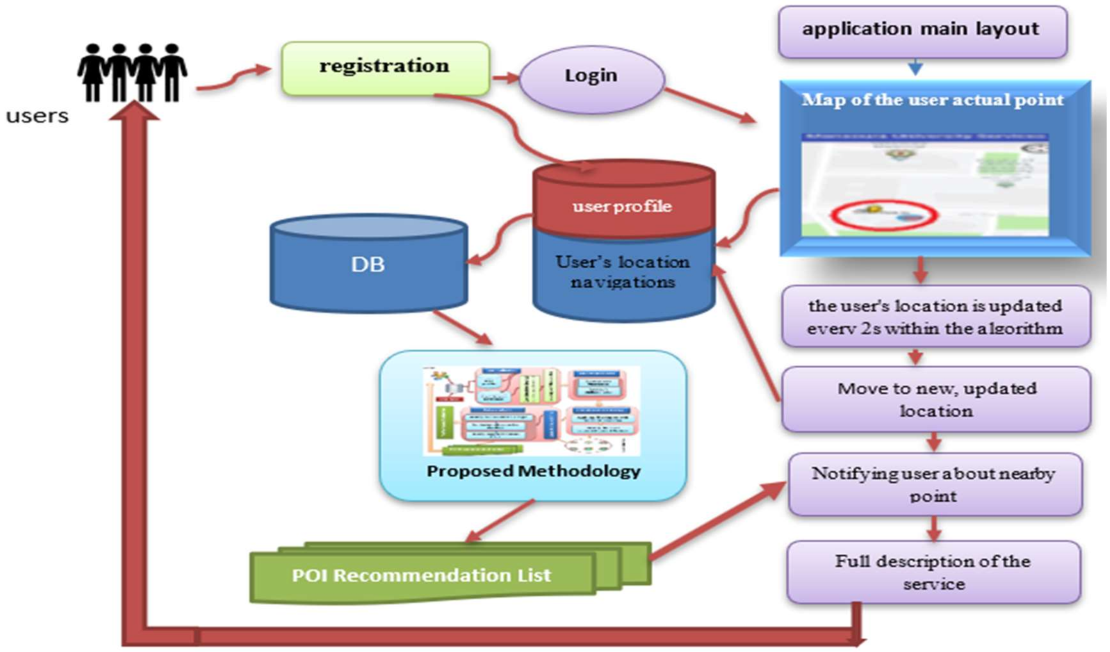


*Figure 7: Location-Based Services Platform Description.*

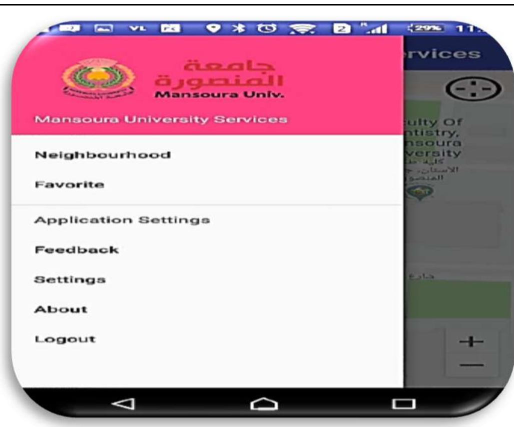


*Figure (8.a): The application Homepage Menu*


*Figure (8. b): Details Screen within A service*

### 6.1 Points of Interest Notifications Results

Table 5 shows the summarized results of the different POIs notifications where time accuracy explains differences between arrival and alert timing.

*Table 5: Points of Interest Notifications Results*

| Point of Interest | Alert Time H:M:S | Arrival Time H:M:S | Time Accuracy (Ss) |
|---|---|---|---|
| Faculty of Education | 10:01:40 | 10:01:47 | 7s |
| Student Services Complex | 10:30:49 | 10:30:53 | 4s |

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| | | | |
|---|---|---|---|
| Communications and Information Technology Center | 10:41:23 | 10:41:29 | 6s |
| Central Library | 10:01:38 | 10:52:41 | 3s |
| Faculty of Pharmacy | 10:59:29 | 10:59:37 | 8s |
| Faculty of Dentistry | 11:05:22 | 11:05:26 | 4s |
| Scientific Computing Center | 11:11:48 | 11:11:53 | 5s |

As seen in Table 5, the most accurate alert time was 3 seconds before arrival, and the average timing accuracy for these interest points was 5.28 seconds earlier. Figure9 shows the differences between arrival and alert timing. On the other hand, there were some differences between the user and the point of interest when notification and alert occurred, as shown in Figure 10.

The application can run on different versions of operating systems based on Android, and this data is analyzed and observed through the firebase control panel as the following Figure 11.

