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Cultural Tourism Recommender Based on User Behaviour Modelling and Polynomial-Based Graph Convolutional Neural Networks for Personalized Experiences

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Abstract: - Cultural tourism has witnessed a surge in popularity as travelers seek unique and personalized experiences that cater to their individual preferences. Cultural tourism presents challenges due to diverse user preferences and evolving interests. Traditional recommender systems often struggle to adapt to these dynamics, necessitating a more sophisticated approach. Hence, the limitations in adaptability observed in traditional approaches underscore the need for an innovative solution. In this manuscript, Polynomial‑Based Graph Convolutional Neural Networks (PGCNN) is proposed. Initially data is taken from TRD dataset. Afterward the data is fed to federated neural collaborative filtering (FedNCF) based pre-processing process. The pre-processing output is given to Adaptive and Concise Empirical Wavelet Transform (ACEWT) to extract the optimal features for enhancing the discriminative power and capturing intricate patterns in the cultural tourism data, thereby contributing to the improved accuracy and effectiveness of the recommendation system. After that, the extracted features are provided to Polynomial‑Based Graph Convolutional Neural Networks (PGCNN). The PGCNN is employed to enhance the accuracy of personalized cultural tourism recommendations. The PGCNN is used to model intricate relationships within user behavior data, capturing nuanced preferences and historical interactions. By leveraging the intelligent capabilities of the neural network, the objective is to provide accurate and context-aware recommendations, adapting dynamically to individual users' evolving cultural interests. The learnable parameters of the PGCNN is optimized using LOA. MATLAB is used to implement the proposed approach, and the proposed method's effectiveness To estimate CTR-UBM-PGCNN, several performance assessment criteria are employed, such as recall, accuracy, precision, f1-score, and computational time. The proposed CTR-UBM-PGCNN method shows the highest accuracy of 99%, precision of 99%, and F1-score of 97% while comparing other existing methods such as Cultural Tourism Recommender Based On User Behaviour Modelling using Convolutional Neural Network (CTR-UBM-CNN), Cultural Tourism Recommender Based On User Behaviour Modelling using Deep Learning (CTR-UBM-DL) and Cultural Tourism Recommender Based On User Behaviour Modelling using Machine Learning (CTR-UBM-ML respectively.

Keywords: Cultural tourism, Polynomial‑Based Graph Convolutional Neural Networks(PGCNN), User behaviour, Information, Travellers, Social networks, Federated Neural Collaborative Filtering (FedNCF)

I. INTRODUCTION

The rapid expansion of global tourism, fueled by factors such as supply-side reforms, consumption upgrades, and evolving leisure preferences, underscores the pressing need for effective tools in navigating the over whelming influx of tourism information on the internet [1-4]. Amidst this vast array of resources, users often grapple with the challenge of identifying suitable destinations. The core of accurate tourism recommendations lies in comprehending tourists' preferences and crafting effective recommendation algorithms. However, the elusive nature of comprehensive tourist information makes it difficult to cluster preferences. The rise of social networks, like microblogs, has introduced both opportunities and challenges with rich user behavior data for accurate tourism recommendations. The distinct complexity of tourism, influenced by subjective decision-making and contextual factors, sets it apart from other recommendation projects like books and films [5-7].

In response to the dynamic cultural tourism landscape, this research introduces a Cultural Tourism Recommender System, highlighting the utilization of User Behavior Modeling and Neural Networks [8-11]. These technologies aim to decode intricate travel patterns, incorporating individual preferences ranging from historical sites to culinary interests. The integration of Neural Networks ensures continuous learning and adaptation, making recommendations not only personalized but also responsive to evolving traveler preferences [12-16]. The research aspires to redefine cultural tourism experiences, fostering a deeper connection between travelers and cultural heritage through personalized recommendations, ultimately enhancing the overall tourism landscape [17, 18].

In this work, the focus is on proposing a novel approach to cultural tourism recommendations by integrating User Behavior Modeling with Polynomial-Based Graph Convolutional Neural Networks. The objective is to solve the shortcomings of past recommendation algorithms by leveraging the power of polynomial-based graph convolutions to capture intricate relationships within user behavior data. This innovative approach seeks to offer personalized experiences by deciphering the nuanced preferences of individual travelers, contributing to a paradigm shift in cultural tourism.

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A. Contribution statement:

- Introduces a novel approach, Polynomial‑Based Graph Convolutional Neural Networks (PGCNN), in addressing challenges in cultural tourism recommender systems.
- Utilizes Federated Neural Collaborative Filtering (FedNCF) as a pre-processing step on the TRD dataset, showcasing a comprehensive and advanced methodology.
- Emphasizes the role of ACEWT in feature extraction, highlighting its capacity to derive optimal features that contribute to enhanced data representations.
- Highlights the use of PGCNN to model intricate relationships within user behavior data, emphasizing the system's ability to capture nuanced preferences and historical interactions dynamically.
- Introduces a novel optimization method using Learnable Parameters Optimization (LOA) for fine-tuning the PGCNN, contributing to the model's efficiency and personalized recommendation accuracy.
- Demonstrates practical applicability by implementing the proposed method, CTR-UBM-PGCNN, in MATLAB, providing a transparent and accessible framework for potential adoption.
- Utilizes a comprehensive set of performance metrics, including accuracy, precision, recall, f1-score, and computational time, for a thorough analysis of the proposed method's efficiency and effectiveness.
- Conducts a thorough comparison with existing methods (CTR-UBM-CNN, CTR-UBM-DL, and CTR-UBM-ML) to establish the superior performance of the proposed CTR-UBM-PGCNN, showcasing its significant contribution to the field.
- Presents outstanding results with the proposed CTR-UBM-PGCNN method, achieving the highest accuracy of 99%, precision of 99%, and an impressive F1-score of 97%, thereby demonstrating its superiority over existing methodologies.

