Optimizing Convolutional Neural Networks with Fish Swarm Algorithms for Mitigating Financial Risks in the Digital Economy

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Due to the fast growth and development of the digital economy, the method of exchanging and transacting money has changed drastically. However, this change also poses a previously unseen threat to the economy, particularly during periods of unexpected financial disasters. Complex emergency risk avoidance tactics are necessary in these kinds of scenarios. This project aims to construct a robust framework that can forecast and mitigate the impact of sudden financial crises on the digital economy using an intelligent fish swarm-optimized ensemble convolution neural network [IFSO-ECNN]. The proposed Deep Learning (DL) approach constructs prediction models by integrating relevant socioeconomic factors, market indicators, and a wealth of historical financial data. The financial data was prepared by applying min-max normalization. The features were extracted from the preprocessed data using kernel principal component analysis (K-PCA). This study contributes to our knowledge of how IFSO-ECNN can help the digital economy better prepare for and recover from unexpected financial catastrophes. Using both historical and real-time data, the suggested framework shows that it is possible to make smart judgements and proactively reduce financial risks. Experimental results validate the validity of the IFSO-ECNN model at 97.14% accuracy, 95.23% sensitivity, 96.25% specificity, and a 95.51% F1-score, surpassing the previous baseline traditions. The new hybrid model is more efficient than the previous models and has a new impact on AI-powered financial risk forecasting. The evaluation provides policymakers, financial institutions, and enterprises with useful insights for developing more resilient strategies in the face of unforeseen economic shocks by integrating modern IFSO-ECNN methodologies with domain experience.

Povzetek: Članek obravnava napovedovanje nenadnih finančnih kriz v digitalnem gospodarstvu. Predlaga metodo IFSO-ECNN, ki združuje min–max normalizacijo, nelinearno izluščanje značilk s K-PCA ter optimizacijo konvolucijskih nevronskih mrež z algoritmom inteligentnega ribjega roja. Model doseže visoko točnost in robustnost pri obvladovanju finančnih tveganj.

1 Introduction

The increasingly digital economy is transforming the way financial trading: transactions, capital flows, and business activities occur through interconnected digital platform. Digital platforms enable economic activity to move faster and more cheaply than ever before [1]. However, they also introduce new financial risks, from hacking and algorithmic trading failures to sudden market crashes. These emerging risks are often unexpected and demand large-scale detection and mitigation strategies [2]. The digital transition is altering not just the velocity of money but also the organizational structure and economic behavior of all markets [3]. Traditional financial structures are being altered progressively with digital systems, which opens up opportunities for more complexity and accelerated change [4]. The digital economy manages data to determine the next best steps in real-time, with interrelated systems requiring communication among automated agents and performance relying on artificial intelligence and big data analytics. Alternatives to traditional markets are being adopted fast to create competitive and sustainable prospects [5].

The digital economy will also bring new dynamics and dependencies that will affect financial stability. As data is generated and used at ever-increasing rates, decision-makers must interpret changes in financial patterns and trends that occur more rapidly than ever before [6]. Complexity continuous to increase, creating a greater need to understand economic behavior and the complexities in play during times of hardship, uncertainty, and volatility, and how this relates to financial conditions. In addition, digital systems are affected by numerous socioeconomic indicators, market signals, and geopolitical events [7]. The capability to quickly and intelligently respond to these influences has been termed a key condition of contemporary financial thinking. As businesses and investors, along with regulators, to examine move ahead with forward-looking approaches that allow for early detection of potential disturbances to the economic order, and better measures to allow for the necessary prevention [8].

The increasing digitization and interconnectivity of financial markets with the financial world mean that resilience and adaptability are vital. It has never been more critical to formulate a coherent approach to risk management and forecasting that contributes to sustainability in financial planning [9]. This means that data analytics and smart decision-support are, more than ever, relevant as we consider the role of policy, financial health, and the longer-term sustainability of economies in a digital age [10]. The recent financial disruptions across the world have underscored the weaknesses of established forecasting frameworks. Traditional statistical methods, along with many machine-learning methods, do not adjust well to the volatility and high dimensionality of contemporary financial systems. This suggests a clear, compelling need for more intelligent, adaptive, and real-time systems that can forecast and mitigate sudden financial disasters in digital ecosystems.

