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Predictive Modeling of Library Circulation Trends Based on Time Series Analysis

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Abstract: **-** Time series analysis forecasts future patterns based on past data, but it might not take into consideration abrupt changes or outside influences that could have a big impact on circulation patterns. Unexpected occurrences could cause trends to diverge, modifications in user behavior, shifts in the economy, or the arrival of new technology. In this manuscript, Predictive Modeling of Library Circulation Trends Based on Time Series Analysis (PMLCT-TSA-DTGMGCN)is proposed. Initially, the data collected from the Fine Free Public Library Circ Totals by Month (FFPLCTM) are given as input. Afterward, the collected data are fed to pre-processing. In the preprocessing stage, input data is normalized using Privacy-Preserving Distributed Kalman Filtering (PP-DKF). The preprocessed data is then fed into a DTGMGCN to predict library literature circulation. In general, the DTGMGCN predictor does not indicate how to modify optimization algorithms to find the ideal parameters for precise library literature circulation prediction. Hence, the Pufferfish Optimization Algorithm (POA) is to optimize the weight parameter of DTGMGCN which accurately predict the library literature circulation. The effectiveness of proposed PMLCT-TSA-DTGMGCN approach is implemented in python and evaluated through performance metrics, like accuracy, precision, recall, F1score and error rate is analyzed. The performance of the proposed PMLCT-TSA-DTGMGCN approach contain 27.36%, 26.42% and 28.17%high accuracy; 28.26%, 25.42% and 29.27% high precision when analysed to the existing methods like methods A Seasonal Autoregressive Integrated Moving Average with Exogenous Factors Forecasting Model-Based Time Series Approach (SARIMAX-FMTSA-LSTM), Deep Transformer Networks for Anomaly Detection in Multivariate Time Series Data(DTNAD-MTSD-BNN), and Short-Term Traffic Flow Prediction for Urban Road Sections Based on Time Series Analysis(STTP-TSA -BILSTM) respectively.

Keywords: Detection and Classification using Dual Temporal Gated Multi Graph Convolutional Network, FFPLCTM, Privacy-Preserving Distributed Kalman Filtering.

I. INTRODUCTION

The university library is a valuable resource for educators and learners to conduct research and study [1]. The way books are circulated might give insight into how they are used in libraries and how professionally they are run [2].If the circulation of literature can be predicted, library staff members will be able to predict it in a timely manner and make adjustments to the gathered literature structure [3]. The dissemination of written works can be influenced by a number of intricate variables, including time, the quantity of teachers and pupils in classrooms, the caliber of the literature, and other non-linear traits [4].Although it is challenging to predict the circulation of literature using the classic linear method, techniques like the neural network method have demonstrated good results in data prediction of a variety of non-linear situations used an upgraded radial basis function (RBF) neural network using 72-hour data based on 24-hour input data to estimate the wind farm's short-term wind speed and power with a high computation efficiency. Using a wavelet-based neural network (WNN), forecasted floods and demonstrated the model's validity for long-term prediction using block bootstrap sampling, this is helpful for the implementation of flood management [5].Using the maximum correntropy criteria (MCC) algorithm enhanced the BP neural network and demonstrated the method's dependability through example analysis [6]. Convolutional neural networks (CNNs) are capable of predicting network traffic in data centers by using the nonlinear law of network flow [7]. Using an artificial neural network, forecasted the daily NASDAQ stock exchange rate and demonstrated the predictive power of this technique by using data from January 28, 2015, to June 18, 2015 as their data set. A local linear radial basis function neural network [8]. The model's validity was demonstrated by testing diabetic data after the parameters was trained using the gradient descent learning approach [9]. Two neural network models for rainfall rate prediction and work flow. How accurate the initial model was on average was almost 98%, but the second model's was roughly 75% [10]. Both models functioned adequately. There was little variation in the amount of rainfall. Seven factors, including elevation and latitude, were utilized as ANN inputs [11]. The trial demonstrated that the method's average absolute

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percentage error ranged from 1.67 to 4.25%, indicating a good prediction effect. In their study of real-time tidal prediction, is used data from four US tidal stations to demonstrate the validity of their model [12]. They also expressed the influence of celestial body factor using traditional harmonic analysis and the non-linear influence of meteorological factor using neural networks [13].

Predictive modeling for library circulation trends faces several challenges, including the necessity for high-quality, extensive historical data which may often be incomplete or inaccurate, and the requirement for specialized technical expertise to handle complex statistical models [14]. These models can be resource-intensive, demanding significant computational power and time for development and fine-tuning [15]. They also risk overfitting, where they perform well on historical data but poorly on future data, and may struggle to adapt to unpredictable external events or non-quantifiable factors like shifts in user behavior [16]. Additionally, integrating these models with existing library management systems can be technically challenging, and the opacity of advanced algorithms can hinder interpretability and trust among library staff [17].