In summary, the manuscript contributes by introducing a sophisticated PGCNN approach, employing advanced pre-processing techniques, optimization strategies, and a thorough evaluation framework, ultimately showcasing superior performance in personalized cultural tourism recommendation. The reminder of this manuscript is arranged as: segment 2 recent research work, segment 3 Proposed methodology, segment 4 Results and discussion and segment 5 conclusions.

II. RECENT RESEARCH WORK: A BRIEF REVIEW

In literature, various studies are available based on the cultural tourism recommender by user behaviour modelling with various techniques and aspects. Several of these reviews were subsequently pursued,

An and Moon [19] explored the significance of sentiment analysis techniques in texts across various fields, notably in decision-making systems. Numerous studies have actively investigated approaches like word frequency and morphological analysis, as well as the utilization of complex neural networks for sentiment analysis. This study evaluated evaluations of sightseeing using sentiment analysis technologies with a deep neural network. Reviews that did not have ratings were given them, and further information was added to enable varied classification according to the season or weather. The system was designed to allow custom recommendations based on the analyzed data. The study also looked at the contextual aspects of tourist destinations, and the findings were used to create an effective pre-processing method.

Jeong et al. [20] explored the wealth of tourist-related data available on the Internet, encompassing not just basic tourist information but also diverse user ideas and opinions. To extract meaningful insights from this extensive data, social network analysis of tourist keywords was employed to determine keyword frequency and relationships between them. This approach allows for the identification of clear recommendation criteria for tourist attractions and their interconnections, enhancing the suitability of recommendations for users. The research focused on designing a recommendation system grounded in big data social network analysis of tourist site information. By integrating user personality information, the study employed deep learning to categorize types of tourism suitable for users. In addition, a network analysis of tourism-related terms was carried out to identify connections between tourist destinations that fall under particular tourism categories. Through tagging, suggestions for tour information relating to related tourist destinations on blogs and social media platforms were made possible.

Srisawatsakul and Boontarig [21] have observed the significant integration of recommender systems into various online services like Netflix, YouTube, and online shopping over the past decade. Recommender systems are now part of the offerings of travel companies like Expedia and Trip Advisor. Recognizing the crucial role of the tourism industry as a major revenue source for Thailand, the study addresses the existing inefficiencies in trip planning recommender systems for the country. The study's main goal was to create a prototype travel recommender system that is especially useful for organising visits to Thailand, aiming for a more effective and user-friendly experience. The main goal was to develop a system that, in the absence of direct user input, can recognise user preferences for preferred tourism destinations automatically. Machine learning techniques were employed to extract user preferences from their Instagram pictures. After that, these preferences were used to calculate the degree of similarity between 23 sample tourist destinations in Ubon Ratchathani Province and their qualities. To assess the prototype's effectiveness, a user study involving 42 participants was conducted to preliminarily evaluate precision and adoption.

Liu et al. [22] have introduced a system for classifying cultural tourism destinations that, unlike traditional surveys that depend on respondents' stated answers, infers visitors' preferences from their observed behaviours. This method makes use of location-based social network data to provide insights into the real travel paths used by visitors. The study used Instagram data from visitors who geotagged certain local sites between May 2018 and April 2020 to precisely apply this technique to Central, a neighbourhood of Hong Kong. Using cluster analysis, 4 distinct groups were identified, resulting in the creation of a typology of cultural tourism sites based on the significance of current and historical components. The findings emphasised notable distinctions between the designated clusters and within the short-haul markets of Hong Kong. Notably, visitors from Thailand tended to like "historic sites" and "street markets," but Japanese visitors showed a preference for "art galleries/performance venues" and "Heritage centres." This study offers a novel method for differentiating cultural tourism destinations and offers insightful information for identifying possible travellers.

Esmaeili et al. [23] have explored the impact of Web 2.0 and its services, particularly social networks, on various industries, with a significant influence on e-commerce, leading to the emergence of a new era known as Social Commerce. The tourism industry offers a wide range of services and goods, making it difficult for customers to choose among the many choices for vacation packages, lodging, and tourist destinations. To address this, tourism recommender systems have been identified as a solution by both researchers and businesses. In the framework of social commerce, this study offers a social-hybrid recommender system specifically made to suggest tourism destinations, given that travel decisions are frequently influenced by these attractions. The goal of the research is to provide each traveller with a customised list of tourist sites by utilising variables including user wishes and interests, relationships, trust, reputation, and social networks. The proposed method differs from conventional approaches such as content-based, collaborative filtering, and hybrid approaches by leveraging social relationships among individuals and incorporating elements of trust in recommendation resources.

Gamidullaeva et al. [24] addressed the hindrance in the development of tourism despite having established tourism infrastructure and software. The impediment stems from the absence of comprehensive information support encompassing various aspects of travel implementation. This study emphasises how different strategies and techniques must be combined to develop a global tourism information recommender system that can be used to design customised travel itineraries. The purpose of the study was to provide the idea of a general information recommender system designed specifically for creating customised travel itineraries. A method for compiling and arranging information in order to synthesise tourism products, a procedure for designing products based on consumer preferences, and the first steps of putting this methodology into practice are all included in the design idea for such a system. In order to ensure information security while collecting and storing data from actual passengers, the report proposes applying blockchain technology. The article presents the model that delineates the fundamental elements of the tourist route planning process. In order to improve digital business system design and implementation within the tourist industry, it is meant to act as a reference and knowledge source for system designers, analysts, and implementers of digital tourism firms.

