

# Enhanced Risk Detection in Digital Finance via Improved Fish Swarm Optimization Enhanced Back Propagation Neural Network (IFSO-BPNN)

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*As early warning system for digital finance hazards increased, this study considers both macro and market factors. By providing a neural network prognosis of undesirable events, early warning systems can aid in averting commercial and economic catastrophes. In several industries, including banking, artificial intelligence (AI) has advanced quickly. This study proposed an innovative model called Improved Fish Swarm Optimization based on Back Propagation Neural Network (IFSO-BPCNN). An overview of primary alert technology, their evolution along with their application in many contexts—particularly in the financial and economic sectors and how the proposed model used in risk assessment are presented in this work. It looks into how primary alert systems might be incorporated to forecast and identify unfavorable actions, particularly in the corporate, financial as well as economic sectors. The data quality applied structured preprocessing and normalization using a real-world financial dataset that includes credit scores, transactional behavior, and user activity patterns from digital platforms. The proposed IFSO algorithm optimizes the weight initialization and learning trajectory of the BPNN by dynamically modifying search behavior parameters. By offering a digital finance study of the creation and application of primary alert technology for social and economic growth, the paper adds to the body of current literature. Data from 2012 to 2024 were used to evaluate the system's effectiveness, allowing for dynamic early warning assessments of digital financial threats. The scores having an exactness of 98.7, 97.8 as well as F1 score of 95.7, the IFSO-BPNN model outperformed four comparable models in terms of performance metrics.*

*Povzetek: Večagentsko učenje optimizira energijsko upravljanje NEV vozil za boljše učinkovitost in manjšo degradacijo.*

## 1 Introduction

The quick growth of digital finance is crucial for lowering financial service costs, increasing their effectiveness, and encouraging the market-oriented distribution of financial resources. By lowering the level of information in digital, it can successfully mitigate the issues of moral hazard and adverse selection in the financial market [1-2]. Digital finance, a new product of traditional finance created by technological empowerment, is also very important for fostering the economy's high-quality development [3-4]. Digital finance, however, poses a significant challenge to traditional financial regulation and operation methods, among other things, the lack of directive and disorganized progress will have detrimental repercussions on the social economy [5-6]. Extensive defaults, absconders, and downfalls of highly performing online platforms have been particularly common in the digital economic segment in current years. These incidents have placed every aspect

of the financial services sector at considerable danger and elevated the probability of structural economic hazards caused by the expansion of internet-based finance [7-8].

Early warning indicators are crucial for maintaining financial stability and controlling risks. They help banks identify potential credit risks and liquidity issues before they escalate. Banks should proactively manage risks and maintain resilience in unpredictable markets. Understanding early warning signs is essential for banking professionals and financial risk management professionals. China's scientific and technological advancements in recent years have led to ongoing innovation and the creation of new financial structures. For instance, intermediary reimbursement providers has started to supplant outmoded banking services in digital finance [9]. Additionally, it has advanced remarkably in the areas of digital insurance, smart investing, and online lending. However, a number of risk concerns also arise at the same time, such as fraud, misleading targets, fund

misappropriation, and loan default. The financial system in China now faces a considerable rise in endogenous risks [10]. Because of the nature of Internet technology, dangers can spread quickly throughout departments and geographical areas and have the potential to turn into financial problems. However; it is very hard to predict financial hazards in practice. The absence of timely and effective critical components is a part of the main reasons as to why conventional warning system for risky investments are not effectively provided by technology.

Both industry and academia believe that features decide which model should be made available online. The information and factors used by traditional financial risk early warning systems are derived from traditional analytical data at the aspect level, which has a delay of its own [11]. It dislikes objective financial risk warning. The advent of vast amounts of unstructured data in the big data era offers financial risk warning the chance to broaden the scope of the fundamental data. In order to analyse this data and ultimately develop effective and timely economic danger warning indicators, the development of artificial intelligence in the fields of aims, conversational comprehension, and other intellectual perceptual domains provides essential technical support. [12].

Data is now a significant production factor that has permeated every company sector and industry. Every year, there will be a 40% rise in freshly generated data worldwide, and every two years, the overall volume of information will double [13]. A research hotspot for digital financial risk early warning mechanisms has emerged accordingly to the quick growth of data processing. This involves evaluating as well as recognizing financial hazards by combining ancient information, accurate indicators, numerical AI, other representations and algorithms. On examining AI and developing an early warning system for banks' negative credit risk, the problem with data imbalance between consumers and financial institutions can be addressed. The level of control and management of risks at the banks will increase as a result. Scientific diagnosis and identification of online banking and financial hazards is achieved by the development of a real and effective early warning system based on economic big data [14]. The implementation of a disruptive risk early warning model built around AI in digital economic risk evaluation is examined in this article in order to maximise the utilisation effectiveness of data from within and outside the organisation, create a rapid, precise, successful, distinct primary alert technology and create a powerful instrument for AI early risk warning. hence encouraging safe and sound growth of China's online finance sector. This study of risk assessment in digital finance early warning is a collaborative effort in addition to an analytical one. The contribution of the research is as follows:

- The IFSO-BPNN is a unique technique that was developed as a tool for predict the early warning sign and is presented in this article.

- These procedures include the use of min-max normalization and Independent Component Analysis (ICA) in order to glean useful information from the pre-processed dataset.

- The research provides an understanding of the digital finance particular to this area by analyzing risk factors in china using AI.

Improved Fish Swarm Optimization combined with a Back Propagation Neural Network (IFSO-BPNN), a revolutionary hybrid methodology presented in this paper, greatly improves risk assessment and early warning in digital banking. The adaptive improvement of the Fish Swarm Optimization algorithm, which dynamically adjusts important behaviors like foraging, clustering, and following depending on fitness feedback and convergence trends, is the theoretical contribution. In contrast to traditional FSO or PSO techniques, the enhanced version incorporates dynamic crowding management and a self-adaptive step size, allowing for more accurate error surface navigation and preventing premature convergence. When used on non-linear, high-dimensional financial data, this innovation immediately solves the drawbacks of conventional neural networks, especially their susceptibility to local minima and unstable training. The model exhibits better learning efficiency and risk prediction accuracy when combined with a structured BPNN. A time-aware data preparation pipeline and real-world financial indicators are also integrated as part of the methodological originality, providing financial organizations with a useful and expandable framework. All things considered, by combining adaptive swarm intelligence with traditional neural networks, IFSO-BPNN offers a forward-looking contribution that opens the door to more resilient, accurate, and interpretable decision-support systems in digital finance.