Overcoming the challenges of predictive modeling for library circulation trends involves enhancing data quality through robust cleaning and standardized collection protocols, and augmenting limited historical data with external sources [18]. Building technical expertise via staff training and collaboration with data scientists is crucial, as is selecting appropriate, interpretable models and using ensemble methods to improve accuracy [19]. Investing in necessary computational infrastructure and prioritizing critical areas for resource allocation can mitigate resource intensiveness [20]. Regularly updating models for adaptability, employing scenario analysis, and ensuring model transparency through interpretable techniques and visualization tools are essential.

The following sums up this research work's primary contribution:

- In this research work Predictive Modeling of Library Circulation Trends Based on Time Series Analysis (PMLCT-TSA-DTGMGCN)is proposed.
- In pre-processing the aims normalize the input data using Privacy-Preserving Distributed Kalman Filtering (PP-DFK).
- DTGMGCN for to predict potential issues and library circulation.
- The obtained results of proposed PMLCT-TSA-DTGMGCN algorithm is comparing to the existing models such as DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM and STTP-TSA-BILSTM methods respectively.

The remaining manuscript is structured as: Segment 2 Literature Survey, Segment 3 Proposed methodology, Segment 4 Results with discussions, and Segment 5 conclusion.

II. LITERATURE SURVEY

Several works have presented previously in literatures were depending on Predictive Modeling of Library Circulation Trends Based on Time Series Analysis. Few of them were mentioned here,

Chen and Yang, [21] have presented a model designed for RBF neural networks are used to forecast and analyse the circulation of literary loans in university libraries. The experimental findings demonstrated that, with a relatively small prediction error, with a high degree of accuracy, the IGWO-RBF could forecast the flow of literature. The models that fit the real curve the best were the RBF-GWO and RBF-IGWO, then the RBF prediction curve. Strong prediction accuracy was demonstrated by the IGWO model's low root-mean-square error and mean absolute percentage error. This study demonstrates the RBF optimized model's efficacy in predicting library circulation, paving the way for its practical application and widespread adoption.It provides high accuracy, and it provides low precision.

Tuli et al. [22] have presented a DTNAD-MTSD-BNN. Tran AD relies on adversarial training to achieve stability and employs score-based self-conditioning to deliver dependable multi-modal feature extraction. Moreover, you may train the model with a little amount of data thanks to model-agnostic Meta learning. It provides high precision and it provides low accuracy.

Alharbi and Csala, [23] have presented a SARIMAX-FMTSA-LSTM. The aforementioned parameters in Saudi Arabia were projected using the model in this study over a 30-year period, from 2021 to 2050. The historical data used in the model came from Saudi Arabia and was gathered quarterly over a 40-year period (1980–2020). Even in situations when the lengths of the input and output datasets are near, the SARIMAX strategy uses a time series approach with exogenous and seasonal influencing factors to assist decrease error values and improve overall model accuracy. It provides low error rate, and it provides high accuracy.

Ma, et al. [24] have presented STTP-TSA-BILSTM. The accuracy and real-time performance of the traffic flow forecast directly affected the flow's efficiency. Intelligent transportation involves several hotspots, including guidance systems and flow of traffic forecast. Two models were presented to increase the accuracy of short-term traffic flow prediction: one based on traffic flow time series analysis and the other on an updated LSTM. The traffic flow data should be analysed using time series analysis first, and then the data should be standardised and smoothed to create a stable time series. As a result, a wide range of feature values will have less of an influence and the model training accuracy will rise. It provides high precision, and it provides low accuracy.

Dalzell, et al.[25] have presented available Random quantum circuits convert local noise to global white noise. We explore the measurement outcome distribution of noisy random quantum circuits in the bad fidelity domain, which is the case when the computation encounters at least one gate-level mistake with a frequency of about one. It provides high accuracy, and it provides high error rate.

Giwa, [26] presented an Over the Counter Stocks Data Acquisition & Analysis with Time Series Prediction. The goal of this project was to gather, examine, and estimate future price movements using time series prediction algorithms on OTC stock data. This allows for obtaining historical price and volume data, company information, and industry trends. An LSTM-CNN time series prediction model was used for technical analysis, while a redesigned BERT model was used for fundamental analysis to forecast future market movements. OTC stocks are securities that are often issued by smaller enterprises and are traded off-traditional exchanges. It provides high accuracy, and it provides low precision.

Zaheer, et al. [27] suggested a Multi Parameter Forecasting for Stock Time Series Data Using LSTM and DLM. One kind of historical time series data that was commonly used in data analysis jobs was financial data, which offers a wealth of information. Both investors and financial professionals are still interested in learning how to predict stock values. The substantial noise, non-linearity, and volatility of time series data on stock prices make stock price forecasting extremely difficult. Prior research has concentrated on a particular stock characteristic, like close price. A forecasting model utilizing hybrid deep learning was suggested. It provides high precision and it provides low error rate.