Hassannia et al. [25] aimed to use web and agent technologies to build a recommended system with a hybrid suggestion filtering method for the smart tourist sector. The agent-based hybrid recommendation system was developed with online contact with several tourist industry sectors in mind, including agencies and the tourism supply chain. The contract net protocol served as the basis for the organisation of the online communication across sectors through agents. Using the Java Agent Development Framework, the intended system was put into practice and made available as a web application. The recommended web application increased the rate of client referrals, according to case study results that looked at two situations with 100 consumers each.

III. PROPOSED METHODOLOGY

The study technique for tourist recommendations is well described in this segment. Figure 1 depicts the CTR-UBM-PGCNN block diagram. Consequently, a thorough explanation of CTR-UBM-PGCNN is provided below.

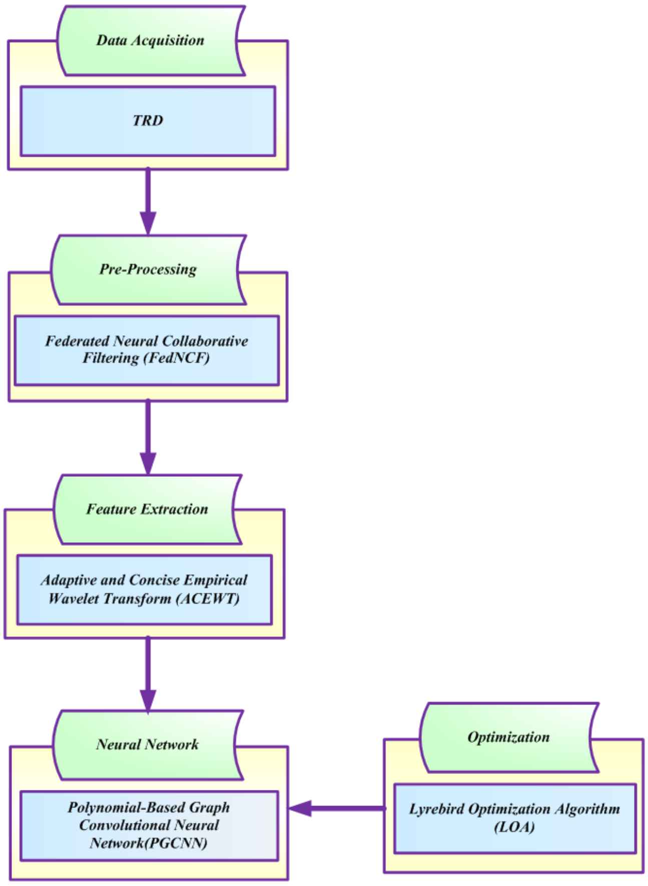

Fig 1: The CTR-UBM-PGCNN block diagram

A. Data collection

The Tourism Recommendation Dataset (TRD) is a comprehensive collection of data specifically curated for the purpose of developing and evaluating tourism recommendation algorithms [26]. This dataset encompasses a diverse range of information related to tourist preferences, attractions, and contextual factors, drawn from various sources like social networks, online platforms, and user behavior data. TRD is a useful tool for practitioners and scholars studying tourist recommendation systems, facilitating the exploration of innovative approaches to enhance personalized travel experiences.

B. Pre-Processing Using Fed NCF

Additionally, to improve the data's cleanliness, here employed the federated neural collaborative filtering (Fed NCF) [27]. In this step, Fed NCF performs the data pre-processing, which is utilized for reducing the noise in the dataset. The primary issue pertains to the process of updating the item profile. The agreed-upon samples are subsequently employed to produce a random matrix IR_{ij} , which is determined by the item profile's size, here $j \in C, j \neq i$.

Finally, the updated item profile is expressed by:

$$MI_{t+1}^{i} = I_{t+1}^{i} + \sum_{i \in C; i<j} IR_{ij} - \sum_{i \in C; i>j} IR_{ji} \tag{1}$$

When i and j in an efficient pair $(i, j), i < j$ agree on an initial parameter, a random matrix called IR_{ij} is formed, and the marked estimated weights are represented by MI_{t+1}. The coordinated server computes the following after gathering each MI_{t+1}^{C}:

$$I_{t+1}^{SUM} = \sum_{i \in C} MI_{t+1}^{i} \tag{2}$$

The I_{t+1}^{SUM} parameter, which is generated, comprises of the modifications to the total weight associated with the item profile that has to be combined. The system can generate the aggregated weights in the following manner in the most basic form of an aggregation step:

$$I_{t+1} = \frac{MI_{t+1}^{SUM}}{|C|} \tag{3}$$

However, $|C|$ indicates the count of chosen participants at time-step t .But still, this form of aggregation fails to account for individual item adjustments, which leads to slower convergence.

