An Advancing Financial Credit Risk Forecasting Model Using Graph Convolutional Networks for Sustainable Economic Analysis

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ABSTRACT

Credit risk management is essential for financial stability in lending organizations. It involves evaluating the probability that borrowers will fail to repay their debts, which could lead to substantial losses for the institution. Accurate credit risk forecasting is crucial for safeguarding institutions from defaults and maximizing returns. Conventional statistical methods, though effective, often fail to capture complex, nonlinear relationships among variables, resulting in prediction errors in diverse credit profiles. The advent of Artificial Intelligence (AI), particularly Deep Learning (DL), in credit risk management signifies a key progression in addressing these drawbacks. AI, especially DL, enables processing of extensive data and the extraction of significant insights to enhance predictions. This paper presents an Advancing Financial Credit Risk Forecasting Model using the Graph Convolutional Network (AFCRFM-GCN) technique. The aim is to develop a robust and intelligent framework for accurate credit risk prediction to support sustainable economic analysis. In the data preprocessing stage, the min–max scaling method is used to normalize the financial data. Furthermore, the Pelican Optimization Algorithm (POA) is employed in the Feature Selection (FS) process. Moreover, the Graph Convolutional Network (GCN) is utilized for credit risk classification. Finally, the Levy Flight-based Red Fox Optimization (LFRFO) is implemented for parameter tuning. The comparison study illustrates a superior accuracy value of 98.56% over existing models on the Credit Risk dataset.

Keywords-financial risk; Artificial Intelligence (AI); Graph Convolutional Network (GCN); credit risk forecasting; Feature Selection (FS)

I. INTRODUCTION

With the rapid evolution of Internet technologies, the conventional financial sector is advancing, and, therefore, faces increasing risk-related challenges [1]. Financial credit risk valuation is paramount for the financial field, involving judgments based on the analysis of issues and risk levels encountered by customers in essential economic activities [2]. Credit risk valuation includes assessing the probability of borrowers defaulting on dept, which is critical for making wise lending decisions and managing the whole portfolio risk [3]. Effective corporate credit risk management is crucial for organizations, as companies often rely on external financing through bank loans [4]. A high debt ratio may indicate limited borrower rights and potential bankruptcy [5]. Traditionally, financial entities assess credit risk using techniques such as credit scoring, statistical methods, and financial ratios, each with its own strengths and limitations [6]. Credit scoring methods are statistical approaches utilized for evaluating the credit rating of debtors [7], and play a critical part in deciding whether a borrower qualifies for a loan [8]. Machine Learning (ML), a subdivision of Artificial Intelligence (AI), has attained importance in present years [9]. Moreover, Deep Learning (DL) and Neural Network (NN) models enable more complex pattern recognition and predictive algorithms in credit risk assessment [10].

Authors in [11] presented a method using a stacked ensemble approach integrated with a hybrid information resampling method. The Synthetic Minority Oversampling Technique–Edited Nearest Neighbor (SMOTE-ENN) model was used for handling imbalance. Authors in [12] proposed a DL-integrated model. Authors in [13] emphasized the role of innovative financial analytics in improving strategic decision-making and predictive risk management within world markets. Authors in [14] introduced a method for predicting credit risk using Graph Convolutional Neural Networks (GCNNs). A typical subgraph convolutional method was used for extracting attributes, and the hybrid GCNN combined global and local convolutional operators to capture an inclusive representation of node features. Authors in [15] recommended a credit risk forecasting method leveraging Long Short-Term Memory (LSTM) for long-scale time-sequence forecasting, integrated with a Convolutional Neural Network (CNN). Authors in [16] highlighted the role of AI-driven predictive financial models in risk management.

This paper presents an Advancing Financial Credit Risk Forecasting Model using Graph Convolutional Network (AFCRFM-GCN). The major contributions are:

- Initially, min–max scaling is used for normalizing financial data, ensuring consistent preprocessing across features, which improves reliability of subsequent analysis and overall performance.
- The Pelican Optimization Algorithm (POA) is used for selecting the most relevant features and improving efficiency while mitigating noise. The Graph Convolutional Network (GCN) is utilized to classify the credit risk and to effectively capture relational dependencies among entities, improving prediction accuracy.
- The Levy Flight-based Red Fox Optimization (LFRFO) technique is employed for efficient parameter tuning to optimize key hyperparameters, ensuring more accurate and stable credit risk predictions.
- Integrating GCN with advanced optimization techniques, including POA for Feature Selection (FS) and LFRFO for parameter tuning, presents a novel framework that improves both accuracy and robustness, providing a more effective approach for financial credit risk forecasting.

