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Tourism Recommendation System Using Indistinct Rule-Based Feature Selection and Classification for Tourists

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Abstract:-The purpose of recommendation systems in the tourism industry is to satisfy visitors by helping individuals make better informed decisions and selecting optimal tours based on daily varying parameters. In the modern era numerous techniques are being used in recommendation systems as a result of an increasing volume of data studies. In this research, real-time unstructured data are gathered from several kinds of travel-related websites, online data providers, and manual data sources. The recommendation system is built around the feature selection method that is described here, and in this work, semantic rules are constructed for unstructured information on the basis of daily-increasing user preferences. The recommendation system sensitive to strong structural assumptions includes proposed embedded feature selection recommendation models. Based on user preferences that continue to evolve regularly, semantic rules are created for the chaotic data sets that are now accessible. In order to increase the accuracy of recommender systems, a fuzzy semantic classification method that combines the fuzzy data classifier approach with semantic analysis is described in this research.
Keywords: tourism, recommendation system, fuzzy semantic rule, fuzzy inference system, feature selection, classification, spot identification.

1. Introduction

In this era where new tactics are being introduced in technology everyday it is necessary to update the data according to the needs of the tourists and their expectations. The tourist sector, e-commerce services, manufactured goods, films, search engines, social networking, and online learning are just a few examples of the various industries that employ recommender systems. The potential of the recommendation system to deliver a perfect response to the user's search interest depends on continuous quality improvement.

In the field of tourism, it is understood to be an effective information filtering system that makes recommendations to users for all data sets depending on their needs, with reference to suitable destinations and the goods, deals, and services offered at those places. In other words, the recommendation system is created to meet the demands of the users by analysing the data from previous tourists who have taken the trip in accordance with their needs.

The objective of the feature selection approach is to increase the recommendation method's prediction accuracy. The volume of data gathered for analysis and the number of data storage are both decreased through the process of choosing review data for the tourist industry. The machine learning algorithm that is used to process the data is made more effective with the assistance of this technique. Both a filter-based technique and a wrapper-based technique may be used to choose such features. In this research, for the reason of choosing a new feature for a trip recommendation system, an embedded technique that combines these two approaches is used.

Fuzzy or Indistinct concepts are those that lack a clear definition or specific meaning, yet meaningless or ambiguous concepts can nevertheless be classified. The concept of semantics can only be fully described, hence the approach used to do so might be referred to as a semantic tree. In the proposed work, it is simpler for travelers to identify tourist places when we utilize a fuzzy logic-based recommendation system that uses the Fuzzy Inference System (FIS).Although the kind of inputs to be built is fuzzy, we nevertheless employ unconstrained fuzzy sets. When utilizing FIS as a controller, fuzzy variables are crucial. In other words, the fuzzification unit converts the crisp input variable and fuzzy variables into the fuzzy input variable. After that, the FIS crisp variable created by the defuzzification unit converts the fuzzy output variable. The places will be determined by the proposed recommendation system based on user desire and budget. In order to suggest appropriate travel places, the recommendation model additionally considers the attributes of the tourist site, such as security, facilities, dietary requirements, and traveler preferences.

Following is how the remaining parts are organised: The research activities and results are discussed in Section II. The data utilised and the input variables are described in Section III. Section IV provides a description of the methods used for the research. The analysis and explanation of the consequences are presented in Section V. The results' planned application is explained in Section VI.

2. Literature Survey

The literature has a large number of publications on recommendation systems. In order for a visitor to learn more about the many sorts of lodging that are offered in Delhi, the capital city of India, Kaushik, S. et al. [12] developed a crowd-based recommendation system. The traveller may use this to enter his location and request the recommended malls and internet cafes in the area. The user's favourite places are presented, sorted, and contacted based on the areas they've chosen. Visits by tourists are extremely simple.

A personalised point of interest (POI) recommendation system was put out by Pin, C. et al. [3] and is intended to gather user comments about POIs as subjective qualities and information about the tourist locations around POIs as objective attributes. By taking into account subjective and objective features in personalised POI, Katsumi H et al. [11] suggested a different approach that delivers recommendations based on user characteristic variables including personality, behaviours, and social aspects.