III. PROPOSED METHODOLOGY

This section discusses PMLCT-TSA-DTGMGCN. This section provides a comprehensive explanation of how the FFPLCTM Dataset uses research methods. The new method to predict the FFPLCTM Dataset, it use neural network to create synthetic samples in order to solve the scarcity of data. This enlarged dataset analyzed alongside current data using more especially deep learning models. By identifying important quality determinants, let the models concentrate on making better and more precise quality predictions. Figure 1 depicts the PMLCT-TSA-DTGMGCN block diagram. It includes dataset, pre-processing, prediction, optimization are processes that make up this procedure. Consequently, a thorough explanation of PMLCT-TSA-DTGMGCN is provided below.

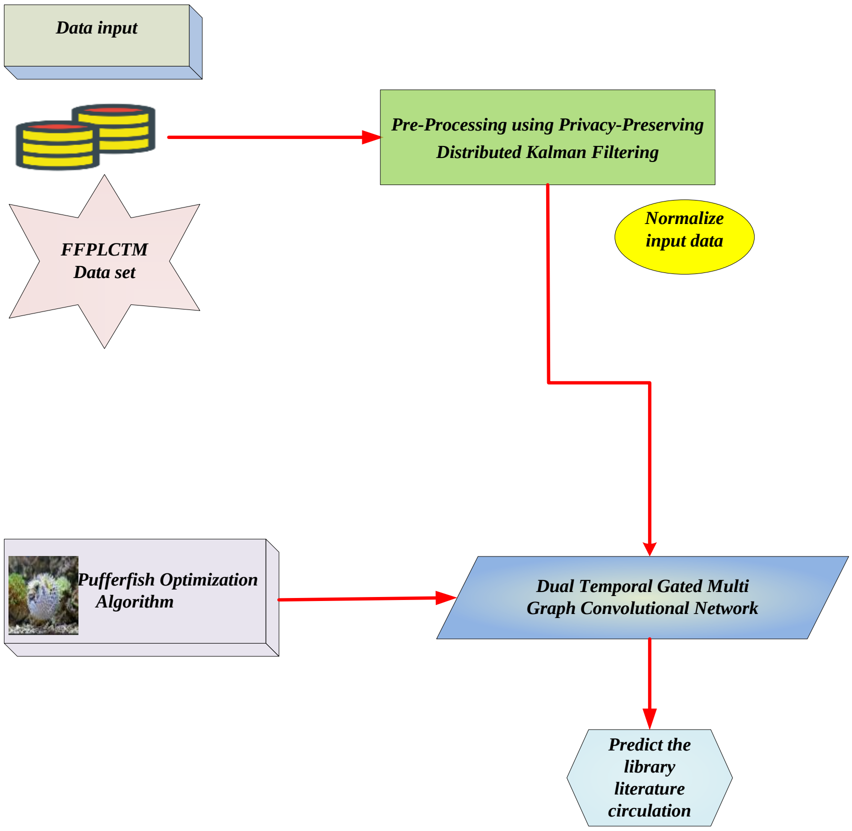

Figure 1: Block Diagram of the proposed PMLCT-TSA-DTGMGCN

A. Data Acquisition

I The FFPLCTM dataset is the source of the input data used in this section [28].More and more public libraries are doing away with their users' late charges. As the "imposition of monetary library fines creates a barrier to the provision of library and information services," the American Library Association (ALA) adopted a resolution in 2019 (p. 2). We discovered that since 2015, the number of libraries implementing fine-free policies has almost doubled annually using data that was obtained from End Library Fines and the Urban Libraries Council in August 2019.More and more public libraries are doing away with their users' late charges. Recognizing the "imposition of monetary library fines creates a barrier to the provision of library and information services," the ALA passed a resolution in 2019.Based on information obtained from End Library Fines and the Urban Libraries Council in August 2019, we discovered that since 2015, the number of libraries implementing fine-free policies has almost doubled annually.

B. Pre-Processing using Privacy-Preserving Distributed Kalman Filtering

In this segment, PP-DKF is discussed [29]. The PP-DKF is used for normalize the input data. Using the Kalman Filter technique, create precise models using historical data to forecast circulation trends in libraries. Libraries can use these models to predict future demand and allocate resources as efficiently as possible. Make sure that each borrower's unique borrowing habits are kept secret and private, safeguarding their private information. Promote information sharing and cooperation while upholding privacy concerns by enabling several libraries or institutions to work together on trend analysis without exchanging raw data. To increase overall operational efficiency, use predictive models to optimize the distribution of library resources, including staffing, collection development, and space utilization. The PPDKF guarantees the confidentiality of individual library circulation data while enabling collective trend analysis through the use of strategies like federated learning and differential privacy. By preventing sensitive data from being centralized, the distributed design of the Kalman Filter lowers the possibility of data breaches and illegal access. Since Kalman Filters are well-known for their efficiency in estimating and forecasting the states of dynamic systems, they are a good choice for reliably anticipating trends in library circulation. The proposed PP-DKF uses, to keep an eye on the state of the dynamic system,

$$\hat{x}_{i,n|n-1} = M\hat{x}_{i,n-1|n-1} \tag{1}$$

$$S_{i,n|n-1} = MS_{i,n-1|n-1}A^T + C_{Vn} \tag{2}$$

In this case, agent i, $\hat{x}_{i,n|n-1}$, and v are the corresponding a priori and a posteriori state vector estimates. Agent i change its local sub states, as stated in equation (3), at the interme of each consensus iteration k.