II. METHODOLOGICAL FRAMEWORK

This manuscript proposes the AFCRFM-GCN technique, consisting of input data preprocessing, dimensionality reduction via POA, GCN-based credit risk classification, and LFRFO-based parameter tuning. Figure 1 depicts the overall diagram of the AFCRFM-GCN approach.

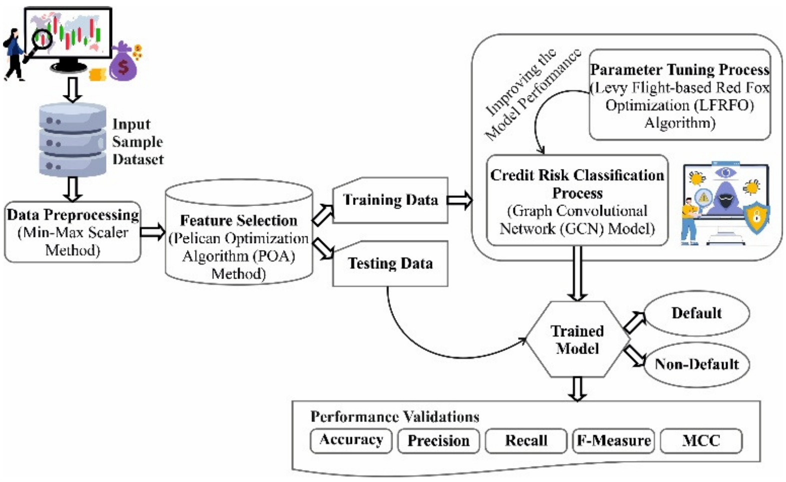

Fig. 1. General diagram of the proposed AFCRFM-GCN approach.

A. Data Preprocessing

In the data preprocessing phase, the min–max scaling method is used to normalize financial data [17]. This method is chosen as it efficiently transforms financial data into a uniform range [0,1]. The model preserves the relationships between features without altering their distribution. Unlike standardization, it avoids negative values, which is crucial for models sensitive to scale and ensures faster convergence in optimization algorithms. Environmental variables often vary considerably in both units of measurement and numeric size. This disparity can cause imbalanced parameter weighting, affecting the ability to capture key relationships and compromising convergence and stability. Hence, all input features were normalized to a comparable range:

$$\text{Normalized } Y_i' = \frac{Y_i - Y_{min}}{Y_{max} - Y_{min}} \quad (1)$$

This formulation changes the raw data into a range of 0 to 1, where Y_{max} and Y_{min} are the largest and smallest numeric values in the dataset, respectively.

B. Pelican Optimization Algorithm-Based Feature Reduction

Following data preprocessing, the POA model is utilized for dimensionality reduction to remove irrelevant and redundant features [18]. This model is employed due to its efficient exploration and exploitation mechanisms. It detects the most relevant features while discarding redundant ones, capturing intrinsic nonlinear relationships in the data more effectively than conventional techniques, thus improving predictive performance. Pelicans are large, social birds with long beaks and neck bags for catching prey, mainly fish or sometimes crustaceans, frogs, and turtles. POA mimics this behavior, treating each pelican as a candidate solution exploring the search space. Initially, population members are randomly positioned within the problem's bounds using (2), forming the starting point for optimization:

$$X = lowb + rand \times (upb - lowb) \quad (2)$$

where X depicts the candidate solution, $lowb$ and upb represent the minimum and maximum limits, respectively, and $rand$ is a random number in $(0,1)$.

POA replicates pelicans' hunting strategies to improve solutions through exploration and exploitation. Exploration searches diverse areas, and random prey placement enhances precision and diversity:

$$X_1(t+1) = \begin{cases} X(t) + rand \times \big(P - I \times X(t)\big), & \text{if } f(P) < f\big(X(t)\big) \\ X(t) + rand \times (X(t) - P), & \text{if } f(P) \geq f\big(X(t)\big) \end{cases} \quad (3)$$

where X_1 represents the pelican's new state according to the first step, P refers to the prey's location, $f(\cdot)$ signifies the objective function representing fitness, and I is a randomly chosen integer (1 or 2) independently assigned for all iterations and members.