By choosing aspects like shopping, food goods, and POIs, Li et al. [14] addressed how 'Top-K' (BP2V) is a beneficial factor for tourist groups. They employed a common method that gathered user temporal and geographic information to assess context-awareness similarities. Users may use it to make a list of recommended POIs that is uniquely theirs. The user can produce educational data like geo-tagged photographs and ratings for POI recommendations. An enhanced POI recommendation system may result from this [12]. Another method is to use GPS-enabled traveller location images to gather data such as photo latitude, photo longitude, travel patterns of tourists, tags, and POIs. This improves the accuracy of the user-developed recommendation system [16].

The Chebyshev polynomial approximation approach is employed in the study put out by Chen B et al. [5] to gauge user interest based on a particular place and its specifics. But in their system, the data gathered to examine the connection between a certain time period and user preferences is not adequately organised. A probabilistic approach was developed by Alianejadi et al. [1] to control the association between review tag and user interest. Using combined learning-to-rank methods, scores on various location-based social networks (LBSN) are computed. There isn't a proper attraction created between the links for a given season.

The three elements of continuity, unpredictability, and periodicity were used as the main determinants in the development of a novel temporal impact recommendation system by Gao R et al [22]. According to research by Khatibi et al. [6], [18], precise forecasting of impending events is essential for tourism enterprises to draw in customers through social media, travel websites, information on natural phenomena, and other country-specific data. A rapid low-rank dynamic tensor and a pigeon-driven heuristic algorithm were two novel strategies used by Liao J et al. [9] to create an effective recommendation system. It requires information about travellers from all around, and recommending a certain location when there are more foreign visitors there is challenging.

The claim made in the study of Lee et al. [13] is that online intelligent tourism data is more economically beneficial for tourism firms and visitors when the offline community has more tourism information data than the offline community of interest. Positive and negative false evaluations were distinguished by Martinez-Torres

MR, Toral SL [17] utilising polarity-based differentiating criteria. The suggestion method is regarded as superior since it distinguishes the review qualities based on feelings. Users who have chosen features from the information database with comparable selections are given recommendations using a collective filtering technique. However, a big amount of data is not a good fit for this recommendation strategy [11].

In order to ascertain travel intent, transportation plans, and online travel merchants through social media, Rashid A et al. [20] reviewed 109 high-quality research papers that were analysed using a screening process and grouped into 8 categories using a categorization of strategies and approaches. According to Ying et al. [29], a metric embedding method that understands the user's presence time in various locations at various times is taken into consideration in the dynamic approach. However, the connection system's effectiveness for particular areas and times of year has to be increased.

The ideal suggestion technique is to keep in mind the demands of the tourists when making plans, without sacrificing any of the numerous alternatives accessible to travellers or suggesting them to make the trip memorable [14]. Sarkar and others [8] Multiple itineraries are offered via Tourist Recommender System (TRS) techniques depending on the preferences of visitors. In other words, a recommendation system is developed based on travellers' top priorities.

A recommender system leverages big data, artificial intelligence, etc. in addition to acting as a smart guide based on user preferences to assist travellers and the tourism industry [19]. Nearly all referral programmes are intended for lone travellers. A suggestion system created in this manner benefits both individual and group travellers [20].

3. Methodology

In order to help visitors, plan their trips, the proposed study aims to develop a recommendation system that can tell them where to go depending on their preferences. Figure 1 depicts a high-level perspective of the proposed architecture for the trip destination recommendation system.