$$\hat{x}_{i,n|n} = \alpha_{i,n}(E)\forall i \in N \tag{3}$$

When each agent's intended PP-DKF activities are $\alpha_{i,n}(E)\forall i \in N$ is used in find the missing values updates its local substates expressed in equation (4)

$$\zeta(e) = \sum_{i=1}^{N}(\alpha_{i,n}(e) + \beta_{i,n}(e)), \tag{4}$$

Where the total of all sub states, or the consensus iterations e, are always time-invariant. This may be confirmed by calculating the noise reduction value represented in equation (5) by simplifying ζ (e).

$$\zeta(e) = \zeta(0) + \varepsilon\sum_{i=1}^{N} d_i\left(\sum_{i=1}^{e-1}\omega_i(l)\right) \tag{5}$$

Here, $d_i = \sum_{J \in N_I}\omega_{IJ}$ and demonstrating that, in the mean square sense, ζ(e) converges to ζ (0) to $\varepsilon\sum_{i=1}^{N} d_i\left(\sum_{i=1}^{e-1}\omega_i(l)\right)$ find the normalization which is expressed in equation (6)

$$\zeta(e) \xrightarrow{m.s.} \zeta(0) \Leftrightarrow \lim_{e\to\infty} E\{\| \zeta(e) - \zeta(0)\|^2\} = 0. \tag{6}$$

In particular, using the $\lim_{e\to\infty} E$ convergence of the decomposition-based consensus processes in Appendix A, it can be shown that, given the symmetric weight condition for the interaction, η(e) converges to η(0) in the mean square sense using $d_i = \sum_{J \in N_I}\omega_{IJ}$ and Finally the PP-DKF is used for normalized the input data and the pre-processed data are given to prediction phase.

C. Dual Temporal Gated Multi Graph Convolutional Network (DTGMGCN)

In this section, prediction using DTGMGCN [30] is discussed. Improving predictive modeling's accuracy for library circulation trends is the main objective. The model aims to represent complex temporal relationships and relational structures in the circulation data by integrating the DTGMGCN architecture, which should result in more accurate predictions. One other goal is to identify new circulation patterns as soon as possible. Librarians can proactively address emerging needs or issues by utilizing the DTGMGCN's capabilities to recognize small changes or abnormalities in circulation trends. By using anticipated circulation trends to guide resource allocation decisions, the approach aims to support libraries in doing just that. Librarians can more effectively distribute staff, materials, and other resources by producing realistic projections. Due to the two temporal gated processes of DTGMGCN, the model may represent both long-term trends and short-term fluctuations in the circulation data. By incorporating the temporal dynamics seen in library consumption patterns, this allows for more accurate forecasts. The modeling of relational relationships between users, library items, and other important entities is made possible by the use of GCNs in DTGMGCN. The model is able to make more accurate predictions and derive valuable insights by taking into account the circulation data's underlying graph structure. When managing extensive circulation datasets, DTGMGCN provides efficiency and scalability. Without sacrificing efficiency, the model can handle a variety of user populations and library collections by utilizing parallel processing and effective graph convolution techniquesis given in equation (7),

$$B_{P,j,i} = sim(F_{uj}, F_{ui}) \in [0,1] \tag{7}$$

Where, F_{uj}, F_{ui} is the feature vector of place $uj\,and\,ui$ respectively, $B_{P,j,i}$ denotes the landscape graph, sim denotes the pertinent temporal information and $\in$ denotes the to destination is given in equation (8),

$$D_{E,i,j} = sim(P_{vi}, P_{vj}) \in [0,1]$$
(8)

Where, P_{vi}, P_{vj} denotes feature vector of place $vi \, and \, vj$ respectively, $D_{E,i,j}$ denotes the historic site and $\in$ denotes the rich properties. Library Circulation, just shut down source computer, transfer all state to target system. Contextual information is generated by combining historical data and neighborhood information to create region descriptions. Graph convolution is also used to aggregate information is given in equation (9),

$$Y^{(q)} = \left[Y^{(q)}, D_F^{s-1}(Y^{(q)}) \right]$$
(9)

Where, $Y^{(q)}$ is the maximum degree and D_F^{s-1} denotes the overall region. In order to sum up each historical observation, they use global average pooling over all regions. It collects contextual information within Library Circulation is given in equation (10),

$$Q^{(x)} = F_{pool}(\hat{Y}^{(x)}) \tag{10}$$

Where, $Q^{(x)}$ denotes the summarized vector, F_{pool} denotes the average pooling and $\hat{Y}^{(x)}$ denotes the graph convolution operation. Predicted the library circulation using equation (10),

$$\widetilde{R}^{(x)} = x(\sigma) + x(t)$$

Where, $\widetilde{R}^{(x)}$ denotes the attain operation, $x(\sigma)$ denotes the trainable weight, $\circ$ denotes the dot value and $x(t)$ denotes the migration function. It isn't realistic choice for cloud providers from business standpoint. Finally, DTGMGCN is used to predict potential issues and library circulation, enabling proactive maintenance strategies and minimizing downtime. In this work, POA is employed to optimize the DTGMGCN optimum parameters $x(\sigma), x(t)$ .Here POA is employed for tuning the weight and bias parameter DTGMGCN.