During exploitation, pelicans spread their wings to herd fish and catch them with their neck bags, modeling the local search process and helping the algorithm converge on better solutions within the search area. The predatory behavior is modeled in (4):

$$X_2(t+1) = X(t) + R \times (1 - t/T) \times (2 \times rand - 1) \times X(t) \quad (4)$$

where X_2 represents the pelican's new state in the second stage, R is a constant equivalent to 0.2, t refers to the current iteration number, and T indicates the highest iteration count.

In both phases, if the objective function improves at the new location, the pelican's position is updated; otherwise, the location is rejected. This effective update prevents the model from moving to non-optimal areas:

$$X(t+1) = \begin{cases} X_s(t+1), & \text{if } f\big(X_s(t+1)\big) < f\big(X(t)\big) \\ X(t), & \text{if } f\big(X_s(t+1)\big) \geq f\big(X(t)\big) \end{cases} \quad (5)$$

where X_s signifies the new state of the pelican at each stage, with s = 1 or 2. The Fitness Function (FF) utilized in POA balances the number of selected features in all solutions (minimized) and the classification accuracy (maximized) achieved by these features:

$$Fitness = \alpha \gamma_R(D) + \beta \frac{|R|}{|C|} \quad (6)$$

where $\gamma_R(D)$ represents the classification error rate. $|R|$ is the feature count of the chosen subset, $|C|$ is the total number of features in the dataset, and α and β are weighting parameters representing the importance of classification accuracy and subset size, with $\alpha \in [0,1]$ and $\beta = 1 - \alpha$.

C. Classification Model

Credit risk classification is performed using a GCN to attain accurate and robust predictions. GCN is a standard branch of Graph Neural Networks (GNNs) that effectively captures spatial and structural relationships in a graph through convolution operations [19]. Overfitting is reduced through renormalized graph convolution and shared parameters, whereas aggregating features across connected nodes ensures stable and robust credit risk predictions. Consequently, an undirected graph is a basic element of GCN. It is defined as $G = \{V, E, A, P\}$, where E signifies the set of edges, V is the set of n vertices, $P \in \mathbb{R}^{n \times m}$ represents the feature matrix of nodes, and $A \in \mathbb{R}^{n \times n}$ denotes the adjacency matrix. The standardized graph Laplacian matrix is defined from the adjacency matrix to examine the graph's mapping properties:

$$L = I_N - D^{-\frac{1}{2}} A D^{\frac{1}{2}} = U \Lambda U^T \quad (7)$$

Here, D is the degree diagonal matrix, and U and Λ are the eigenvector and eigenvalue matrices of the standardized graph Laplacian L. Graph convolution $\langle * \rangle$ is performed in the Fourier domain using this eigen-decomposition.

$$g_\theta * F = U g_\theta(\Lambda) U^T F \quad (8)$$

Here, θ indicates the learnable modal parameter. Moreover, to reduce computation, the K -localized convolution is employed:

$$g_\theta \star F \approx \sum_{k=0}^{K} \theta_k T_k(\hat{L})F \quad (9)$$

Here, $T_k(\hat{L})$ signifies the Chebyshev polynomials, defined as $T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x)$, with $T_0(x) = 1$ and $T_1(x) = x$, θ_k represents the Chebyshev coefficient vector, and $\hat{L} = \frac{2}{\lambda_{\max}} L - I_N$ is the advanced diagonal matrix, with $\lambda_{\max}$ as the largest eigenvalue. Following Kipf and Welling, K is set to 1 to simplify layer-wise convolution, and $\lambda_{\max}$ is estimated as 2:

$$g_{\theta'} \star F \approx \theta_0' F + \theta_1'(L - I_N)F$$
$$= \theta_0' F - \theta_1' D^{-\frac{1}{2}} A D^{\frac{1}{2}} F \quad (10)$$

where θ_0' and θ_1' are two free parameters. Subsequently, to further reduce free parameters, they are specified as $\theta = \theta_0' = -\theta_1'$:

$$g_\theta \star F \approx \theta\left(I_N + D^{-\frac{1}{2}} A D^{\frac{1}{2}}\right)F \quad (11)$$