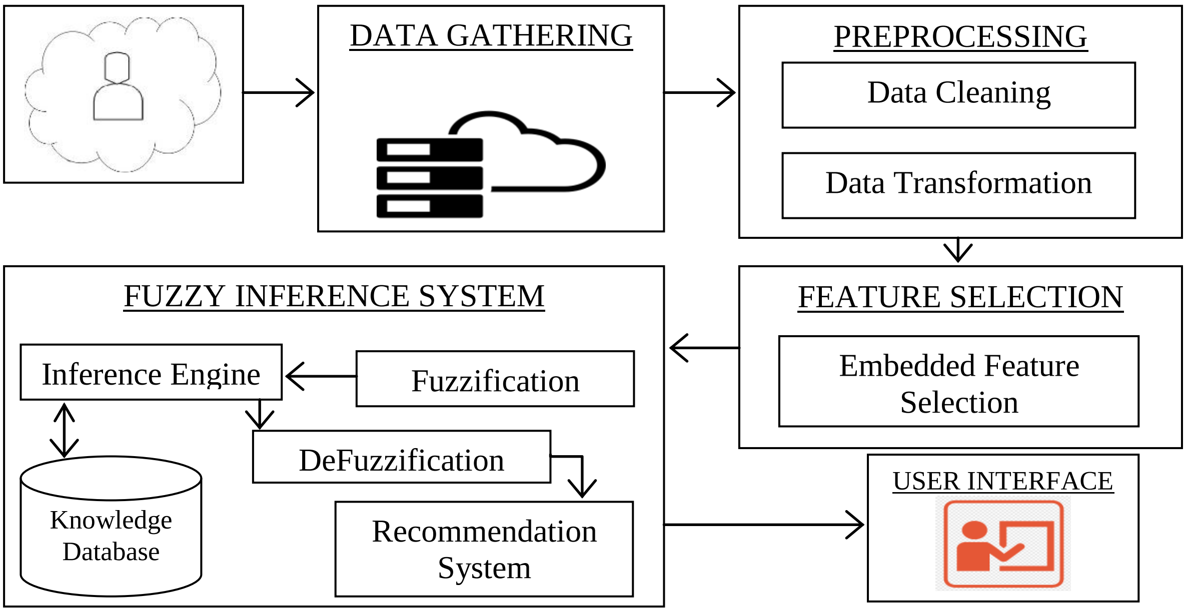


Figure1. System Architecture

It has four important sections. The first step is data collection, where information about the place's environment, safety, accommodation, transportation, restaurants, budget, best time of the year to visit places, shooting places, best things to buy in lowest price, neighbourhoods and malls etc., are collected. The dataset is cleaned by data pre-processing in the following step, which involved removing extraneous data and filling any gaps. The third stage, feature selection, identifies and extracts relevant attributes from the pre-dataset. After classifying the identified places, in the fourth step classification is performed to provide smooth output using a fuzzy inference method.

Data Gathering

Data about tourist places in CSV or Excel format is gathered from a variety of travel websites, including TripAdvisor, Kaggle, Tour-Trip, and social media platforms. Additionally, data is gathered through web groveler and APIs. The obtained dataset is used to collect a total of approximately 50 characteristics, and ratings are gathered for each attribute. For subsequent study, these estimations were included into the available dataset. Additionally, evaluations are combined by domain for each place.

Data Preprocessing

Data preparation eliminates duplicates and ambiguities from the dataset and converts it into an analytically-friendly format. To do this, data cleansing and transformation tools are employed.

Data Cleaning:"Data cleansing" is the process of removing data from external databases in the manner required for research. This implies that there are two problems with the dataset that is gathered: one involves duplication, and the other involves a column's missing values. Use a universal and simple imputation strategy, such as the distribution, to fill in the missing values using statistical measurements of each attribute to solve the problem of missing values for each variable.

Apply the formula to obtain a constant missing value to replace any missing data. This means, that the mean value is obtained by dividing the total number of observations by the sum of all observational data.

Transformation: The process of organising data such that every record and every field have an identical structure is known as data transformation of data. Database transformation's main objectives are to decrease data update mistakes, eliminate redundant data, and streamline analytical queries. In conclusion that normalising extends beyond just establishing data and has the potential to streamline processes and cut expenses. As a consequence, a normalised threshold is produced processed

using min-max normalisation of the attribute cost that maximises accuracy. The data are normalised from 0 to 1 using a linear transformation known as min-max normalisation.