D. Optimization using Pufferfish Optimization Algorithm (POA)

In this section, the weight parameter $x(\sigma), x(t)$ of DTGMGCN is optimized using Pufferfish Optimization Algorithm. Solving Optimization Problems POA seeks to effectively resolve optimization issues in a variety of fields [31]. These could involve scheduling, resource allocation, and parameter optimization. Bio-inspired Methodology The program aims to mimic the pufferfish's ability to explore complex situations and discover the best solutions by taking cues from their behavior. Effectiveness POA uses a bio-inspired framework to provide effective solutions to optimization challenges. It efficiently traverses search spaces, possibly surpassing the performance of conventional optimization techniques. Flexibility the technique exhibits versatility, making it suitable for a broad spectrum of optimization applications. It can adjust to various issue domains and needs for solutions. Integration of Predictive Modeling POA obtains insights into dynamic environments through the incorporation of predictive modeling approaches, such as time series analysis of library circulation trends. Its capacity to adjust to shifting circumstances and tailor solutions accordingly is improved by this integration. The ability to scale POA exhibits scalability, which allows it to be applied to issues of different sizes and levels of complexity. Large-scale optimization projects can be effectively handled by it.

1) Stepwise Procedure for POA

Here, a stepwise process based on POA is outlined to obtain the optimal value of DTGMGCN. In order to optimise the parameter DTGMGCN Ideal solution, POA first creates an evenly distributed population. This is done by utilising the POA algorithm.

Step1: Initialization

Initialize the input parameter, here the input parameter of DTGMGCN which is denoted as $x(\sigma), x(t)$.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N \times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \cdot^{\cdot^{\cdot}} & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \cdot^{\cdot^{\cdot}} & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N \times m} \tag{11}$$

Where, X represents the matrix of POA populations, $x_{i,d}$ represents the decision variable of dth dimension, N represents the amount of Vulture, m represents the amount of decision variable, i represents $1,2,....,N$.

Step2: Random Generation

After initialization the input fitness function developed randomness via POA.

Step3: Fitness Function

The initialized settings are determined by the best location that is currently available. Determine the individual's fitness value.

$$\text{Fitness function} = \text{F} = \text{Optimizing}\left(x(\sigma), \text{x(t)}\right) \tag{12}$$

Where $x(\sigma)$ represent increasing the accuracy and $x(t)$ represents decreasing the Computational Time.

Step4: Exploration Phase $x(\sigma)$

The population members' placements are altered during the first stage of POA in accordance with a simulation of the predator attack plan targeted at the pufferfish. Hungry hunters can easily catch Pufferfish due to their lethargic movement. To update the POA members' placement inside the problem-solving environment, the predator's movement in position during the pufferfish assault is reproduced. Members of the POA adopt drastically different postures when simulating the predator's approach to the pufferfish, which boosts the algorithm's capacity for global search exploration.

For every member of the population operating as a predator, the POA design takes into account the location of other members of the population with a higher value for the objective function.

$$CP_i = \{X_K : F_i \text{ and } k \neq i\}, \text{where } i=1,2,3,\ldots,N \text{ and } k \in \{1,2,\ldots,N\}, \tag{13}$$

In this case, F_k indicates its objective function value, X_k indicates the member of the population whose goal function value is higher than that of the ith predator and CP_i indicates set of potential pufferfish sites for the ith predator.

$$x_{i,j}^{P1} = x_{i,j} + x(\sigma)\ (SP_{i,j} - I_{i,j} x_{i,j}), \tag{14}$$

In this case, SP_i represents the pufferfish that was selected at random for the ith predator from the CP_i set. The jth dimension is called SP_{ij}, and the ith predator's new location is determined by X_i^{P1} using the projected POA's initial phase, Its jth dimension is denoted by $x_{i,j}^{P1}$, its objective function value is represented by F_i^{p1} i, arbitrary integers from the interval [0, 1] are denoted by $r_{i,j}$, and numbers arbitrarily chosen as 1 or 2 are indicated by $I_{i,j}$.