Finally, the renormalization trick of $I_N + D^{-\frac{1}{2}} A D^{\frac{1}{2}} \rightarrow \widetilde{D}^{-\frac{1}{2}} \tilde{A} \widetilde{D}^{-\frac{1}{2}}$ is implemented to resolve the issue of vanishing or exploding gradients as well as numerical instability, and the graph convolution of mapping features is specified:

$$Y = \widetilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{A}^{-\frac{1}{2}} X W \quad (12)$$

Here, $\tilde{A} = A + I_N$, $\widetilde{D} = \Sigma_j \tilde{A}_{ij}$, $W \in \mathbb{R}^{m \times s}$ is the trainable parameter matrix, and $Y \in \mathbb{R}^{n \times s}$ represents the final output.

D. Parameter Tuning Using the Levy Flight-Based Red Fox Optimization Algorithm

Finally, the LFRFO approach is used for parameter tuning to optimize model parameters and improve classification performance [20]. The approach is also considered for its hybrid strategy, which assists in improving global search and preventing premature convergence. The model also effectually explores intrinsic parameter spaces, enhancing the accuracy and robustness of the CNN compared to conventional optimization methods. Red Fox Optimization (RFO) is a population-based metaheuristic inspired by red fox breeding, and Levy Flight (LF) is added to enhance randomness and convergence. The algorithm emulates fox behavior by balancing global exploration and local exploitation while maintaining a constant population.

All individuals are represented by a point $\bar{a} = (a_0, a_1, \ldots, a_{m-1})$ of m coordinates. The $(\bar{a}_j^i)^t$ denotes the j-th coordinate of the i-th fox at iteration t. The objective function $f \in \mathbb{R}^m$ evaluates each solution, and $\left(\overline{a}^{best}\right)^t$ represents the current best solution. The Euclidean distance of each fox from the best solution is computed as:

$$q((\overline{a}^i)^t, (\overline{a}^{best})^t) = \sqrt{\left\|(\overline{a}^i)^t - (\overline{a}^{best})^t\right\|} \quad (13)$$

The fox positions are updated according to:

$$(\overline{a}^i)^t = (\overline{a}^i)^t + \gamma \operatorname{sign}\left((\overline{a}^{best})^t - (\overline{a}^i)^t\right) \quad (14)$$

where $\gamma \epsilon (0, q((\overline{a}^i)^t, (\overline{a}^{best})^t))$ is a randomly selected scaling hyperparameter applied at each iteration for all individuals. Movement strategies follow the Cochleoid equation:

$$\begin{Bmatrix} \text{Move closer if } \varphi > 0.75 \\ \text{Stay and disguise if } \varphi \leq 0.75 \end{Bmatrix} \quad (15)$$

The vision radius l is defined as:

$$l = \begin{Bmatrix} c\frac{\sin(\varphi_0)}{\varphi_0}, & if\ \varphi_0 \neq 0 \\ \theta, & if\ \varphi_0 = 0 \end{Bmatrix} \quad (16)$$

Here, $\theta \in [0,1]$ represents weather influence, and each individual's movement is computed using (17):

$$\begin{cases} a_0^{new} = c_r \cos(\varphi_1) + a_0^{actual} \\ a_1^{new} = c_l \sin(\varphi_1) + c_l \cos(\varphi_2) + a_1^{actual} \\ a_2^{new} = c_l \sin(\varphi_1) + c_l \sin(\varphi_2) + c_l \cos(\varphi_3) + a_2^{actual} \\ \vdots \\ a_{m-2}^{new} = c_l \sum_{p=1}^{m-2} \sin(\varphi_p) + c_l \cos(\varphi_{m-1}) + a_{m-2}^{actual} \\ a_{m-1}^{new} = c_l \sum_{p=1}^{m-1} \sin(\varphi_p) + a_{m-1}^{actual} \end{cases} \quad (17)$$