Feature Selection

The process of choosing the most important inputs or lowering the quantity of inputs for processing and analysis is referred to as feature selection. Feature selection (or feature extraction) refers to the process of removing useful information or features from existing data. From the pre-processed information, six attributes—place type, food, good looks, budget, security, and convenience—are chosen as the main input variables for this study and stored in a knowledge database based on visitor expectations.

Places: The place type parameter conveys the desired place of tourists. This parameter is used to obtain the pertinent place data from the database and combine it with other place data to determine each place's score for the user's preferred category. There are a total of 1 to 10 possible scores for the place parameter.

Food: The overall quality of food is distinctive, among other characteristics. In the database, each site is given a meal score that ranges from 1 to 10. Each place's expensive, reasonable, and cheapest values are kept in the database and employed to determine a place's food score.

Good Looks: Every place has a unique aesthetic value, and various places have various good looks criteria. The implicit anticipation and the rating of the place's attractiveness are important variables when a visitor takes a trip.

Budget: The cost of essential tourist requirements like food, transportation, and lodging vary based on the area, and a tourist's vacation is determined by their budget. Additionally, the presence of a number of tourist destinations in the agenda emphasises the importance of the budget. For each site, a score and fuzzy value for the budget attribute are constructed, supplemented by the addition of additional necessary elements to the dataset.

Security: An essential part of tourism is security. It provides an optimistic outlook for the customer journey. This encourages users to frequently visit the same secure place. By raising both the revenue for the tourist industry and the number of visitors, it plays an essential role. As a consequence, each destination receives a recommendation along with a safety score and fuzzy value so that travellers may easily assess the level of security.

Convenience: The focus of amenities is on things like where to find basic necessities, transit, and lodging. Making recommendations for amenities for a place is made simpler by creating a score and fuzzy value.

Fuzzy Inference System

A fuzzy inference system is an essential part of a fuzzy logic system, which is in charge of making decisions uses "IF...THEN" procedures using "OR" or "AND" relationships to create important decision-making procedures. The knowledge database, disambiguation, inference engine, and the defuzzification are the four parts of this step.

Knowledge Database: Fuzzy procedures are developed for the full dataset and saved in the knowledge database based on the number of characteristics that have been chosen and the matching number of linguistic parameters. Thus, the data set contains the descriptions of linguistic parameters and the ratings for certain places for each feature. According to the needs of the user, the inference engine element enables filtering rules. Fuzzy rules are created using the recommendation characteristics (a) and linguistic parameters (l) in the knowledge database's stored dataset (Table 1).

Table. 1. Spot Identification

Places	Food	Good Looks	Budget	Security	Convenience	Identify Class label CL
Nice	Costly	Excellent	High	HighlySecure	Good	VeryHigh
Nice	Costly	Excellent	High	HighlySecure	Average	VeryHigh
Nice	Costly	Excellent	Moderate	HighlySecure	Bad	LittleHigh
- - -	- - -	- - -	- - -	- - -	- - -	- - -
- - -	- - -	- - -	- - -	- - -	- - -	- - -
- - -	- - -	- - -	- - -	- - -	- - -	- - -
- - -	- - -	- - -	- - -	- - -	- - -	- - -
Nice	Costly	Excellent	Moderate	ModerateSecure	Average	LittleHigh
Nice	Costly	Excellent	Moderate	ModerateSecure	Bad	Medium
Nice	Affordable	Fine	High	HighlySecure	Bad	Medium

Tourists are given destination recommendations based on the proposed system's six characteristics. Three separate linguistic parameters are used to express each feature, with food being represented as "cheap, affordable, expensive," beauty being "excellent, excellent, excellent," budget being "low, moderate, high," security being "unsafe, moderately safe, high security," and comfort being "bad, average, good." A set of 3^6 rules based on characteristics and pertinent linguistic parameters are created using Equation (3) in the manner previously stated.

Fuzzification: Fuzzification is the procedure of transforming a crisp input value into a fuzzy input value fi(ci) using information obtained from the knowledge base.

Membership functions for fuzzy sets and universal sets are represented by S and U respectively. Using the membership function, the elements of U are denoted by the symbol u and assigned a value between 0 and 1.