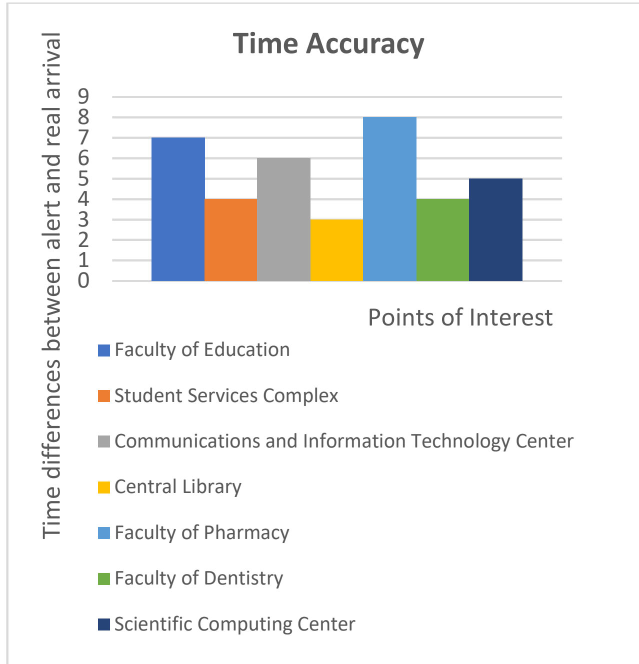


*Figure 9: The differences Between Arrival and Alert Timing (Time Accuracy).*

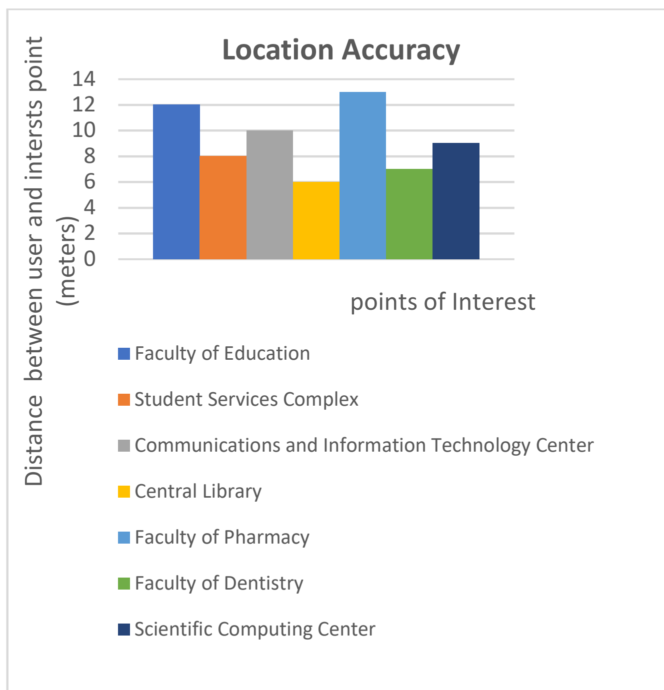


*Figure 10: The distances Differences Between the User and the Point of Interest (Location Accuracy).*

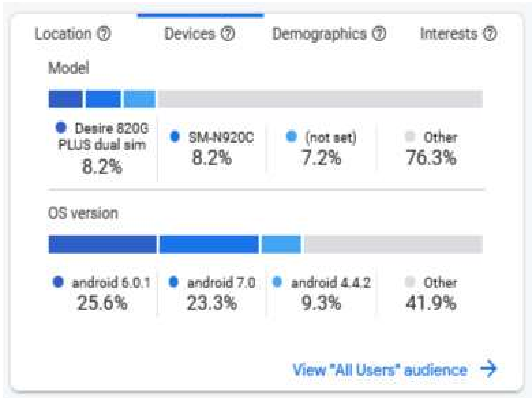


*Figure 11: Devices Audience*

## 6.2 Neighbourhoods and Points of the Interest List

The user can find the essential points around him and the distance he must pass to reach any point of them. Depending on Google services and the proposed algorithms, the application provides a good result in guidance services to users through navigational guidance with maps or voice guidance with steps to reach selected locations, as shown in Figure 12.