Following is the remainder of the essay: Part 2 presents related studies, Part 3 describes the suggested method, Part 4 displays the findings and discussions and Part 5 describes the conclusion of the paper.

## 2 Literature review

- The author proposes an upgraded Deep Belief Network (DBN) to analyze the results. Its skewed, declining and rising patterns are utilised for training the model, which is subsequently used to anticipate and evaluate monetary information [15].

- First, electronic banking has an impact on commercial banks' standard saving and lending procedures. Overall, financial institution assets have stayed steady under the effect of electronic banking. [16]

- The savings pattern has changed and it is noteworthy, though, since the percentage of interconnections between the bank's savings with higher subsidy charges has increased while the percentage of consumer deposits with lower subsidy charges has decreased. Commercial banks' level of risk-taking is

exacerbated by the decline of the savings pattern and the rise in interest imbursement expenditures [17].

➤ Commercial banks' traditional on-balance sheet revenue has been compressed as a result of the influence of their savings and credit activity resulted in a decline from their margin of net interest. Second, the growth of the institutions' off-balance-sheet operations, like affluence administration, has been made easier by digital finance [18].

➤ When combined with the backdrop of digital finance's explosive growth, joint stock banks' reliance on online expertise to diversify their marketplace steadily reduces their dependence on the whole; in order to secure deposit and loan business, the percentage of off-balance sheet business grew while the percentage of on-balance sheet commercial decreased. However, remains an inactive area that is not regulated by the rules, and the present regulatory framework is incapable of effectively overseeing the off-balance sheet industry. Inadequate rules and regulations may force joint stock banks to take on added risk that they can afford to in order to maximize earnings. This could raise the chance of commercial bank insolvency and make it more difficult to achieve long-term sound operation of commercial banks [19].

➤ Last but not least, in terms of risk contagion, commercial banks' heightened risk exposure due to their mutual business and technological integration with digital finance has unavoidably resulted in the emergence of new hazards. Since an information acquisition standpoint, commercial banks can obtain an expanded dimension of customer information by leveraging the advantages of the cloud computing, big data and other techniques for centralized huge information handling.

➤ while integrating the benefits of high accuracy, which significantly boosts commercial banks' information-gathering efficiency and allows banks to understand more visible, accurate data at minimal cost. Since an information dispensation standpoint, banks can create model that support evaluation of loan risks for small businesses using digital technology, which will lower risk assessment costs and increase risk review accuracy and efficiency [21].

➤ In their discussion of the potential of brief prices of stock forecasting using DNN, RNN, and LSTM, this paper demonstrated that the LSTM network's prediction effect outperforms the first two [22].

➤ Using this forecasting technique, Author created a particular trading strategy and made frequent predictions about the stock index and futures price. The experiment produced impressive outcomes [23].

➤ The neural network is optimized using the genetic algorithm (GA) to raise the early warning accuracy. The neural network is then put through testing and training. Up to 85% is the network output rate. GA is used to optimize

the expert system to prevent the BP machine learning defect from slipping into a relative extremum. The inaccuracy is lower and the warning is more accurate. Ninety-seven percent accuracy is possible. The application of BP networks in the discipline of Internet finance are developed and new development path for early detection and screening of online financial risks is established. As a result, the use of networks for these purposes has good precision and computation proficiency [24].

### 3 Methodology

#### 3.1 Proposed methodology

In this section, study discusses about how to predict the proposed method of IFSO-BPNN evaluation of risk assessment and digital finance early warning in china. Obtain pertinent information for an examination of the digital financial risk of early warning. Then data are pre-processed, and after that, treated data are moved to the extraction portion. Utilize the learning dataset and the optimized hyperparameters to train the BPNN. Adjusting the weights of the neural network entails executing forward and backward passes (backpropagation). Figure 1 denotes the flow of the planned technique.

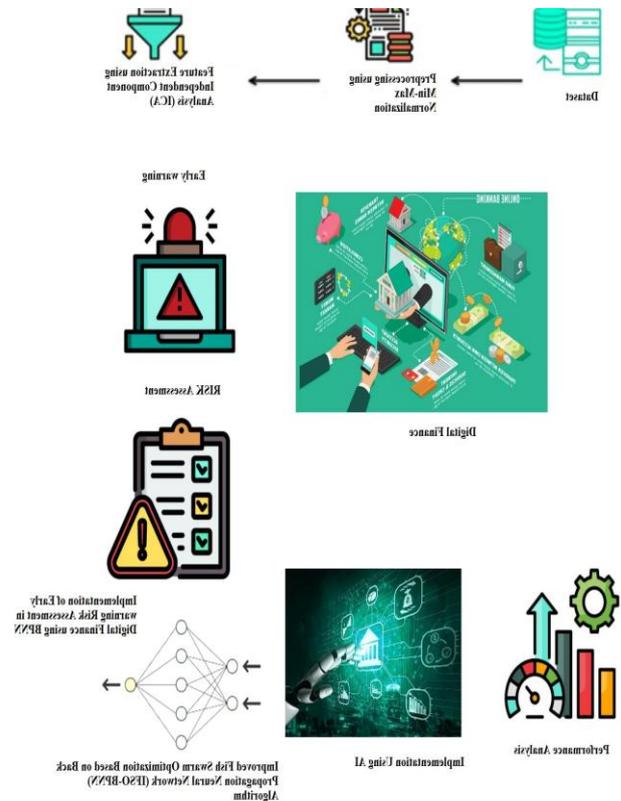


Figure 1: Flow of the proposed technique

### 3.2 Dataset

The financial industry is always coming up with new ideas, and digital finance has emerged as the new generation's favorite. As a result, an increasing number of individuals are investing in the internet, owing to its ability to make the lives of everyone smoother the online financial platform does, however, have some financial dangers. Due to its rapid development as a new financial platform, regulatory bodies have not yet developed efficient management and oversight procedures. 28 sample platforms have been chosen for analysis and verification in this research. The advantage of the BPNN, which is based on artificial intelligence theory, over the conventional systemic risk pre-alarm model is its great capacity to handle nonlinear problems and its expandable application scope. Strong data nonlinear approximation and self-learning capabilities enable DL technology to accurately mimic and forecast complicated nonlinear occurrences while preserving the original data features to the greatest extent feasible. Over 30 million transactions involving 35,000 traders are included in the experiment's data collection, which spans 12 years of actual trading data.