$S = \{u, \mu_S(u) \mid u \in U\}$

Each element in a fuzzy set is mapped to the range between 0 and 1 using the membership function. As a consequence, the fuzzy set becomes more of a "fuzzy bounded set" than the crisp set.The membership function is shown by $\mu_S(u)$ in this case.

$\mu_S(u) \in [0,1]$

This value denotes the degree of membership or membership value of an element u in the set S. A fuzzy set's degree of membership, which each of its members possesses, is quantified. A membership degree is another name for a fuzzy set. The size of the number is increased by addition. The conversion of u to $\mu_S(u)$ is referred to as "fuzzification".

In fuzzy theory, the fuzzy set S of the universe U is defined by a function $\mu_S(u)$ called the membership function of the set S.

$\mu_S(u)$: U → [0, 1],

where $\mu_S(u) = 1$

if u∈U or μ(u) = 0

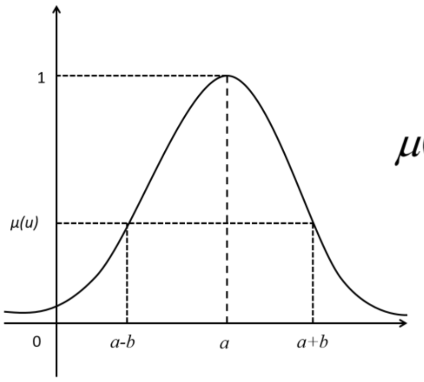
if u∉U or 0 <U< 1

if u is partly in S.

With this set, a range of possibilities are obtainable. For each element u of the universe U, the membership function $\mu_S(u)$ is such that u is an element of the set S. This degree, which has a value between 0 and 1, represents the membership degree, also known as the membership value, of an element u in S.

Gaussian Membership function:

The usual representation of the Gaussian membership function is Gaussian (x: a, b), where a, b stands for the mean and standard deviation. For a fuzzy set S, let a-b, a, and a+b represents the three vertices' x-coordinates (a-b: lower boundary and a+b: upper boundary where membership degree is zero, a: centre where membership degree is 1).



$$\mu(u) = \begin{cases} \frac{1}{2} e^{-\left(\frac{u-a}{b}\right)^2}, if x \le a \\ 1 - \frac{1}{2} e^{-\left(\frac{u-a}{b}\right)^2}, if x \rangle a \end{cases}$$

For example, when the crisp value of the attribute is u = 9 and the vertices of the trianglein x-coordinates a = 10 and b = 3, since its u value is between the values of b and c, thevalue of the membership function for the value of u is generated as $e^{-1/2((u-a/b))^{\wedge}2}$according tothe formula of the Gaussian membership function.

(i.e)u=9,uliesbetween3≤u≤10.

$$\mu_S(u) = e^{-\frac{1}{2}\left(\frac{u-a}{b}\right)^2}$$

$$\mu_S(u) = e^{-\frac{1}{2}\left(\frac{9-10}{3}\right)^2}$$

$$\mu_S(u) = 0.9459$$

□ $\mu_S(u) = 0.95 \Rightarrow F(0, 0.95, 0)$, which is the fuzzy input variable for the Inference Engine module.

Inference Engine: The fuzzy results value, which is the input of the defuzzification module, is calculated using the tourist preferences and the fuzzy input value produced by the fuzzification module. The knowledge base module's parameters are narrowed using tour preferences. Through the user interface of the suggested recommender system, the preferences of the visitors are ascertained as yes or no.

Low, medium, and high are the three linguistic parameters for each aspect that describe the place's status. Two out of the three linguistic parameters for the characteristic are taken into consideration if the tourist selects "yes." The final two linguistic parameters in the array for the characteristic are considered if the user chooses "no." Rules are chosen from a list of pre-generated rules in the knowledge base based on the preferences gathered. As a fuzzy rule construction method, 25 of the 3^6rules that the knowledge database created based on user preferences may be obtained.