Following local training and parameter exchange, to produce $|C|-1$ random vectors and $2(|C|-1)$ arbitrary matrices, from which, $|C|$ specifies that count of participants in the existing cycle. The number of parameters in each model under consideration increases in accordance with the count of items $|I|$ and the designated size, D in the profile. For the GMF model, each produces a distinct output that consists of a single linear layer and a single processing unit.

$$(|C|-1).(D.|I| + D + 1 + |I|) \tag{4}$$

Based on the designated seeds, the parameters are established. The numbers in the item profile are indicated by $D.|I|$ in this context, the neural architecture's amount of inputs and biases is represented by $D+1$, and the quantity of variables that comprise the arbitrary interaction vector is shown by $|I|$. The model becomes standard MF and the number of generated parameters drops to $(|C|-1) \bullet (D+1+|I|)$ when the neural design is surpassed. In contrast, the MLP model makes use of a framework that has at least one hidden layer. The quantity of CPUs inside every concealed layer and the total amount of hidden layers that are offered determine how many more parameters must be developed thereafter. With greater precision, an individual produces a designated quantity of parameters.

$$(|C|-1).\left(D.|I| + 2D + h1 + \left(\sum_{i=1}^{n-1} h_i . h_{i+1} \right) + h_n + \left(\sum_{i=1}^{n} h_i \right) + 1 + |I| \right) \tag{5}$$

After the agreement on the initial parameters, the total number of parameters to be generated is determined. These parameters include $2D.h1$, which represents the input size, $\sum_{i=1}^{n-1} h_i . h_{i+1}$, which represents the count of weights, and $\sum_{i=1}^{n} h_i + 1$, which represents the network bias. The value of h_i represents the number of CPUs on the ith hidden layer. Particularly necessary parameters pertain to the article profile $2D.I$ in the NeuMF model, which is formed by concatenating GMF and MLP.

$$\left(|C|-1\right).\left(2D.|I|+2D+h1+\left(\sum_{i=1}^{n-1}h_i\,.h_{i+1}\right)+D+h_n+\left(\sum_{i=1}^{n}h_i\right)+1+|I|\right) \tag{6}$$

Before any calculation begins during a federated recommender's training process. The entire amount of items $|I|$, the quantity of processing units h_i , and the dimension size D are all predetermined.. The number of players participating in each aggregation cycle dictates the growth in parameters. In the context of cultural tourism recommendation, as in MF-SecAvg, clients execute fundamental matrix operations following a local update. These operations utilize parameters generated randomly according to a predefined sequence. They then distribute the final result by performing element-wise subtraction or addition of the computed weights. Finally, the pre-processed data is supplied to the feature extraction phase.

C. Feature Extraction Using Adaptive and Concise EWT

The Fourier spectrum is divided using the scale-space representation by the empirical wavelet transform technique [28]. Empirical Wavelet Transform (EWT) is effective in separating different components in signals that are free from noise. However, in reality, noise is difficult to avoid. This is especially challenging for EWT as signals are often in a non-stationary state. The size of the sampling frequency is usually related to the Fourier spectrum displayed. Elevating the sample frequency yields finer details in the signal; nevertheless, it also adds complexity, necessitating greater effort in the scaling-space representation. In order to depict the distribution of components, power spectral density can be utilized in place of the complex Fourier spectrum. The distribution of power with respect to frequency is accurately depicted by the spectral density of power. Equation (7) provides a mathematical expression for the average power R in the situation of signal $X(t)$, whose Fourier transform is $\hat{X}(f)$.

$$R=\lim_{t\to\infty}\frac{1}{2t}\int_{-t}^{t}X(T)^2\,dT \tag{7}$$

In the range [0, t], provided that the signal's fourier transform is;

$$\hat{X}(f)=\frac{1}{\sqrt{t}}\int_{0}^{t}X(T)e^{-i2\pi ft}\,dT \tag{8}$$

Consequently, the definition of the power spectral density is;

$$S_{xx}(f)=\lim_{t\to\infty}E\left[\left|\hat{X}_t(f)\right|^2\right] \tag{9}$$

From the pre-processing output, significant features related to cultural tourism preferences are extracted using ACEWT. These features include attributes such as Cultural Diversity, Historical Significance, Local Relevance, Artistic Expression, and Cultural Harmony. ACEWT assists in identifying these features, which are essential for understanding users' cultural interests and preferences in tourism recommendation systems.

Identification of Maxima:

$$\frac{d}{dn}ACEWT(x)[n]=0 \tag{10}$$

Here, $A_j[n]$ and $D_j[n]$ represent the detail and approximation coefficients at scale j , correspondingly. The function Θ denotes the thresholding function, and $p(ACEWT(x)[n])$ represents the probability distribution of the ACEWT coefficients. These denotations clarify the specific symbols used for each feature in the extraction process.

These features collectively contribute to the system's ability to enhance discriminative power and capture intricate patterns, improving the accuracy and effectiveness of cultural tourism recommendations. Then these extracted features are given into Graph Learning process which is done by PGCNN. The section below contains information on the Graph Learning procedure in depth.

D. PGCNN-Based Graph Learning for Personalized Cultural Tourism Recommendations

PGCNN, is a specialized neural network architecture designed for graph-based learning tasks [29]. In the context of personalized cultural tourism recommendations, PGCNN excels at modeling intricate relationships within user behavior data. It employs polynomial-based operations to capture higher-order dependencies in the graph structure, making it highly effective for scenarios where understanding relationships and contextual information is essential.

1) Representation of Features:

Represent the extracted features from ACEWT as a feature matrix $X_{features}$

2) Construction of Graph:

Build a graph representation G using the user behavior data. This could be a user-item interaction graph where nodes represent users or cultural attractions, and edges signify interactions.