To tackle this issue, the research suggested an innovative intelligent fish swarm-optimized ensemble convolutional neural network (IFSO-ECNN) in an attempt to yield accurate indicators and help reduce sudden financial crises in the digital economy. By integrating deep learning models, socioeconomic indicators, and real-time data, its performance improves forecasting accuracy, thereby enabling proactive decision-making to fortify economic resilience against unforeseen disruptions through intelligent, data-based risk management approaches. The research's key contribution is as follows:

- The dataset of this research includes historical financial information and real-time socioeconomic (soc) and financial market indicator data.
- The financial data are pre-processed using min-max normalization to scale the features between 0 and 1. This preprocessing step will improve the convergence of the model and help to avoid the dominance of features during the training.
- The K-PCA method was used to extract nonlinear and high-variance features from the normalized features. K-PCA can reduce dimensionality while also allowing the underlying financial characteristics to be retained and utilized for prediction modelling.
- The research proposes an IFSO-ECNN for crisis prediction. The hybrid deep learning (DL) model combines feature learning, optimization, and ensemble prediction to provide strong forecasts.

This section of the paper follows the same format: Section 2 reviews literature, Section 3 details IFSO-ECNN, Section 4 presents experiments and results, and Section 5 summarizes findings and suggests future research.

2 Literature review

A survey of the literature, also known as a review of literature or systematic review, is a necessary component of research in many fields. It comprises a careful examination and interpretation of the collection of research, as presented in Table 1.

Table 1: Relevant studies

References	Objectives	Summary of findings
Poonia et al. [11]	To create a powerful AI-based framework, Nature-inspired Red-optimized Stochastic Artificial Neural Network (NRFO-SANN) for early identification and prediction of global financial crises, particularly those affecting small and medium-sized enterprises (SMEs).	The NRFO-SANN model obtained 96% accuracy, 96.5% F-score, 94% sensitivity, and 95% specificity while detecting financial irregularities in 1 second, improving global crisis prediction and economic resilience.
Asif [12]	To create an AI-based dynamic risk management model for equity portfolios, which will improve resilience during crises such as pandemics and market crashes.	The approach outperforms standard static models by combining real-time data and machine learning, providing better risk prediction and portfolio performance under turbulent environments.
Borowski et al. [13]	The research was conducted to better comprehend how internal and external contextual elements affect customers' decisions for ride-sourcing services during small-scale urban evacuations.	To demonstrate the results, three ride-sourcing initiatives based on various evacuation needs are employed.
Luo et al. [14]	The findings provide empirical support and a basis for making decisions in favor of the cooperative relationship between DIE and GDE.	The study advocates accelerating the development and upkeep of digital infrastructure, strengthening DIE's potential as an enabler, and creating a differentiated DIE strategy.

Quan et al. [15]	To improve corporate financial risk management and crisis warning systems, a hybrid model combining gated recurrent units-temporal convolutional networks (GRU-TCN) and attention mechanisms is proposed.	The suggested model enhances risk prediction accuracy, efficiency, and stability by 46.8% in floating-point operation and 48.5% in inference time, exceeding baseline models.
Yin [16]	To create a machine learning-based early warning system for systemic financial crises utilizing macroeconomic data from 35 nations (1970-2022).	Ensemble models (Random Forest, XGBoost) had an AUROC of 0.97, beating conventional models and detecting major nonlinear risk variables such as GDP growth, trade, and demography.
Seddighi et al. [17]	The exploratory research approach used in this work consists of two stages and seeks to close the gap. To determine how much the Sharing Economy (SE) is taken into account in disasters, the researchers first undertake a comprehensive literature review.	The research makes two contributions in total. First off, the research provides a fresh perspective on the literature by identifying the various functions that the SE may play in disasters. Second, the study offers methods for collaboration and partnerships that can support coordination and logistics in catastrophes from the point of origin through delivery.
Odion et al. [18]	To investigate the role of deep learning algorithms (RNN, LSTM, and GAN) in revolutionizing financial risk assessment and business analytics via real-time modeling and predictive insights.	Deep learning improves fraud detection, credit risk assessments, and investment strategies by analyzing complicated, real-time data. The study emphasizes its impact on accuracy, ROI, and resilience, and includes case studies demonstrating practical success.
Juraboeva et al. [19]	To evaluate the use and efficacy of AI and machine learning approaches in predicting financial crises compared to classic econometric models.	AI technologies such as RNN, LSTM, transformers, and sentiment analysis outperform classical models when dealing with nonlinear and high-dimensional data. The study identifies research gaps and suggests improvements to model credibility, cross-country generalization, and real-time forecasting.
Murugan [20]	To create a big data-driven financial risk prevention model utilizing KNN, logistic regression, and XGBoost, to forecast loan defaults and optimize investment risk.	Cluster-based machine learning models, particularly XGBoost, outperformed traditional methods for predicting loan defaults. With IoT implementation, the model maintained ideal consumption stability below 5% and investor wealth risk between 0.02 and 0.09, hence improving real-time financial risk control.
Song et al. [21]	Create an accurate and efficient financial distress prediction model utilizing a deep learning architecture that combines CNN, BiLSTM, and attention methods.	The 1CNN-1BiLSTM-AT model beat ten alternatives in accuracy and speed when verified using 2025 data from two firms across 100 tests, demonstrating good real-world stability.
Sefidi [22]	To improve systemic risk identification, a market crisis prediction model will be developed that incorporates multilayer network analysis, Granger causality, Random Forest, and LSTM.	The hybrid model surpasses previous techniques by properly capturing temporal and cross-sector connections, allowing for improved forecasting of market instability and offering early warning tools to policymakers.
Chinonyerem et al. [23]	Using large-scale financial data from 2010 to 2024, develop and compare machine learning models for accurately predicting corporate financial distress in US companies.	XGBoost outperformed Neural Networks, Random Forest, and SVM in terms of accuracy (93.2%), proving ensemble models as the strongest instruments for predicting early financial hardship.