As an illustration, tourist's preferences include food, beauty, budget, security, and convenience. Food = "cheap, affordable," beauty = "good, excellent," budget = "low, moderate," and safety = "unsafe, moderately safe." Based on a survey of travellers' preferences, each feature is represented by a separate language variable. Poor, Average describes an amenity.

Both the value of the fuzzy input variable and the set of rules produced as a result of the screening procedure assist to identify the value of the fuzzy output variable and the linguistic parameter for that expression. For instance, it determines the value of both the linguistic and fuzzy output variables for that parameter as indicated in the table below.

Table 3 Output Variable

Place	$\mu_S(u)$
Medium	0.5
- - -	- - -
- - -	- - -
Low	0.2

Defuzzification: In the defuzzification process, a single number is taken from the integrated fuzzy set's output. It is used to transform an unclear hypothesis' findings into a clear output. In other words, defuzzification is achieved by the decision-making process of choosing the ideal smoothness value depending on the fuzzy set. The centre of gravity defuzzification approach is the most popular, but all of them appear decent. Finding the point u where a vertical line splits the mass into two equal masses is the key element of the center of gravity approach.

For instance, the recommended crisp values u*= 4.8are determined using the sample dataset and the aforementioned the Center of Gravity algorithm. The rating of places based on this soft value, u* = 4.8, gives Palavakkam Beach a modest recommendation from us.

4. Implementation And Results

In order to implement fuzzy inference for the purpose of recommending tourism destinations, the Indistinct Inference Semantic Classifier (IISC) system is being developed in Python. It seeks to identify and suggest the ideal trip place using the user's wide range of inputs as parameters. Fuzzy input variables of two of the three linguistic parameters are chosen from among five features for this purpose. This section displays the findings from a comparison between the existing and the current recommendation model.

The dataset also contains user ratings, and scores are constructed for certain input parameters in accordance with the pertinent information gathered from the datasets gathered. 70% of the data is employed as training data, while 30% is employed for testing.

Evaluation Metrics: In order to assess the effectiveness of the proposed IISC recommendation system algorithm, this section looks at the Root Mean Square Error (RMSE), coverage value, accuracy value, f-measure value, and technique running time.

RMSE: The root mean square error of also known as the root mean square deviation, is one of the most used methods for improving assessments. To calculate how much forecasts, deviate from measured true values, Euclidean distance is used.

Coverage: A recommender system's capacity to present users with recommendations for every item in a training dataset is known as coverage. This form of recommender may recommend every place or option in a random dataset of visitors, giving it approximately hundred percentage of coverage.

Precision: Precision in a recommender system establishes what percentages of the system are relevant.

F-Measure: A statistical test's accuracy is gauged by the F-measure. It considers both the precision and recall aspects of the advice when calculating the score.

Figure 2 illustrates the proposed algorithm's absolute improvement over the RMSE value of the current techniques. Additionally, the trust walker method estimates ratios using random input. The relational trust walker and social relevance trust walker algorithms both take into account the level of trust between the user and place type.