3) Node Embedding with PGCNN:

Apply the Polynomial-Based Graph Convolutional Neural Network (PGCNN) to obtain node embeddings $H^{(0)}$

$$H^{(0)} = X_{features} \tag{11}$$

4) Graph Convolutional Layer:

Propagate information through graph convolutional layers to capture relationships. The l -th layer of the PGCNN can be represented as:

$$H^{(l)} = \sigma(\hat{D}^{-\frac{1}{2}} \hat{A} \hat{D}^{-\frac{1}{2}} H^{(l-1)} W^{(l)}) \tag{12}$$

Here, $\hat{D}$ represents $\hat{A}$ degree matrix, $W^{(l)}$ represents the l th layer's weight matrix, σ represents activation function, and $\hat{A}$ represents the adjacency matrix with extra self-loops.

5) Training Process:

Train the PGCNN on the user behavior data, adjusting the weights to minimize prediction errors and capture intricate relationships within the graph.

E. Optimization using LOA

In this part, the LOA—a special metaheuristic algorithm with a bio-inspired design that emulates lyrebird activity in the wild—is introduced [30]. Lyrebirds in this scenario carefully survey their surroundings before making their move to flee or conceal in hiding. The theory of LOA is explicated and subsequently computationally represented in two stages: (i) investigation, grounded in the model of the lyrebird's escape strategy, and (ii) utilisation, grounded in the simulation of the concealing plan. One of Australia's most well-known native birds, the lyrebird is distinguished by its distinctive plumes of neutral-colored tail feathers. The suggested LOA technique, which is covered below, was created using mathematical modelling of this lyrebird tactic in times of peril.

Step 1: Initialization

The initialization learnable parameter of PGCNN

***Step 2*:** Random Generation

As a member of the LOA, each lyrebird determines the decision variable values based on its position inside the problem-solving domain.. Together, LOA members make up the algorithm's population, which may be represented theoretically as a matrix in accordance with Equation (6).

$$Z = \begin{bmatrix} Z_{1,1} & Z_{1,2} & \cdots & Z_{1,H} \\ Z_{2,1} & Z_{2,2} & \cdots & Z_{2,H} \\ \cdots & \cdots & \cdots & \cdots \\ Z_{n,1} & Z_{n,2} & \cdots & Z_{n,H} \end{bmatrix} \tag{13}$$

Here Z denotes the LOA population matrix, H indicates the count of decision variables, and n indicates the count of lyrebirds, respectively.

Step 3: Fitness Function

An arbitrary solution is generated based on initialised judgements. As seen in equation (14),

$$Fitness\ function = Optimizing[H] \tag{14}$$

Step 4: Escaping Strategy

During this phase of LOA, a model that mimics the lyrebird's migration from the area of danger to the areas of safety is used to update the location of the population member in the search area. When the lyrebird is moved to a secure environment, it undergoes significant positional changes and searches various regions of the problem-solving space, demonstrating LOA's capacity for total hunt exploration. The locations of other population members with greater goal function values represent a member's safe areas in the LOA design. Consequently, Equation (15) may be used to determine all members' unique set of safe zones of the LOA.

$$DB_j = \{Z_P, \quad E_P < E_j \ \ and \ \ P \in \{1, 2, ..., M\}\}, \qquad Where\ j = 1, 2, ..., M, \tag{15}$$

Here, Z_P implies the P th row of Z matrix, and DB_j implies the group of places where the JTH Lyrebird is safe, This, when compared to the jth LOA member, has a higher objective function value.

According to the LOA design, the lyrebird is said to haphazardly fly to one of these safe havens. Using equation (16), each LOA member's new rank is established based on the finished Lyrebird displacement modelling in this stage. According to Equation (17), the relevant member's prior position will be replaced by this new location if the target function's value increases.

$$z_{j,i}^{k1} = z_{j,i} + l_{j,i} \cdot \left(SSB_{j,i} - J_{j,i} \cdot z_{j,i}\right) \tag{16}$$

$$Z_j = \begin{cases} Z_j^{k1}, E_j^{k1} \le E_j \\ Z_j \ , \ Else \end{cases} \tag{17}$$

Here, $SSB_{j,i}$ indicates its ith dimension, SSB_j indicates the region designated as safe for j[th] Lyrebird, $z_{j,i}^{k1}$ indicates its ith dimension, E_j^{k1} indicates its aim function value, $l_{j,i}$ are arbitrary figures from the period [0, 1], z_j^{k1} indicates the new location determined for the JTH Lyrebird using the suggested LOA's escape plan and $J_{j,i}$ are figures that are arbitrarily particular as 1 or 2.

Step 5: Exploitation Phase for optimizing θ

During this phase of LOA, the location of the population members is updated in the search area according on the lyrebird's modelling approach for hiding in its surrounding safe zone. The lyrebird's location varies somewhat as a result of precisely monitoring the surroundings and taking little steps to get to a good hiding place; this shows how LOA may be used in the local search. Equation (18) is utilised in LOA design to choose a new site for each LOA member by mimicking the lyrebird's migration towards the closest suitable hiding place. This new location replaces the relevant member's previous placement if it raises the objective purpose value in line with Equation (19).

$$z_{j,i}^{k2} = z_{j,i} + (1 - 2l_{j,i}) . \frac{vc_i - qc_i}{T} \tag{18}$$

$$Z_j = \begin{cases} Z_j^{k2}, E_j^{k2} \le E_j \\ Z_j \ , Else \end{cases} \tag{19}$$

Here, $z_{j,i}^{k2}$ represents the ith dimension, E_j^{k2} represents the objective function value, $l_{j,i}$ are random integers from the interval [0, 1], T represents the iteration counter, and z_j^{k2} represents the new location determined for the jth lyrebird based on concealing technique of the proposed LOA.