Step5: Exploitation Phase $x(t)$

Population members are moved in the 2nd phase of POA in accordance with a model that imitates a pufferfish's defensive mechanism against predator attacks.. When a pufferfish senses an impending predator, it fills its very elastic stomach to the brim with sharp spines. Instead of taking advantage of the easy meal, the predator in this scenario flees from the pufferfish's location. Little shifts in the POA members' positions arise from simulating the predator evading the pufferfish, which boosts the algorithm's capacity for local search exploitation.

$$x_{i,j}^{P2} = x_{i,j} + (1 - 2r_{i,j}) \frac{ub_j - lb_j}{x(t)} \tag{15}$$

Here, X P2 i represents the new location determined for the ith predator using the projected POA's 2nd phase; t is the iteration timer; F_i^{p1} represents the value of its objective function; $x_{i,j}^{P2}$ represents its jth dimension; and $r_{i,j}$ are arbitrary integers from the interval [0, 1].

Step6: Termination

In this stage, the weight parameter $x(\sigma), x(t)$ using to predicate Dual Temporal Gated Multi Graph Convolutional Network is optimised with POA's assistance, repeating the stages repeatedly until the optimal answer is obtained. The use of POA allows for more efficient training and fine-tuning of the neural network design, resulting in improved predicting accuracy. Then finally proposed PMLC-DTGMGCN is accurately Predictive Modeling of Library Circulation Trends Based on Time Series Analysis.

IV. RESULT WITH DISCUSSION

This segment discusses the research outcomes of the proposed methodology. The proposed method is then simulated in python using the mentioned performance indicators. The proposed PMLCT-TSA-DTGMGCN approach is implemented in python versions. Several performance measures like accuracy, precision, recall, F1score and error rate are obtained. The obtained outcome of the proposed PMLCT-TSA-DTGMGCN approach is analysed with existing system like DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM, and STTP-TSA - BILSTM respectively.

A. Performance Measures

Performance measurements include things like mistake rate, F1-Score, recall, accuracy, and precision. It is determined to scale the performance parameters using the confusion matrix.

1) Precision

One measure of DLM effectiveness is precision, or how well the model makes good predictions. As stated in equation (16), by dividing the total count of positive predictions by the total count of TP, precision is computed.

$$\Pr ecision = \frac{TP}{TP + FP} \tag{16}$$

Here, TP signifies true positive and FN signifies false negative.

2) F1-Score

A Deep Learning model's performance is assessed using a statistic called the F1-score. Equation (17) shows how it integrates memory and accuracy into a single score.

$$F1 - Score = 2 * \frac{precision * recall}{precision + recall} \tag{17}$$

3) Recall

True positive rate or sensitivity is terms used to describe recall. Thus is expressed in equation (18)

$$\operatorname{Re} call = \frac{TP}{(TP + FN)} \tag{18}$$

Where TP denotes true positive and FN denotes false negative.

4) Error rate

The degree of prediction error of a model made in relation to the genuine model is measured by the error rate. Equation (20) is used to calculate this.

$$ErrorRate = 100 - Accuracy \tag{19}$$

B. Performance Analysis

The simulation results of the proposed PMLCT-TSA-DTGMGCN approach are displayed in Figure 2 to 6. Then, the proposed WQP-AIDINN approach is likened with existing DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM, and STTP-TSA-BILSTM methods respectively.

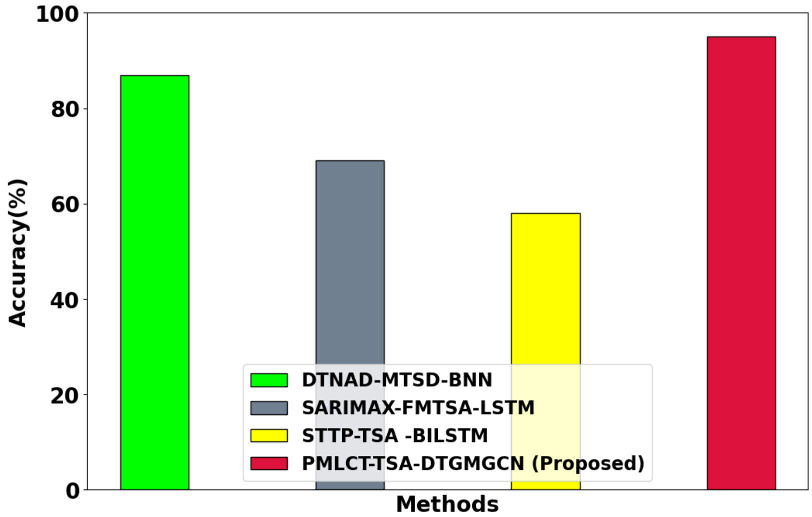

Figure 2: Performance Analyses of Accuracy

Figure 2 displays a performance Analyses of accuracy for four different methods. The proposed method, PMLCT-TSA-DTGMGCN, achieves the highest accuracy at 98%, surpassing the other methods significantly. DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM, and STTP-TSA-BILSTM each have accuracies less than 95%, indicating their comparatively lower performance. This graphical comparison clearly illustrates that the PMLCT-TSA-DTGMGCN method is the most accurate among the evaluated techniques, highlighting its superiority in achieving higher accuracy.