Based on $\varphi_1, \varphi_2, \ldots \varphi_{m-1} \in [0,2\pi)$, for all points, all angular values are randomized to represent each fox's stance while waiting to attack prey or searching for other individuals. The two top-performing individuals, $(\overline{a}^{(x)})^t$ and $(\overline{a}^{(y)})^t$, are then selected, and the center of the alpha couple's environment is calculated using (18):

$$(habit^{center})^t = \frac{(\overline{a}^{(x)})^t + (\overline{a}^{(y)})^t}{2} \quad (18)$$

The squared Euclidean distance of the environment for the alpha couple is computed as:

$$(habit^{diameter})^t = \sqrt{\|(\overline{a}^{(x)})^t + (\overline{a}^{(y)})^t\|} \quad (19)$$

Movement decisions follow:

$$\begin{Bmatrix} \text{New nomadic individual if } p \geq 0.75 \\ \text{Reproduction of the alpha couple if } p < 0.75 \end{Bmatrix} \quad (20)$$

New individuals are generated by averaging the alpha couple. Specifically, the two top individuals, $(\overline{a}^{(x)})^t$ and $(\overline{a}^{(y)})^t$ are combined as $(\overline{a}^{reproduced})^t$, as shown in (21):

$$(\overline{a}^{reproduced})^t = p\frac{(\overline{a}^{(x)})^t + (\overline{a}^{(y)})^t}{2} \quad (21)$$

The lowest-scoring individual is chosen to start mating. The fitness function in LFRFO is computed using classification accuracy as the key metric:

$$Fitness = \max(P) \quad (22)$$

$$P = \frac{TP}{TP+FP} \quad (23)$$

Here, TP and FP represent the true positive and false positive counts, respectively.

III. EXPERIMENTAL EVALUATION

In this section, the AFCRFM-GCN model is evaluated on the Credit Risk dataset [21]. The method is implemented in Python 3.6.5 on a system with an Intel i5-8600k CPU, 4 GB

GPU, 16 GB RAM, 250 GB SSD, and 1 TB HDD. The model is trained using a learning rate of 0.01, ReLU activation, 50 epochs, a dropout rate of 0.5, and a batch size of 5. Out of 11 features, 9 are selected for the model. Table I describes the dataset.

TABLE I. DETAILS OF THE CREDIT RISK DATASET

Status	Number of instances
Default	7,108
Non-default	25,473
Total	32,581

Figure 2 presents the classifier outcomes of the AFCRFM-GCN model for the training phase (TRPHE) and testing phase (TSPHE) using a 70:30 split, with confusion matrices illustrating accurate detection of each class.

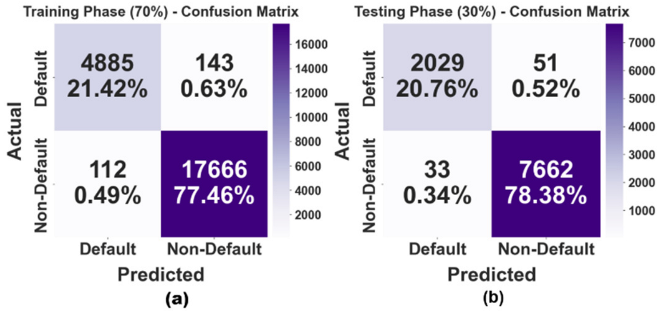

Fig. 2. Confusion matrices with a 70:30 split, illustrating default and non-default predictions: (a) training phase, (b) testing phase.

Table II presents the credit risk detection performance of the AFCRFM-GCN model at 70:30. On 70% TRPHE, the model achieves an average accuracy, precision, recall, F1-measure, and Matthews Correlation Coefficient (MCC) of 98.26%, 98.48%, 98.26%, 98.37%, and 96.74%, respectively. On 30% TSPHE, the model achieves 98.56%, 98.87%, 98.56%, 98.71%, and 97.43%, respectively.