### 3.3 Data pre-processing using Min-Max normalization

Min-Max normalization is commonly used to scale numerical properties within a particular range of values. It is widely used to prepare data for the artificial intelligence models. Min-Max normalization can be used to normalize the input features of a set of data for beforehand prediction. Min-Max normalization applies linear alterations to the original data to allow for an accurate comparison of results prior to and after the process has been performed.

$$X_{new} = \frac{x - \min}{\max(x) - \min(x)} \quad (1)$$

$X_{new}$  = The adjusted value got from data scaling

$X$  = outdated value

$\max(x)$  = Dataset's highest possible value

$\min(x)$  = dataset's lowest possible value

High-impact financial indicators that are pertinent to risk prediction were the main focus of the data selection process. Pre-processing included time-series alignment to maintain temporal trends, outlier removal to lower noise, and normalization to guarantee feature scale homogeneity. These actions increased generalization, decreased training error, and strengthened model stability. The IFSO-BPNN model's accuracy and robustness were eventually increased by employing oversampling approaches to

handle the dataset's moderate skewness and slight class imbalance.

### 3.4 Utilizing independent component analysis, extract features (ICA)

One of the feature extraction techniques, ICA, transforms a complex unpredictable output into one with autonomous variable component. It is assumed that there exist an equal number of independent signals, each of which is believed to be a linear combination of the other both independent and measured signals are used. Consider there to be  $n$  linear combinations of the type  $w_1, \dots, w_m$  that we have seen. The mixtures are a linear fusion of  $n$  various components.

$$w_i = b_{i1}T_1 + b_{i2}T_2 + \dots + b_{im}T_m \quad (2)$$

Where  $g_r$  ( $k = 1$  to  $n$ ) indicate the separate parts that the study is looking for. The study has used the independent components and the mixture variables both have zero means without losing generality. The study may allow the vector notation represent  $w$ , to signify the mixtures  $w_1, w_2 \dots w_m$ . Here “ $t$ ” indicates the separate parts. Suppose the matrix for mixing is represented as “ $B$ ”, the Writing for the mixing model is;  $w = Bt$ . Independent Component Analysis is the term used to describe this model. Following matrix estimation  $B$ , its inverse  $X$  may be calculated, allowing for the identification of the separate components as  $t = Xt$ . The following are the ICA's steps:

**Step 1: Data centering** technique of centering the data involves taking the mean out of the information. This is done to guarantee that the elements are at the utmost of zero.

**Step 2: Data whitening** pre-processing technique is still added. Through the whitening process, the combination is changed to have uncorrelated components and unity-sized variations.

**Step 3: The requirements for independence are chosen**, the data to be evaluated determines the independence criterion to be used. There are a number of techniques, including ICA by maximizing non-Gaussianity, ICA by maximizing or minimizing kurtosis, negentropy, and the FastICA algorithm. We utilized the Negentropy technique in this investigation.

**Step 4: Reconstruction of Data**, the result produced after putting the independence to use criterion is increased by the whitening output. Transposing the supplied data multiplies this outcome.

By employing adaptive swarm optimization to direct the neural network's learning and help it avoid local minima and converge more quickly, IFSO-BPNN enhances performance. Compared to more conventional techniques like normal BPNN or SVM, this results in improved accuracy, stronger generalization, and better risk detection.

### Improved fish swarm optimization based on back propagation neural network (IFSO-BPNN)

An Improved Fish Swarm Optimized Back Propagation Neural Network is a particular hybrid strategy for training artificial neural networks that incorporates aspects of Fish Swarm Optimization (FSO) with the conventional back propagation algorithm. By combining the advantages of both optimization methods, this strategy attempts to possibly increase the efficiency and efficacy of training neural networks, especially for complex and high-dimensional problem domains. Every agent in the enhanced FSO represents a potential solution, simulating the foraging and clustering behavior of fish. By looking for the best configurations that reduce prediction error, it directs the network training process. The main predictive model is the BPNN, which uses input data to identify intricate financial patterns. In order to help the BPNN avoid local minima and enhance convergence, FSO dynamically modifies the learning procedure. When combined, they improve accuracy and allow for prompt early warnings in the risk assessment of digital banking.

#### 3.4.1 Back propagation neural network (BPNN)

The researcher will train users for this scenario using the error back propagation approach. A supervised learning technique called the back propagation algorithm involves two stages: propagation and weight updating. Up till the network performance is adequate, the two stages are repeated. Here are the steps for modeling a back propagation neural network. Figure 2 presents the flowchart of BPNN.