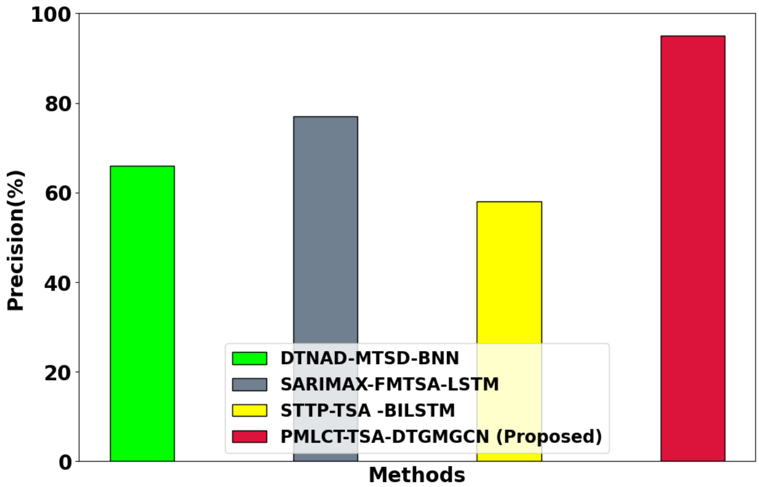

Figure 3: Performance Analyses of Precision

Figure 3 displays a performance analysis of precision for four different methods used for a task. The proposed method, PMLCT-TSA-DTGMGCN, achieves the highest precision at 98%, outperforming the other methods. Specifically, DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM, and STTP-TSA-BILSTM each exhibit a precision of 95%. This comparison highlights the superior precision of the PMLCT-TSA-DTGMGCN method.

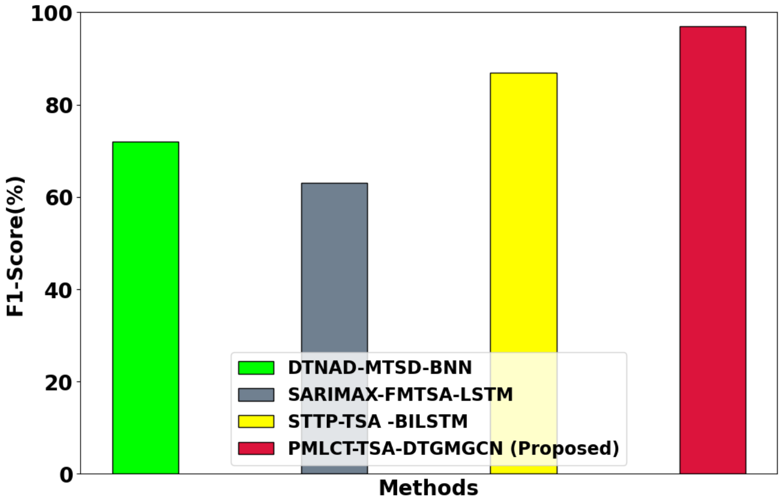

Figure 4: Performance Analyses of F1-Score

Figure 4 displays a performance Analyses of F1-Score for four different methods. The proposed method, PMLCT-TSA-DTGMGCN, achieves the highest F1-Score at 98%, surpassing the other methods. The other three methods, DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM, and STTP-TSA-BILSTM, each have F1-Scores below 95%. This highlights the superior performance of the PMLCT-TSA-DTGMGCN method in achieving a high balance of precision and recall. An F1-Score of 98% signifies that the proposed technique is highly effective in minimizing both FP and FN, making it the most reliable among the compared methods.