2.1 Research gap

The accelerated pace of the digital economy has revolutionized financial transactions but also introduced vulnerabilities to unexpected crises. Existing forecasting institutions struggle to effectively predict and manage such financial shocks, paving the way for new, smart solutions. Small and medium-sized enterprises (SMEs) are most prone to financial crises because they lack resources and are poorly supported with risk buffers. Current prediction systems lack real-time accuracy. There is a necessity for a reliable AI-based system that can precisely identify financial anomalies well ahead of time and improve world crisis prediction to aid in economic resilience [11]. Conventional models cannot forecast country-level systemic financial crises with macroeconomic nonlinearities [16]. For the 1970–2022 time period, with financial interconnectedness and volatility in the global economy, there exists an urgent need for an efficient early warning system. The present study fulfils the need for machine learning ensemble models using large-scale economic indicators so as to correctly and promptly detect crises. The IFSO-ECNN methodology proposed is more than the issue of sudden financial crises in the digital economy, as it synergizes fish swarm optimization and deep learning. The hybrid model enhances risk estimation, facilitates timely decision-making, and provides policymakers and financial institutions with a solid tool for anticipatory crisis management and strategic resilience.

3 Methodology

This sub-section explains the complex proposed IFSO-ECNN architecture in detail. The model consists of various steps, including initially discovering the preprocessing of financial time-series data through min-max normalization, then extracting nonlinear features through K-PCA, then optimizing convolutional neural network parameters through an enhanced fish swarm optimization algorithm (IFSO), and lastly training multiple CNNs as an ensemble model. Prediction of an Ensemble is utilized through majority voting. IFSO-ECN is a combined model that is also oriented to enhancing flexibility and precision in financial crisis event forecasting. Figure 1 depicts the suggested method's organizational structure.