Step 6: Termination Criteria

Here, the optimal feature is selected depending on LOA Algorithm iteratively repeat step 3 till fulfill $Z = Z + 1$ halting criteria. The chosen characteristics are then provided as the classification's input. When all steps are completed, an accurate feature will be chosen to improve the production process. Fig 2 shows Flowchart for LOA.

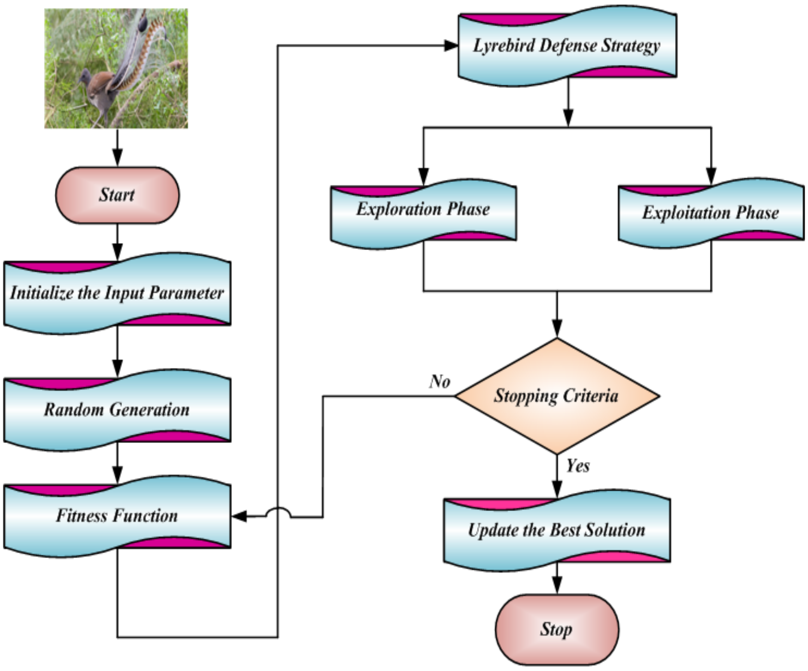

Fig 2: Flowchart for LOA

IV. RESULT AND DISCUSSION

This segment presents the experimental results of the proposed technique. The proposed technique is then simulated using MATLAB and the given performance requirements. The TRD dataset is used in MATLAB to execute the proposed CTR-UBM-PGCNN technique. The obtained outcome of the proposed CTR-UBM-PGCNN technique is analysed with existing systems such as CTR-UBM-CNN, CTR-UBM-DL, and CTR-UBM-ML respectively.

A. Performance Measures

1) Accuracy

It is the proportion of the entire amount of predictions produced for a dataset divided by the count of precise forecasts. It is quantified using Equ (20).

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{20}$$

Here, TP implies as true positive, TN implies as true negative, FN implies as false negative and FP implies as false positive.

2) Precision (P)

A statistic called precision counts the count of correctly predicted favourable outcomes. The scale for this is equation (21).

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{21}$$

3) F1 Score

The accuracy and precision weighted mean is called the F1-Score.Equation (22) is used to express it.

$$F1Score = \frac{TP_\alpha}{\left(TP_\alpha + \frac{1}{2}\left[FP_\lambda + FN_\gamma\right]\right)} \tag{22}$$

4) Recall

This is defined with the help of eqn (23),

$$\operatorname{Re} call = \frac{\delta}{\delta + \lambda} \tag{23}$$

B. Performance Analysis

The simulation outcomes of the proposed CTR-UBM-PGCNN approach are illustrated in Figure 3 to 7. Then, the proposed CTR-UBM-PGCNN method is contrasted with existing approach like, CTR-UBM-CNN, CTR-UBM-DL, and CTR-UBM-ML respectively.

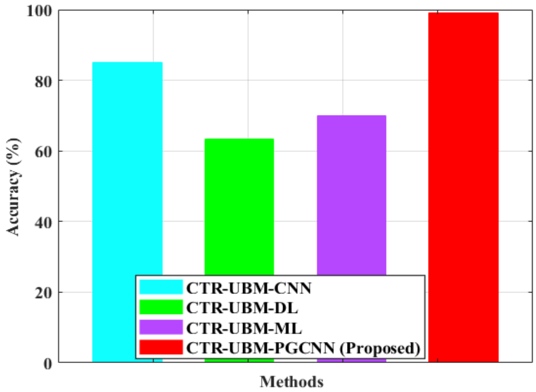

Fig 3: Comparison of accuracy with proposed and existing approach

Fig 3 shows the comparison of accuracy with proposed and existing approaches. In CTR-UBM-CNN method the accuracy is 85%. In CTR-UBM-DL method the accuracy is 62%. In CTR-UBM-ML method the accuracy is 70%. In the proposed CTR-UBM-PGCNN method the accuracy is 99% which higher than the existing approaches.

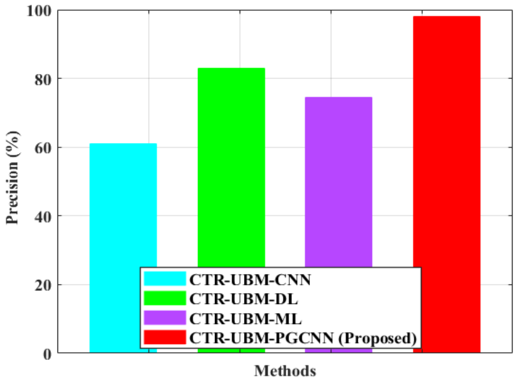

Fig 4: Comparison of precision with proposed and existing approaches

Figure 4 compares the accuracy of the proposed and existing approach. In CTR-UBM-CNN method the precision is 61%. In CTR-UBM-DL method the precision is 82%. In CTR-UBM-ML method the precision is 75% and in the proposed CTR-UBM-PGCNN method the precision is 98%. When contrasted to other existing methods, the proposed approaches have a very high accuracy.