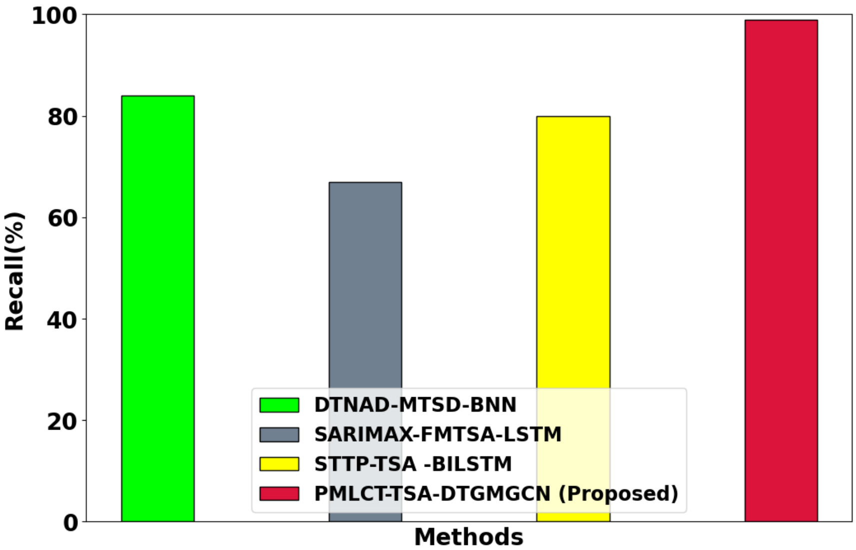

Figure 5: Performance Analyses of Recall

Figure 5 shows a performance Analyses of recall for four different methods used for a task. The proposed method, PMLCT-TSA-DTGMGCN, achieves the highest recall at 99%, indicating its superior ability to identify all relevant cases from the dataset. The other methods, DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM, and STTP-TSA-BILSTM, have recall values of 85%, 65%, and 80%, respectively. This demonstrates the exceptional performance of the PMLCT-TSA-DTGMGCN method in capturing all positive cases. The balance between recall and precision is crucial for optimal model performance.

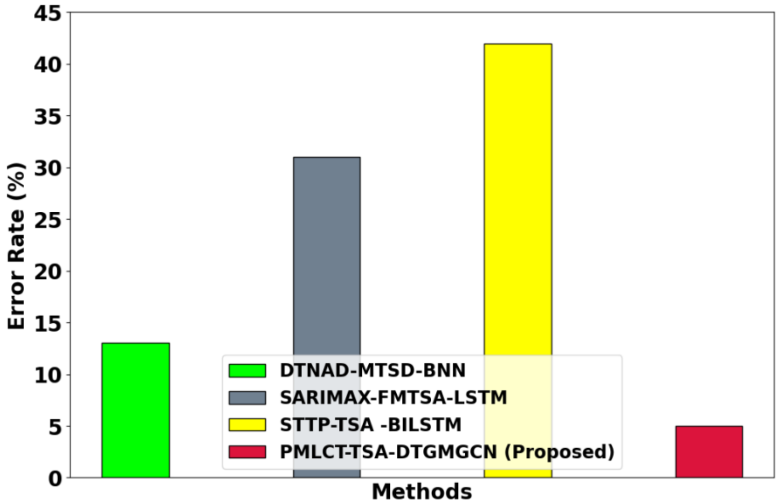

Figure 6: Performance Analyses of Error rate

Figure 6 shows a performance Analyses of error rates for four different methods. The proposed method, PMLCT-TSA-DTGMGCN, demonstrates the best performance with the lowest error rate of 5%. The other methods, DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM, and STTP-TSA-BILSTM, exhibit higher error rates of 15%, 20%, and 25%, respectively. This indicates that the PMLCT-TSA-DTGMGCN method has the smallest percentage of incorrect predictions, showcasing its superior accuracy compared to the other methods. The error rate is a critical metric, as it reflects the proportion of predictions that were incorrect, with a lower error rate signifying more reliable performance.

C. Discussion

A novel PMLCT-TSA-DTGMGCN model to Predictive Modeling of Library Circulation Trends Based on Time Series Analysis. In this paper, data collected from FFPLCTM Dataset. The model PMLCT-TSA-DTGMGCN includes pre-processing of the FFPLCTM Dataset using Privacy-Preserving Distributed Kalman Filtering, prediction using DTGMGCN finally, the DTGMGCN model is used to carry out the prediction procedure. The approach's average results were compared to those of other approaches, including DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM, and STTP-TSA -BILSTM, using the FFPLCTM Dataset as an example. However, the proposed PMLCT-TSA-DTGMGCN method uses the Pufferfish Optimization Algorithm in conjunction with a quicker DTGMGCN, which leads to a more effective data collection and improved handling of the model over-fitting issue. Compared to current methods, the proposed approach has higher evaluation criteria for accuracy and precision. As a result, the proposed technique is less expensive than the comparative methods. Consequently, the proposed method more accurately predicted the library literature circulation.

V. CONCLUSION

In this section, Predictive Modeling of Library Circulation Trends Based on Time Series Analysis (PMLCT-TSA-DTGMGCN) is successfully implemented. The proposed method is simulated using Python. The performance of technique is examined using performance metrics. The performance of the proposed PMLCT-TSA-DTGMGCN accuracy is 23.70%, 23.21%, 25.52% greater F1-Score, 21.17%, 25.22%, 25.35% greater recall and 21.17%, 25.22%, 25.35% greater error rate when compared with existing methods such as DTNAD-MTSD-BNN, SARIMAX-FMTSA-LSTM and STTP-TSA-BILSTM. Future work in Predictive Modeling of Library Circulation Trends Based on Time Series Analysis, Predictive modeling of library circulation trends may take many different paths in the future. Prediction accuracy can be increased by taking into account extraneous variables like weather and socioeconomic statistics. Models can be made to respond to changing patterns by using dynamic model update techniques. Personalized services catered to various user groups are made possible by user segmentation. Analysis of long-term trends might shed light on slow changes in library usage. For more effective resource allocation, spatial analysis takes geographic variations in circulation patterns into account. Creating thorough evaluation metrics guarantees the usefulness of the models.

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