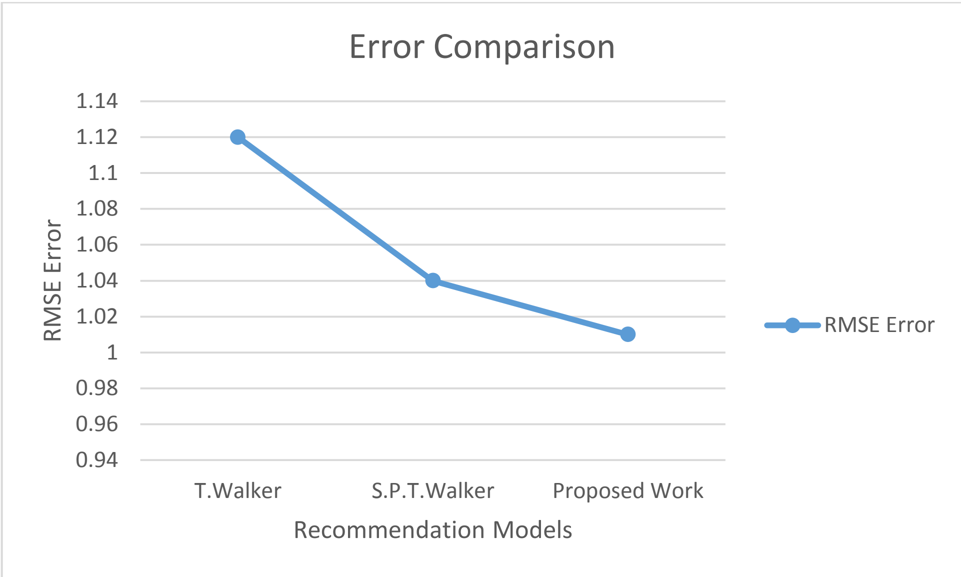


Figure 2. Root Mean Square Error Comparison

According to RMSE values of 1.001, Figure 2 demonstrates that the suggested method has the lowest error rate. As a result, it is acknowledged that the trust walker algorithm makes less errors than both the relational trust walker and the socially relevant trust walker algorithms.

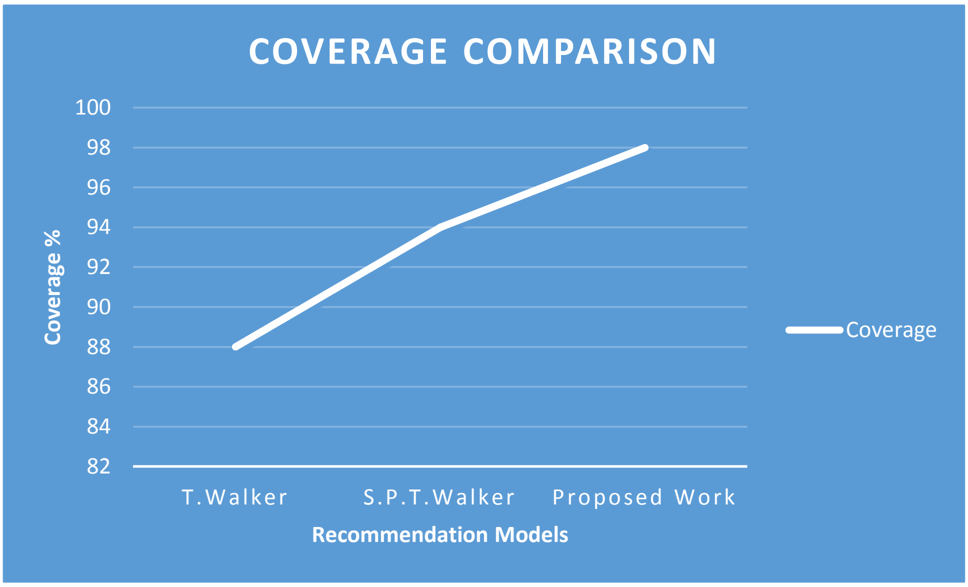


Figure 3. Coverage Comparison

The proposed algorithm has a larger coverage value than the existing trust walker and social involved trust walker algorithms, as illustrated in Figure 3.

It performs better than the trust walker and social relational trust walker algorithms, as seen in Figure 3. That means, 97.32% of the population is covered by the recommended IISC algorithm.

Figure 4 demonstrates how the system's performance is correlated with the proposed method's accuracy. It is evident that the suggested IISC algorithm is more accurate when compared to the social involved trust walker, and trust walker algorithms.