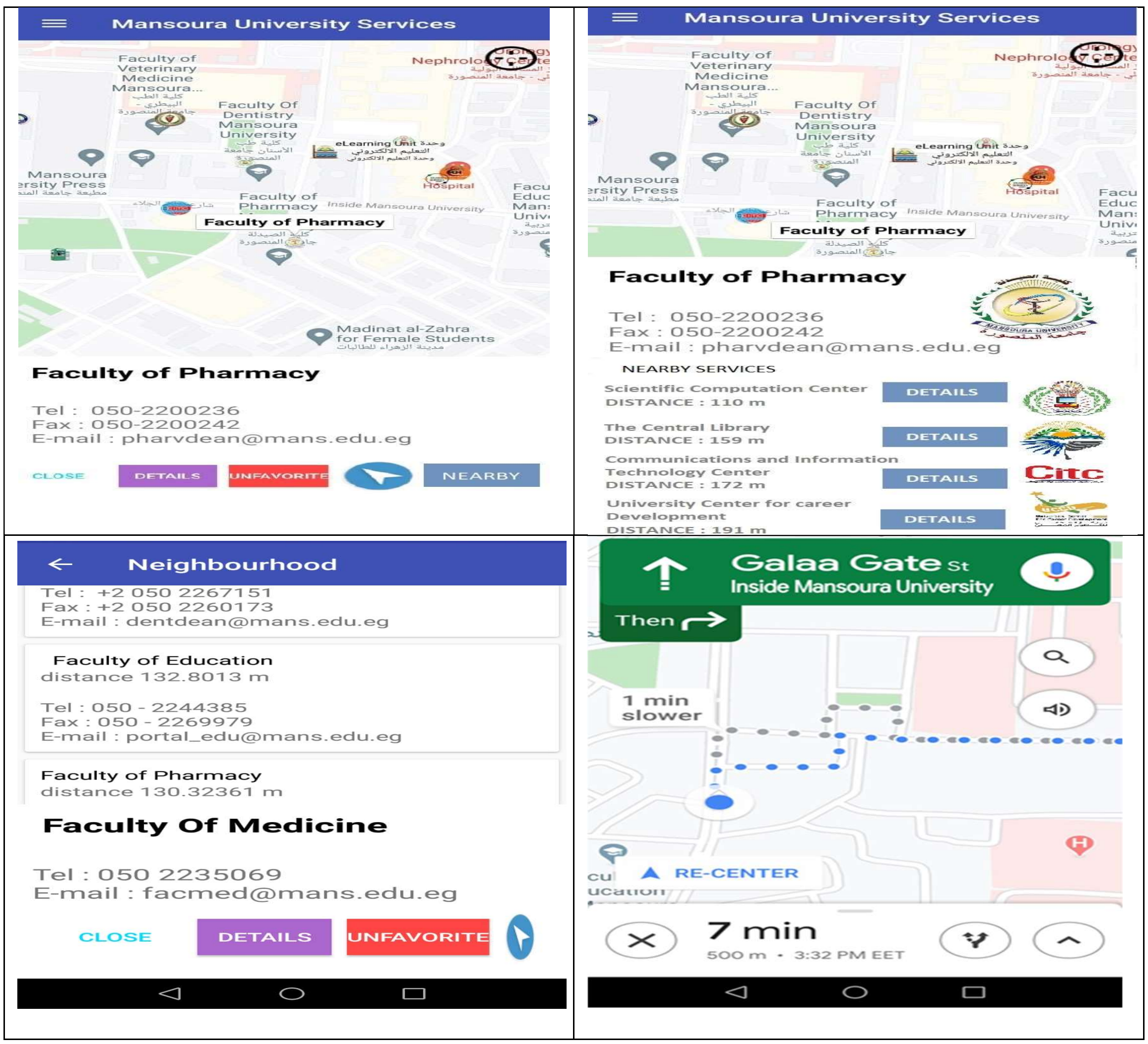


*Figure 12: Neighbourhoods Distance and Points of Interest Navigation List.*

## 7. CONCLUSION

This study proposed a system to develop modern ways of connecting between services and their beneficiaries to achieve the optimal benefit during Covid-19 in Mansoura University. Our system uses android platforms and their open-source environment to build a geographical database of various interest points within Mansoura university that allows users campus pioneers to closely view the details of each service while touring the campus by surfing neighbouring services. It also provides many recommendations with the essential points of interest that can benefit users based on their preferences and measure their similarities. The proposed system has achieved satisfactory results, with the mean of F-measure and the accuracies 94.8 % and 94.2, respectively. The results can be improved in future work by expanding the system's knowledge base to include new communities outside the campus of Mansoura University.

The suggested approach enables service providers to update their information or add new services that have recently been introduced to users' phones. The system knowledge base is intended to store data generated by system operations, such as user databases, user favourites, user checked points, available interest points, and user information collected from their devices (device model, OS version, and others) for performance purposes while respecting user privacy. One of limitations of the proposed system is that it only works on Android smartphones; however, it might be developed or comparable systems presented for use with other operating systems. The results also can be enhanced by increasing the system's knowledge base to cover as many interest points inside Mansoura University as possible, as well as introducing and maximizing the use of variable services. The proposed approach can be tailored to new communities that include a plethora of new digitalized services.

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