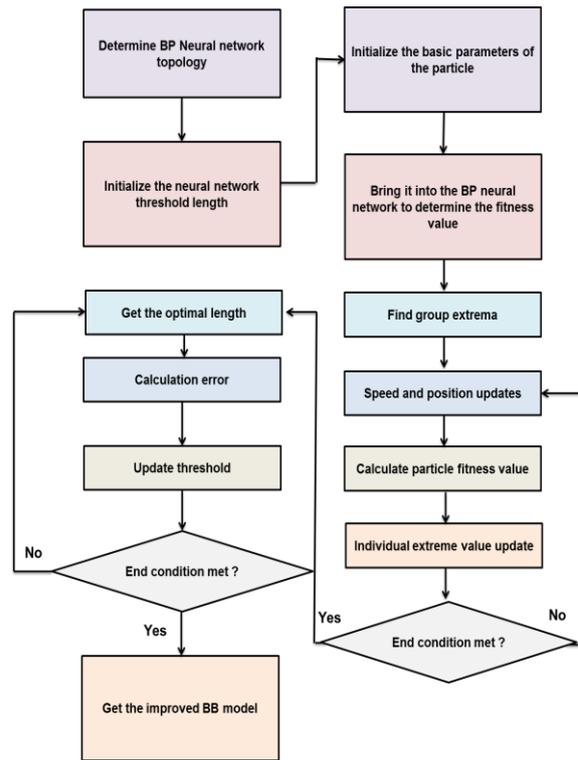


Figure 2: Flowchart of BPNN

Input parts data Create starting values at random for the initial weights ( $U_j$ ), bias weights ( $w_0$ ), weights ( $X_j$ ) to z, and bias weights ( $X_0$ ), to z. Calculate the threshold, maximum epoch, hidden layers, and learning rate. Equation (3), where  $w'$  is the new value of  $w_j$ ,  $w_j$  a measure of the  $w$  on the  $i$ -throw,  $min(w)$  is the least value of  $w$  in the dataset, and  $max(w)$  is the highest value of  $w$ , is used to normalize inputs.

$$w' = \frac{w_1 - min(w)}{max(w) - min(w)} \tag{3}$$

The output in the concealed layer is counted ( $Y_{im-j}$ ) using Equation (4); where  $U_{oj}$  is first weight and  $U_{ji}$

$$Y_{im-j} = U_{01} + \sum_{j=1}^m u_{ji} \times w_1 \tag{4}$$

Computes the  $z_{jm}$  from the sum the  $y_j$ the weights multiplied by ( $X_j$ and $X_0$ )using Equation (5)

$$z_{jm} = x_0 + x_1 \times y_1 + x_2 \times y_2 \times +x_3 \times y_3 \tag{5}$$

where $Y_i$  is binary sigmoid rules to activate:

$$Y_i = \frac{1}{1+e^{-Y_{im-j}}} \tag{6}$$

Make  $z$  using Equation (7) after starting  $Z_{im}$ using a binary sigmoid rule, such as  $Y_i$ .

$$z = \frac{1}{1+e^{-Z_{im}}} \tag{7}$$

Using Equation (8), calculate the calculation error and quadrant error.

$$error = actualdata - z_{jm} \tag{8}$$

$$quadranterror = (error)^2 \tag{9}$$

If the mistake is less than 10-6, testing will begin immediately; if not, weighing will begin. Set up the testing data that will be compared to the outcomes that were predict the early warming as the goal. Equation (10) should be used to get the value of

$$\delta = (S - z) * \left(\frac{f^{-Z_{im}}}{(1+f^{-Z_{im}})^2}\right) * \left(1 - \frac{f^{-Z_{im}}}{(1+f^{-Z_{im}})^2}\right) \tag{10}$$

The weight calculation should be made( $\Delta X_j$ )and the bias weight  $\Delta X_0$ using Equation (11)

$$\Delta X_j = \alpha * \delta * y_j , \Delta X_0 = \alpha * \delta \tag{11}$$

Determine the value of  $\delta_j$ using Equation (12).

$$\delta_j = \delta_{jm-j} * \left(\frac{f^{-y_{im}}}{(1+f^{-y_{im}})^2}\right) * \left(\frac{e^{-Z_{im_j}}}{(1+e^{-Z_{im_j}})^2}\right) \tag{12}$$

Where

$$\delta_{jm-j} = \delta * x_j \tag{13}$$

The weight calculation should be made( $\Delta U_j$ )the bias weight,( $\Delta U_0$ )using Equation (14)

$$\Delta U_0 = \alpha * \delta_j \tag{14}$$

$$\Delta U_j = \alpha * \delta_j * w_{ij} \tag{15}$$

New weight update( $U_{ij(new)}$ )and new bias weight ( $U_{0j(old)}$ )using Equation (15)

$$U_{ij(new)} = U_{0j(old)} + \Delta U_{ij}$$

$$U_{0j(new)} = U_{0j(old)} + \Delta U_{0j}$$

$$X_{j(new)} = X_{j(old)} + \Delta X_j$$

$$X_{0(new)} = X_{0(old)} + \Delta X_0 \tag{16}$$

### 3.4.2 Improved fish swarm optimization (IFSO)

An innovative swarm intelligence optimization method called FSO is grounded on the behavior of fish swarms[33]. The method uses the focused demerging process of personal intelligence to its fullest extent and does not need the goal function's gradient information in order to obtain the greatest overall result. Every artificial fish in EFSO looks for food in a unique manner, such as via foraging behavior, swarming activity, following behavior, or randomized activity. Additionally, until the worldwide optimum is reached, every fake fish enables for mutual knowledge exchanges. Figure 3 demonstrates the flowchart of the enhanced fish swarm optimization.