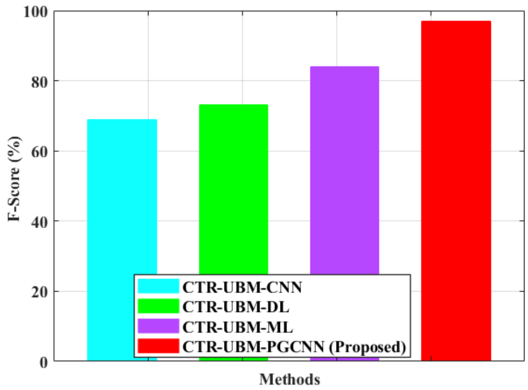

Fig 5: Comparison of F-score using proposed and existing approach

Figure 5 displays the comparison of the F-score using the current and proposed strategies. In CTR-UBM-CNN method the F-score is 70%. In CTR-UBM-DL method the F-score is 75%. In CTR-UBM-ML method the F-score is 85%. In the proposed CTR-UBM-PGCNN method the F-score is the highest of 98%.

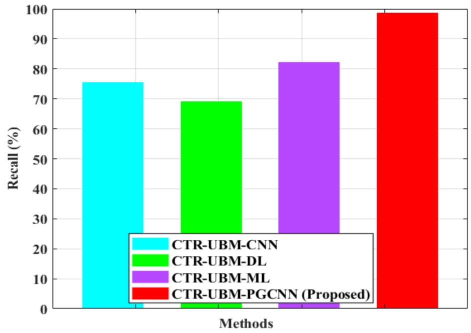

Fig 6: Comparison of recall with proposed and existing approach

Figure 6 displays the comparison of recall using proposed and existing approach. The CTR-UBM-CNN method has the recall of 76%. The CTR-UBM-DL method has the recall of 69%. The recall of the CTR-UBM-ML approach is 82%.The recall of the proposed CTR-UBM-PGCNN approach is 98%. The proposed technique has the highest recall while compared with other existing approach.

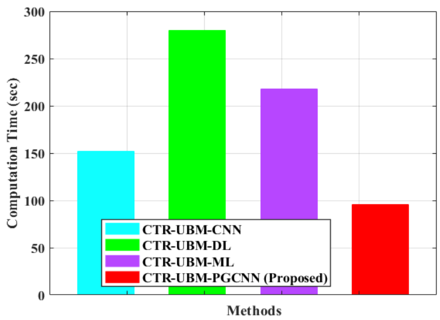

Fig 7: Comparison of computation time with proposed and existing approach

Fig 7 displays the comparison of computation time with proposed and existing approach. The computation time is 150sec for CTR-UBM-CNN method and 280sec for CTR-UBM-DL method. For CTR-UBM-ML method the computation time is 220sec. For the proposed CTR-UBM-PGCNN method the computational time is 95sec which is very less while comparing to other existing methods.

V. CONCLUSION

In conclusion, this research harnesses the power of Polynomial-Based Graph Convolutional Neural Networks (PGCNN) to significantly advance the realm of personalized cultural tourism recommendations. By incorporating ACEWT-derived features and modeling intricate relationships within user behavior data, the proposed approach demonstrates remarkable efficacy in capturing nuanced preferences and historical interactions. The stepwise integration of feature extraction through ACEWT, graph representation, and PGCNN-driven graph learning contributes to an unparalleled accuracy in cultural tourism recommendations. The results, evaluated through metrics like accuracy, precision, recall, and F1-score, underscore the superiority of the proposed technique, CTR-UBM-PGCNN, over existing models. This research not only exemplifies the potential of advanced neural network architectures in cultural tourism but also sets a foundation for future endeavors in personalized experience recommendation systems. The seamless amalgamation of feature engineering and graph-based deep learning emerges as a pioneering paradigm, paving the way for enhanced user satisfaction and engagement in the dynamic landscape of cultural tourism. The proposed CTR-UBM-PGCNN method shows the highest accuracy of 99%, precision of 99%, and F1-score of 97% while comparing other existing methods such as CTR-UBM-CNN, CTR-UBM-DL, and CTR-UBM-ML.

REFERENCES

[1] Xing, N. (2022). Selection and Exploration of Cultural and Creative Tourist Attractions Based on BP Network. *Computational Intelligence and Neuroscience, 2022.*

[2] Konstantakis, M., Alexandridis, G., &Caridakis, G. (2020). A personalized heritage-oriented recommender system based on extended cultural tourist typologies. *Big Data and Cognitive Computing, 4*(2), 12.

[3] Delic, A., Neidhardt, J., Nguyen, T. N., & Ricci, F. (2018). An observational user study for group recommender systems in the tourism domain. *Information Technology & Tourism, 19*, 87-116.

[4] Han, D. I., tom Dieck, M. C., & Jung, T. (2018). User experience model for augmented reality applications in urban heritage tourism. *Journal of Heritage Tourism, 13*(1), 46-61.

[5] Ponsignon, F., &Derbaix, M. (2020). The impact of interactive technologies on the social experience: An empirical study in a cultural tourism context. *Tourism Management Perspectives, 35*, 100723.