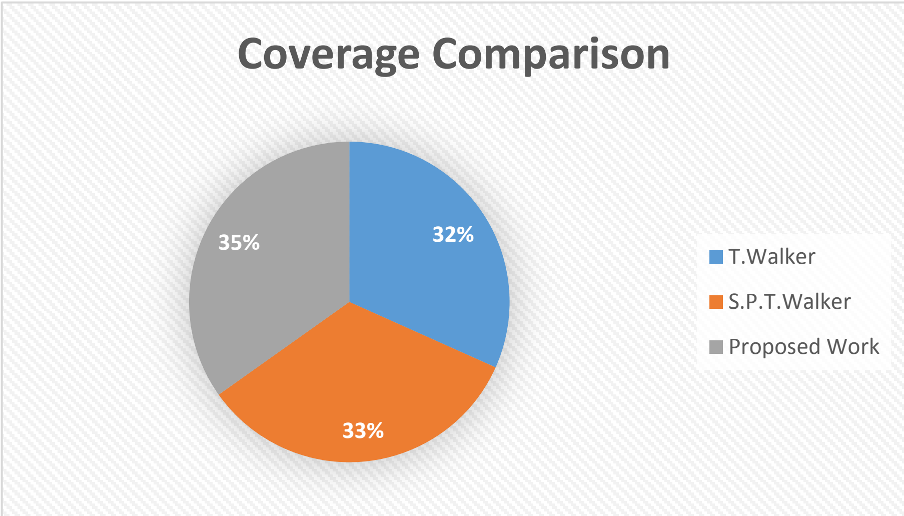


Figure 4. Precision Comparison

The accuracy of the suggested suggestion approach is 0.7812, as shown in Figure 4. It is established that the proposed technique is more precise than the trust walker and social relational trust walker algorithms that are already in use.

The F-measure results of the proposed IISC technique and the current relational trust walker, social concern trust walker, and trust walker techniques are compared in Figure 5. The F-measure is often calculated to range from 0 to 1. Additionally, defined as 0 in the absence of relevant data and 1 in the presence of relevant data.

In Figure 5, the proposed IISC technique outperforms the social concern trust walker, and trust walker algorithms in terms of F-measure.

The proposed IISC algorithm is compared to trust walker and socially relevant trust walker, algorithms in Figure 6 to assess the novel proposal technique's time-cost characteristics.

Comparing the IISC recommendation system's use of a score generator to the current Trust Walker and Socially Appropriate Trust Walker algorithms, Figure 6 demonstrates the time savings.

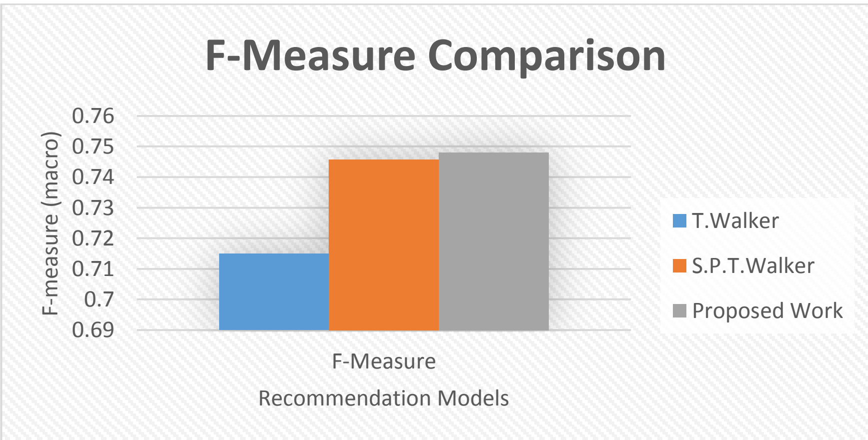


Figure 5. F-measure Comparison

Figure 6. Time Comparison

5. Conclusion

This research proposes a fuzzy rule-based intelligent tour selection system based on semantic tree modelling and fuzzy inference. One of the key industries in the advancement of contemporary technology is tourism. Therefore, individuals prefer the tourist sector to modernise their way of life, and everyone utilises a communication gadget. Because individuals prefer to arrange their own trips to their favourite tourist destinations online, there is a large demand for and application of the suggested tourist spot suggestion system. The majority of currently used recommendation systems are created either on user preferences or geographical preferences. While taking into account user preferences, place characteristics, climate, environment, and available features, facilities, amenities, etc., the suggested recommendation system is constructed utilising a semantic tree and fuzzy categorization technique. As a result, the suggested recommendations system may provide visitors more precise recommendations for tourism destinations. The proposed tour suggestion system's key benefits are improved accuracy and time and cost savings. The performance of this system will be significantly improved in the future using an optimisation method.

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