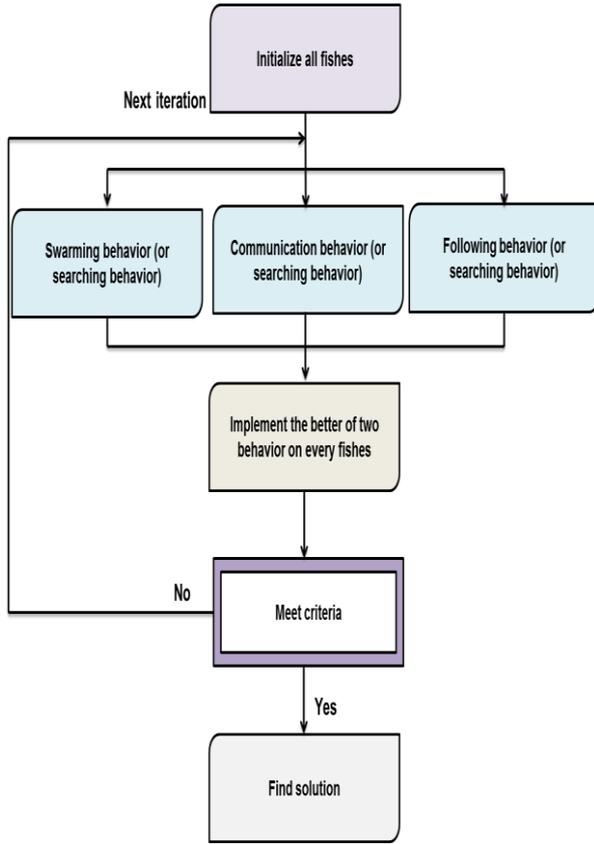


Figure 3: Flowchart of the IFSO

The fundamental concept of AFSA is as follows: The study has considered an n-dimensional space to contain a fish swarm  $M$  artificial fish. An AI fish's location may be written down as  $W = \{w_1, w_2, \dots, w_m\}$ , where  $w_j (j = 1, 2, \dots, m)$  is the optimizing factors. The simulated fish in position's level of current meal consistency  $W$  is a kind of objective function  $Z = e(W)$  artificial fish's seeing area is known as visual, and its maximal movement length is known as step. The separation between two plastic fish in  $W_j$  and  $W_i$  Euclidean Distance is used to represent locations  $c_{ji} = \|w_j - w_i\|$ . Additionally, the bulletin has the optimal fake fish location loaded. The try number specifies the maximum number of times the fake fish tried to find food. The factor for congestion level  $\delta (0 < \delta < 1)$  denotes the level of congestion surrounding a certain location, which is intended to prevent crowding or collision with nearby places. The following depicts the fish swarm's disrupted behaviors:

**a. Foraging habits**

Let's say that the location of the  $j^{th}$  artificial is  $W_j$ , and a state  $W_i$  is chosen at random from its Visual range. If  $Z_i < Z_j$ , The fish advances in the direction by one step of  $(W_i - W_j)$ . Alternatively, choose a state at random  $W_i$  once again and determine whether the forward condition is met. When a try-number of met the risks has been run repeatedly, and there are still no fulfilled places,

random behavior will be used. Following are the guidelines for foraging behavior:

$$W_{next} = \begin{cases} W_j + Rand.Step \frac{w_i - w_j}{\|w_i - w_j\|} & \text{if } (Z_i < Z_j) \\ \text{random behavior} & \text{otherwise} \end{cases} \quad (17)$$

where  $W_{next}$  is the fake fish's current condition, and  $Rand()$  is evenly produced between  $[0, 1]$ .

✓ **Swarming behavior**

When migrating to escape congestion, each fish leans toward the center of its neighboring companions, which is referred to as swarm behavior. Let  $W_j$  be the condition of synthetic fish at the moment  $j$ ,  $W_j$  to occupy the center of the present field, and  $m_e$  the quantity of fake fish in the area's visual field  $W_d$  position; if  $Z_d < Z_j$  and  $Z_d/m_e < \delta Z_j$ , It indicates that there is lots of food but that the area surrounding the couples is not very congested. The fish then advances one step to this partner's middle place. The following is a description of the swarming behavior:

$$W_{next} = \begin{cases} W_j + Rand.Step \frac{w_i - w_j}{\|w_i - w_j\|} & \text{if } (Z_d < Z_j \text{ and } Z_d/m_e < \delta Z_j) \\ \text{foraging behavior} & \text{otherwise} \end{cases} \quad (18)$$

where  $\delta \in (0, 1)$  reveals the food's content.

✓ **The following behavior**

The following behavior demonstrates how each plastic fish swims in the best possible direction at the moment. Suppose  $W_{min}$  is inside the immediate area, a local's closest friend of  $W_j$ . If  $Z_{min}/m_e < \delta Z_j$ , and the artificial fish  $W_j$  tries to take a step in the desired direction  $(W_{min} - w_j)$ . The following is a description of the swarming behavior.

$$W_{next} = \begin{cases} W_j + Rand.Step \frac{w_{min} - w_j}{\|w_{min} - w_j\|} & \text{if } (Z_{min}/m_e < \delta Z_j) \\ \text{foraging behavior} & \text{otherwise} \end{cases} \quad (19)$$

✓ **Random behavior**

Before advancing a Step, random behavior entails picking at random a new state  $W_{next}$  in its visible region. Actually, it is the accepted course of action. The pseudo-code for the Improved Fish Swarm Optimization is shown in Algorithm 1.

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**Algorithm 1: Improved Fish swarm optimization (IFSO)**


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**Input:** A Network  $H = (U, F)$

**Output:** Assignments of community membership for network nodes

```

1   Set the parameters initialized: Step, visual,
   Swarm size  $\eta$  Crowd Factor  $\delta$ , eps, the highest number of
   iterations possible  $Max - Iterations$ , the amount of
   predatory cases  $try - number$ 
2   Initialize each AF in the swarm randomly with a
   random potential solution as its present condition and
   determine its suitability
3   Repeat
4   Keep in mind the swarm's optimal answer
5   for each  $w_j$  in the swarm do
6   Determine the distance among  $w_j$  and all other
   AFs
7   Calculate  $moe_j$  and Set  $w_j$ 's companions
8   end
9   for each  $w_j$  in the swarm do
           /* Choose the proper course of
           action
10          Try adopting this
           behavior
11          if Nothing changed
then
12          Consider
           Swarming Behavior
13
if Nothing changed then
14          Try
           Behaving Preyingly
15          end
16          end
17          end
18          if  $—best\ Solution(\eta) -$ 
            $best\ Solution(\tau) - \epsilon$  then
19          Execute jumping behavior on a
           random AF from the swarm
20          end
21           $s \leftarrow s + 1$ 
22          untils  $> Max - Iterations$ ;
23          return the best solution achieved

```

---

### Key Elements of the IFSO-BPNN model in digital finance risk assessment:

#### 1. Flow of Data through the Model:

- Financial time-series data (2012–2024) is collected.