TABLE II. PERFORMANCE OF THE AFCRFM-GCN MODEL FOR CREDIT RISK DETECTION USING A 70:30 SPLIT

Class label	Accuracy	Precision	Recall	F1-measure	MCC
TRPHE (70%)					
Default	97.16	97.76	97.16	97.46	96.74
Non-default	99.37	99.20	99.37	99.28	96.74
Average	98.26	98.48	98.26	98.37	96.74
TSPHE (30%)					
Default	97.55	98.40	97.55	97.97	97.43
Non-default	99.57	99.34	99.57	99.45	97.43
Average	98.56	98.87	98.56	98.71	97.43

Table III compares the AFCRFM-GCN model with existing models on the Credit Risk dataset [22, 23]. The AFCRFM-GCN model achieves a maximum accuracy of 98.56%, outperforming the Multilayer Perceptron (MLP), three-layer stacked LSTM, Gaussian Mixture (GM), Rotation Forest (ROF), XGBoost-SMOTE-ENN, Artificial Neural Network (ANN), and Gradient Boosting (GB) models. Additionally, the AFCRFM-GCN technique attains the lowest Computational Time (CT) of 6.88 s.

TABLE III. COMPARISON OF AFCRFM-GCN WITH EXISTING MODELS ON THE CREDIT RISK DATASET

Method	Accuracy	Precision	Recall	F1-measure	CT (s)
MLP [22]	76.89	79.55	84.40	82.78	25.56
three-layer stacked LSTM [22]	87.69	81.45	83.18	80.63	32.48
GM [22]	74.20	90.26	75.60	74.10	15.04
ROF [22]	77.00	88.23	85.30	90.61	28.12
XGBoost-SMOTE-ENN [22]	90.29	80.40	91.71	87.51	16.78
ANN [23]	85.33	91.82	91.08	84.08	11.09
GB [23]	87.75	84.84	89.63	82.55	11.16
AFCRFM-GCN (proposed)	98.56	98.87	98.56	98.71	6.88

Table IV presents an ablation study illustrating the impact of FS and parameter tuning on model performance. The AFCRFM-GCN model, which integrates both FS and tuning, achieves the highest metrics, with an accuracy of 98.56%, precision of 98.87%, recall of 98.56%, and F1-measure of 98.71%, outperforming the baseline GCN, GCN+POA, and GCN+LFRFO models.

TABLE IV. ABLATION STUDY ILLUSTRATING THE IMPACT OF FEATURE SELECTION AND PARAMETER TUNING ON MODEL PERFORMANCE

Technique	Accuracy	Precision	Recall	F1-measure
GCN	96.69	96.81	96.77	96.55
GCN+POA (with FS, without tuning)	97.39	97.34	97.49	97.28
GCN+LFRFO (with tuning, without FS)	98.03	98.19	98.02	97.82
AFCRFM-GCN (GCN with FS and tuning)	98.56	98.87	98.56	98.71

Table V reports the computational efficiency of the AFCRFM-GCN approach, which achieves only 43.01 G FLOPs, 986 MB GPU memory usage, and 10.06 s inference time [15]. It outperforms Logistic, Tree, KMV, ZPP, CNN, and CNN-LSTM models, attaining faster inference and lower resource consumption, proving its optimized structure for efficient financial credit risk forecasting.

TABLE V. COMPARISON OF COMPUTATIONAL EFFICIENCY IN TERMS OF FLOPS, GPU, AND INFERENCE TIME

Approach	FLOPs (G)	GPU memory (MB)	Inference time (s)
Logistic	212.00	3,230	49.35
Tree	140.00	2,089	13.29
KMV	205.00	4,090	21.73
ZPP	180.00	3,461	24.12
CNN	150.66	2,207	27.16
CNN-LSTM	109.00	4,367	17.89
AFCRFM-GCN (proposed)	43.01	986	10.06

IV. CONCLUSION

This manuscript proposed the Advancing Financial Credit Risk Forecasting Model using Graph Convolutional Network (AFCRFM-GCN). The AFCRFM-GCN model was designed to provide an intelligent and efficient framework for accurate credit risk prediction, supporting sustainable economic analysis. The approach incorporates min–max scaling for data normalization, Pelican Optimization Algorithm (POA)-based dimensionality reduction, Graph Convolutional Network (GCN)-based classification, and Levy Flight-based Red Fox Optimization (LFRFO) for parameter tuning. The comparison study demonstrated a superior accuracy of 98.56% over existing models on the Credit Risk dataset.

The limitations of this study include the restricted analysis on single-source financial datasets and potential challenges in capturing extremely complex, high-dimensional patterns. Future work may focus on improving the scalability of the AFCRFM-GCN approach to larger or multi-source financial datasets, integrating real-time data streams, and enhancing robustness against noisy or incomplete data for broader practical applications.

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