[6] Sun, X., Huang, Z., Peng, X., Chen, Y., & Liu, Y. (2019). Building a model-based personalised recommendation approach for tourist attractions from geotagged social media data. *International Journal of Digital Earth, 12*(6), 661-678.

[7] Cuomo, M. T., Tortora, D., Foroudi, P., Giordano, A., Festa, G., &Metallo, G. (2021). Digital transformation and tourist experience co-design: Big social data for planning cultural tourism. *Technological Forecasting and Social Change, 162*, 120345.

[8] Chen, H., & Rahman, I. (2018). Cultural tourism: An analysis of engagement, cultural contact, memorable tourism experience and destination loyalty. *Tourism management perspectives, 26*, 153-163.

[9] Renjith, S., Sreekumar, A., &Jathavedan, M. (2020). An extensive study on the evolution of context-aware personalized travel recommender systems. *Information Processing & Management, 57*(1), 102078.

[10] Logesh, R., &Subramaniyaswamy, V. (2019). Exploring hybrid recommender systems for personalized travel applications. *In Cognitive Informatics and Soft Computing: Proceeding of CISC 2017* (pp. 535-544). Springer Singapore.

[11] Logesh, R., Subramaniyaswamy, V., Vijayakumar, V., & Li, X. (2019). Efficient user profiling based intelligent travel recommender system for individual and group of users. *Mobile Networks and Applications, 24*, 1018-1033.

[12] Choi, I. Y., Ryu, Y. U., & Kim, J. K. (2021). A recommender system based on personal constraints for smart tourism city. *Asia Pacific Journal of Tourism Research, 26*(4), 440-453.

[13] Rehman Khan, H. U., Lim, C. K., Ahmed, M. F., Tan, K. L., & Bin Mokhtar, M. (2021). Systematic review of contextual suggestion and recommendation systems for sustainable e-tourism. *Sustainability, 13*(15), 8141.

[14] Smirnov, A., Kashevnik, A., Ponomarev, A., Shilov, N., &Teslya, N. (2014). Proactive recommendation system for m-tourism application. In *Perspectives in Business Informatics Research: 13th International Conference*, BIR 2014, Lund, Sweden, September 22-24, 2014. Proceedings 13 (pp. 113-127). Springer International Publishing.

[15] Missaoui, S., Kassem, F., Viviani, M., Agostini, A., Faiz, R., &Pasi, G. (2019). LOOKER: a mobile, personalized recommender system in the tourism domain based on social media user-generated content. *Personal and Ubiquitous Computing*, *23*, 181-197.

[16] Pan, H., & Zhang, Z. (2021). Research on context-awareness mobile tourism e-commerce personalized recommendation model. *Journal of Signal Processing Systems, 93*, 147-154.

[17] Colomo-Palacios, R., García-Peñalvo, F. J., Stantchev, V., &Misra, S. (2017). Towards a social and context-aware mobile recommendation system for tourism. *Pervasive and Mobile Computing, 38,* 505-515.

[18] Pu, Z., Du, H., Yu, S., & Feng, D. (2020, February). Improved tourism recommendation system. *In Proceedings of the 2020 12th international conference on machine learning and computing* (pp. 121-126).

[19] An, H. W., & Moon, N. (2022). Design of recommendation system for tourist spot using sentiment analysis based on CNN-LSTM. *Journal of Ambient Intelligence and Humanized Computing*, 1-11.

[20] Jeong, C. S., Ryu, K. H., Lee, J. Y., & Jung, K. D. (2020). Deep learning-based tourism recommendation system using social network analysis. *International Journal of Internet, Broadcasting and Communication, 12*(2), 113-119.

[21] Srisawatsakul, C., &Boontarig, W. (2020, October). Tourism recommender system using machine learning based on user's public instagram photos. *In 2020-5th International Conference on Information Technology (InCIT)* (pp. 276-281). IEEE.

[22] Liu, Z., Wang, A., Weber, K., Chan, E. H., & Shi, W. (2022). Categorisation of cultural tourism attractions by tourist preference using location-based social network data: The case of Central, Hong Kong. *Tourism Management, 90,* 104488.

[23] Esmaeili, L., Mardani, S., Golpayegani, S. A. H., &Madar, Z. Z. (2020). A novel tourism recommender system in the context of social commerce. *Expert Systems with Applications, 149*, 113301.

[24] Gamidullaeva, L., Finogeev, A., Kataev, M., &Bulysheva, L. (2023). A Design Concept for a Tourism Recommender System for Regional Development. *Algorithms, 16*(1), 58.

[25] Hassannia, R., VatankhahBarenji, A., Li, Z., &Alipour, H. (2019). Web-based recommendation system for smart tourism: Multiagent technology. *Sustainability, 11*(2), 323.

[26] https://data.mendeley.com/datasets/f3bdjxcb4b/1

[27] Perifanis, V., & Efraimidis, P. S. (2022). Federated neural collaborative filtering. *Knowledge-Based Systems, 242*, 108441.

[28] Zhang, K., Ma, C., Xu, Y., Chen, P., & Du, J. (2021). Feature extraction method based on adaptive and concise empirical wavelet transform and its applications in bearing fault diagnosis. *Measurement, 172*, 108976.

[29] Pasa, L., Navarin, N., &Sperduti, A. (2022). Polynomial-based graph convolutional neural networks for graph classification. *Machine Learning*, 1-33.

[30] Dehghani, M., Bektemyssova, G., Montazeri, Z., Shaikemelev, G., Malik, O. P., &Dhiman, G. (2023). Lyrebird Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm for Solving Optimization Problems. *Biomimetics, 8*(6), 507.