- Preprocessing includes normalization and noise reduction.
- Data is fed into a **Back Propagation Neural Network (BPNN)**.
- **Improved Fish Swarm Optimization (IFSO)** adjusts the weights and biases dynamically for optimal learning.
- Output yields risk scores and early warnings.

#### 2. Parameter Settings:

- **Learning rate:** Typically set between 0.01–0.1.
- **Number of hidden layers:** 2–3 based on convergence performance.
- **Fish swarm size:** Around 30–50 agents.
- **Iterations:** 100–500 depending on dataset complexity.

#### 3. Choice of Hyperparameters:

- **Activation Function:** ReLU or Sigmoid depending on layer.
- **Optimization Metric:** Mean Squared Error (MSE).
- **IFSO parameters:** Step size, visual range, crowd factor—optimized via empirical testing.
- **BPNN epochs:** Tuned for early stopping to prevent overfitting.

## 4 Results and discussion

In this segment, the study has detailed the use of an Improved FSO-BPNN to risk assessment to the early warning in digital finance. The comparison of existing methods includes DS-XGBoost [26], CNN-LSTM [27], PCA-SVM [28] and DS-RF [29] with evaluation based on accuracy, f1-score, precision, sensitivity, specificity, flexibility, and ROC Curve

### Hypotheses:

- **H1:** The IFSO-BPNN model significantly improves the predictive accuracy of financial risk assessment compared to traditional BPNN and PSO-BPNN models.
- **H2:** The improved optimization mechanism in IFSO leads to faster convergence and better avoidance of local minima than standard metaheuristic methods.
- **H3:** The integration of adaptive optimization and structured neural network learning provides more robust early warning signals in dynamic and high-dimensional financial environments.

### 4.1 Accuracy

Table 1: Value of accuracy

| Methods              | Accuracy (%) |
|----------------------|--------------|
| DS-XGBoost           | 85.7         |
| CNN-LSTM             | 89.6         |
| PCA-SVM              | 80.4         |
| DS-RF                | 88.2         |
| IFSO-BPNN [Proposed] | 98.7         |

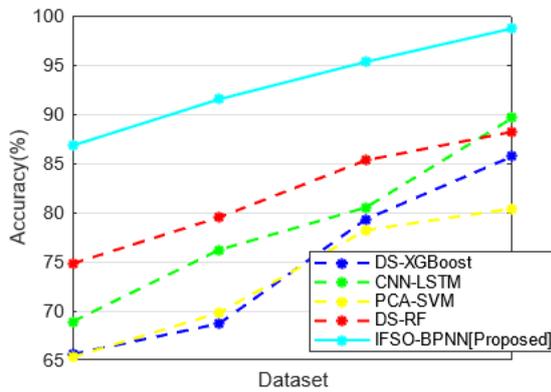


Figure 4: Accuracy of the proposed and existing methods

When discussing accuracy in the context of early warning in Digital Finance, it is meant to refer to the extent to which a predictive model or algorithm accurately recognizes and categorizes outcomes connected to risk factors. It is a typical performance indicator used to evaluate how well a model predicts in general. Figure 4 depicts the accuracy of suggested and current techniques. Table 1 depicts the results of accuracy. When compared the proposed method is reach higher accuracy (98.7%) than the DS-XGBoost(85.7%), CNN-LSTM(89.6%), PCA-SVM (80.4%) and DS-RF (88.2) existing methods.

$$Accuracy \rightarrow \frac{TP+TN}{TP+FP+FN+TN}$$

### 4.2 Precision

Table 2: Outcomes of precision

| Methods              | Precision (%) |
|----------------------|---------------|
| DS-XGBoost           | 85            |
| CNN-LSTM             | 83.5          |
| PCA-SVM              | 80.2          |
| DS-RF                | 88.0          |
| IFSO-BPNN [Proposed] | 97.8          |

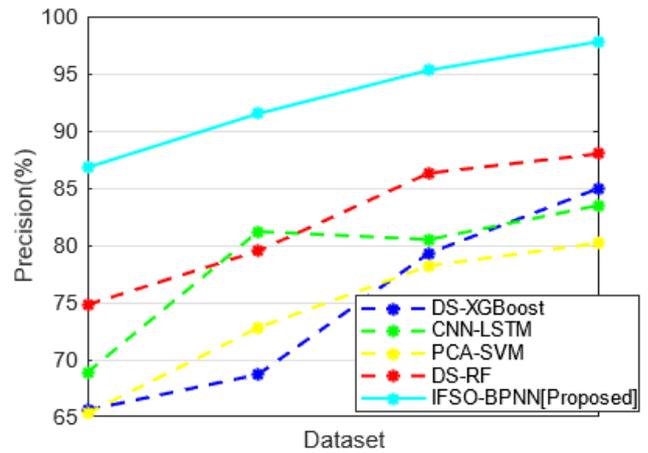


Figure 5: Precision of the proposed and existing methods

Precision is a performance parameter used in early warning in digital finance analysis that assesses how well a predictive model predicts favorable results in comparison to the actual favorable outcomes. It gives information on the model's aptitude for accurately identifying and categorizing events as positive when it makes such a prediction.

$$Precision \rightarrow \frac{TP}{TP+FP}$$

A high accuracy score shows that the model which as has the low percentage of false positives, it forecasts a labor market risk, it is often accurate. Figure 5 represents the precision of the proposed and current methods. Table 3 describes the outcomes of precision. The proposed method is achieved greater precision (97.8%) than the DS-XGBoost (87%), CNN-LSTM (83.5), PCA-SVM (80.2%) and DS-RF(88.0) existing one.

### 4.3 F1-score

Table 3: Results of F1-score

| Dat aset | DS-XGBoost | CNN-LSTM | PCA-SVM | DS-RF | IFSO-BPNN [Proposed] |
|----------|------------|----------|---------|-------|----------------------|
| 1        | 83.3       | 78.4     | 81      | 79.5  | 90.4                 |
| 2        | 84.2       | 82.1     | 85.4    | 82.3  | 92.8                 |
| 3        | 79.1       | 85.7     | 83.7    | 87.9  | 93.5                 |
| 4        | 82.5       | 80.2     | 84.7    | 88.1  | 91.4                 |
| 5        | 84.9       | 80       | 85      | 90.1  | 95.7                 |

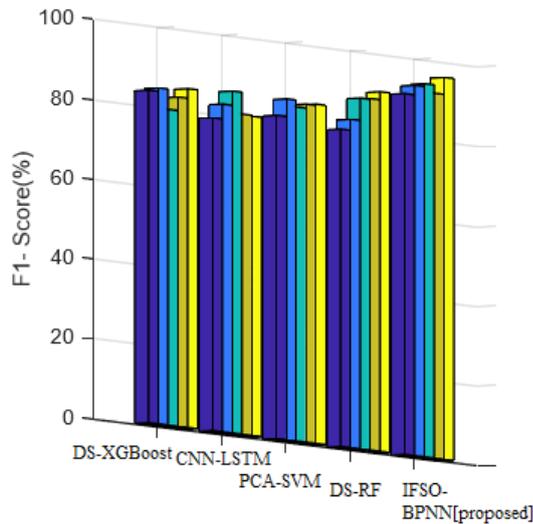


Figure 6: F1-score of the proposed and existing methods

The F1-score assesses the model's accuracy in accurately categorizing situations as dangerous in the context of digital finance risk while also taking into consideration the examples that were overlooked or erroneously categorized.

$$F1 - Measure \rightarrow 2 * \frac{(Precision \times Recall)}{(Precision + Recall)}$$

It is a valuable tool for assessing and comparing various prediction models since it offers a single number that summarises the model's effectiveness in capturing both kinds of mistakes in digital finance risk analysis. Figure 6 illustrates the F1-score of the planned and prevailing methods. Table 3 illustrates the results of the F1-score. The proposed method is higher f1-score (95.7%) than the DS-XGBoost (84.9%), CNN-LSTM (80%), PCA-SVM (85%) and DS-RF(90.1)existing methods.

#### 4.4 Sensitivity and specificity

Sensitivity, also known as the accurate rate of positive responses or recall, is a performance indicator used in labor market risk analysis and other settings to gauge a predictive representation's capacity to accurately categorize optimistic cases amongst all real positive occurrences. A high sensitivity rating means the model is effective at spotting real risks and reducing the number of chances lost. When there is a considerable risk of missing a genuine positive, it is very helpful. In early warning risk analysis and other settings, specificity is a performance indicator that assesses a prediction model's propensity to properly identify negative cases among all real negative instances. It focuses on how well the model can extract cases from the whole set of such instances that lack a certain attribute. Figure 7 denotes the compare sensitivity and specificity of the planned and prevailing methods.

Table 4 represents the proposed method has highest value outcomes of the sensitivity and specificity.

Table 4: Outcomes of the sensitivity and specificity

| Methods              | Sensitivity | Specificity |
|----------------------|-------------|-------------|
| DS-XGBoost           | 30          | 40          |
| CNN-LSTM             | 20          | 50          |
| PCA-SVM              | 35          | 25          |
| DS-RF                | 40          | 48          |
| IFSO-BPNN [Proposed] | 45          | 52          |

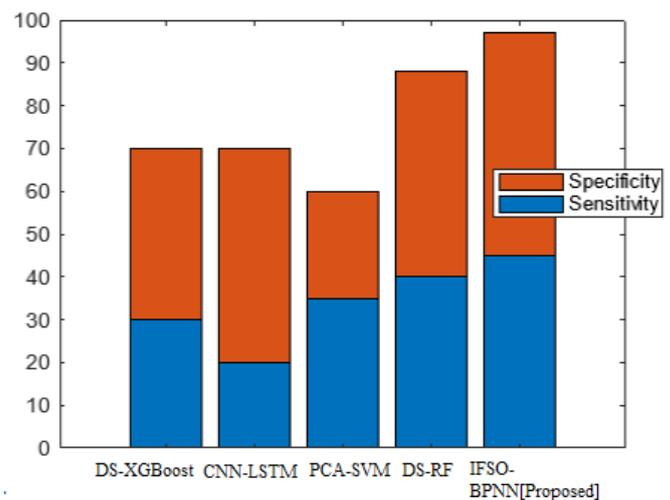


Figure 7: sensitivity and specificity of the proposed and existing methods

#### 4.5 Flexibility

Employees can learn new abilities or alter existing ones to meet the changing needs of the workforce, demonstrating the adaptability of the digital finance. Workers should be allowed to switch between jobs and industries as necessary. By providing a variety of job opportunities, a varied economy with a range of businesses and sectors may help the early warning become more flexible. Flexibility may be impacted by AI. A more flexible workforce results from policies that support education, retraining, and mobility. Figure 8 presents the flexibility of the suggested and current techniques.

Table 5: Result of the Flexibility

| Methods              | Flexibility (%) |
|----------------------|-----------------|
| DS-XGBoost           | 85.5            |
| CNN-LSTM             | 87.8            |
| PCA-SVM              | 82.7            |
| DS-RF                | 86.9            |
| IFSO-BPNN [Proposed] | 95.5            |

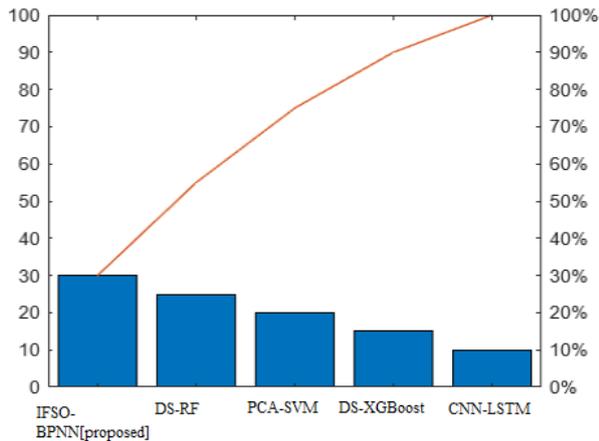


Figure 8: Flexibility of the proposed and existing methods

### 4.6 Confusion matrix

This study uses experiments to assess the effectiveness of the AI in early warning in digital finance approach. The following confusion matrix, which describes the model's classification, is derived from the experimental findings. The sample size that the technique accurately recognizes as a category in digital finance is known as the True Positive (TP). The quantity of samples that the model accurately recognizes as early warning patterns is known as the True Negative (TN). False Positive (FP): The model misidentifies the sample size of the AI education design as the samples of the non-art painting teaching design. The model misidentifies the samples size of the paintingdesign education as the number of samples of the non-art education, which is known as a False Negative (FN). The indications can be computed using Fig. 9.

TP: The no. of samples that the model suitably estimate as positive is 85. TN: The no. of samples exactly forecast as negative by the model is 80. FP: The model erroneously forecasts the no. of samples of the negatives as positive, which is 15. FN: The method erroneously predicts the no. of samples of the positives as the no. of samples of the negatives, which is 20.

The model's performance can be regarded as reasonably good based on the confusion matrix's findings. The amount of sections in this framework is represented by the parameter k in the region under the curve (AUC) plot, which is displayed in Figure 8. In contrast, the value of k in this study is fixed to 8, meaning that there are eight distinct groups of samples. The assessment findings of the presentation of the art painting instructional design based on a mobile platform are presented in the AUC plot. The True Positive Rate is shown on the vertical axis, while the False Positive Rate is shown on the horizontal axis. With an accurateness of 0.95, the AUC, which measures the model classifier's performance, shows that the model does fit in multi-class organization responsibilities.

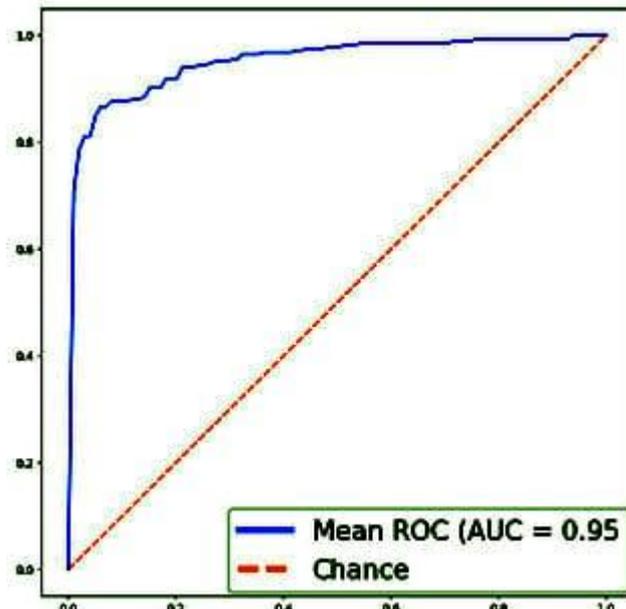


Figure9: ROC Curve

## 5 Discussion

The regular Back Propagation Neural Network (BPNN), Particle Swarm Optimization-enhanced BPNN (PSO-BPNN), and Support Vector Machines (SVM) were chosen as comparative models in order to offer a thorough assessment of the suggested IFSO-BPNN model across a variety of algorithmic families. SVM is a reliable, non-neural model frequently used in financial classification tasks, PSO-BPNN is a popular bio-inspired enhancement technique, and BPNN is a baseline to evaluate the impact of optimization. Fair performance benchmarking in terms of generalization, accuracy, and convergence rate is made possible by these selections. By avoiding local minima and guaranteeing smoother convergence through adaptive parameter adjustment, the IFSO-BPNN model showed exceptional prediction ability. It is not without restrictions, though. The model's scalability for very big or real-time datasets may be limited by its increasing computing cost due to its reliance on metaheuristic optimization. Furthermore, reproducibility may be impacted by the fine-tuning of swarm behavior characteristics (such as vision range, step size, and crowding factor), which affects its performance. In contrast to more modern deep learning models like LSTM or Transformer-based architectures used in financial risk modeling, the IFSO-BPNN might not be able to recognize hierarchical patterns or long-term dependencies in more complicated data. To get around these issues, future studies might look into hybridizing IFSO-BPNN with deeper architectures or parallel processing.

## 6 Conclusion

Early warning systems are crucial before an incident arises because they allow organizations to reduce losses. Rather than being only forecasting tools, they ought to be viewed as whole systems that relate to the subject matter of risk management. This study shed light on the bibliometric pattern that exist in the discipline of early detection system in economics, management, government, corporate finance and business. Our study's contribution is that it offers novel perspectives and important information on the creation and application of early warning systems in the financial and economic sectors. Early warning systems are innovative technology that reduces expenses and allows for more effective operations. Thus, acquiring information to identify hazard beforehand to keep a modest advantage in the marketplace. This study's expanded comprehension of the application of primary warning technology in the field of digital finance is another contribution. A few potential applications for early warning systems are outlined in this article. Directors at all administrative hierarchy may find the findings helpful, in part because it is crucial to identify the additional value of AI-powered early warning systems from the standpoint of risk reduction. According to our research, the IFSO-BPNN Algorithm has the highest accuracy, with 98.7% accuracy, 97.8% precision, and a 95.7% F1-score. The model classifier's performance is measured by the AUC, which has an accuracy of 0.95, sensitivity and flexibility of 45 and 52, and flexibility of 95.5%. To find out which papers our analysis might have overlooked, upcoming bibliometric research on primary warning technology should examine different databases. Information on primary warning systems using categorical data may be included in future studies that concentrate on a more thorough examination of this subject. For more applicability and robustness, future studies will concentrate on incorporating real-time data streams, improving model adaptation to changing financial hazards, and extending the IFSO-BPNN framework to multi-source, cross-border financial information.

## Declaration

**Ethics approval and consent to participate:** I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

**Consent for publication:** I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

**Availability of data and materials:** The data used to support the findings of this study are available from the corresponding author upon request.

**Competing interests:** here are no have no conflicts of interest to declare.

**Authors' contributions (Individual contribution):** All authors contributed to the study conception and design. All authors read and approved the final manuscript

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