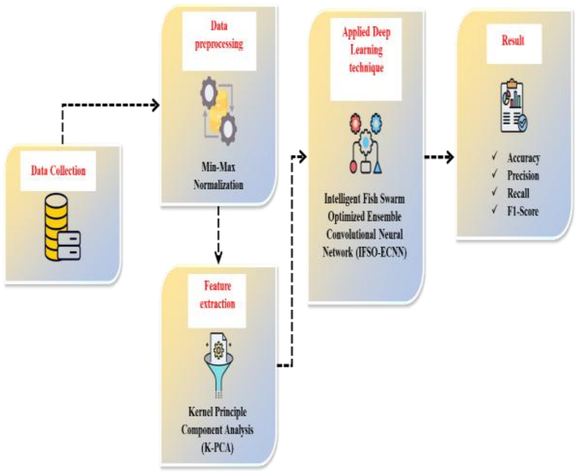

Figure 1: Structure of the proposed method

3.1 Dataset

Critical financial, social, and digital economy risk indicators were gathered from 750 households throughout three monitoring cycles, totaling 13 months. GDP growth, inflation, changes in foreign exchange rates, market volatility, demand for Information and Communications Technology (ICT), and catastrophe effect scores are among the measures included in the data. It is intended for use in emergency risk analysis, crisis response AI model training, and the prediction of unexpected financial catastrophes. The dataset also includes a three-level catastrophe severity goal and a binary classification label. This dataset was separated into 70 % for training and 30 % of testing. The data gathered from Kaggle [24]. They must process the raw financial data using adequate preprocessing methods in order to transform it into a format ready to be advanced in modelling. The initial process entails scaling of the input features via min-max normalization, which makes all variables work within a similar numerical scale and minimizes training bias.

3.2 Min-Max normalization for data preprocessing

Min-max normalization is a commonly used technique for scaling numerical properties within a certain range. It is frequently used to prepare data for machine learning models. The dataset's input features can be normalized using min-max normalization to prepare them for diabetes prediction. A normalizing method called min-max normalization linearly alters the original data to produce a comparable set of values before and after the procedure.$\mathrm{Z_{new}}$ represents the adjusted value obtained through data scaling, and Y denotes the original value.

$$\mathrm{Z_{new}} = \frac{\mathrm{z-min}}{\mathrm{max(z)-min(z)}} \tag{1}$$

Where equation (1), z is the original feature value, z_{min} is the original feature minimum, z_{max} is the original feature maximum, and z_{new} is the normalized value. The next process after normalizing is to lessen the dimensionality of the data without compromising the aspect of the data that is informative. To do this, we would use a nonlinear feature extraction approach of Kernel Principal Component Analysis (K-PCA), which is able to capture nonlinear relationships of complex data.

3.3 K-PCA for feature extraction

The researchers employ a nonlinear function to convert the input data × to the highly dimensional space of features L. $\emptyset\colon K^M \to L, y \to Y$. Assume that the data revolves around the map,$\sum_{r=1}^{N} \emptyset(y_r) = 0$in the feature space L, then the covariance matrix in $L$is $V^L = \frac{1}{N}\sum_{j=1}^{N} \emptyset(y_j)\emptyset(y_j)^D$. The next step is to find eigenvalues $\lambda^L \geq 0$&eigenvectors $U^L \in L/\{0\}$ satisfying $V^L\lambda^L = \lambda^L U^L$. The range of $\emptyset(y_r), \ldots \emptyset(y_n)$ Contains all solutions $U^L$where $\lambda^L \neq 0$. There are coefficients, so$U^L = \sum_{j=1}^{N} \alpha_j \emptyset(y_r)$. Existing for$\alpha_j (j = 1, \ldots., N)$.

$$\lambda^L = \sum_{j=1}^{N} \alpha_j \left(\emptyset(y_r).\emptyset(y_j)\right)$$

$$= \frac{1}{N}\sum_{j=1}^{N} \alpha_j \left(\emptyset(y_r).\sum_{i=1}^{N} \emptyset(y_i))\emptyset(y_i).\emptyset(y_j)\right)$$

$$(r = 1, \ldots, N) \tag{2}$$

Define an $N \times N$ matrix R by

$R_{ji} = \emptyset(y_i).\emptyset(y_i))$.

(3)

So, equation (2) can be written as $N\lambda^L R\alpha = R^2\alpha$.

$$N\lambda^L \alpha = R\alpha \tag{4}$$

Let $\lambda_1^L. \geq \lambda_2^L \geq \cdots \geq \lambda_N^L$represent the eigenvalues, and the entire set of eigenvectors for equation (4) is $\alpha_1, \alpha_2, \dots, \alpha_N$.

The researchers must normalize an eigenvector from the element of an environment L. $\lambda_N^L \neq 0, r = 1,2,..,f$, by equations (2)-(4), $(U_r^L.U_r^L) = 1$is same as $(U_r^L.U_r^L) = \sum_{j,i=1}^N \alpha_j^r \alpha_i^r(\emptyset(y_i).\emptyset(y_i)) = \sum_{j,i=1}^N \alpha_j^r \alpha_i^r R(y_j, y_i) = \lambda_1^L(\alpha^r.\alpha^r) = 1 \quad r = 1,..,f$

(5)

It was necessary to compute the projections of each data point onto the eigenvectors to isolate its principal component.U_r^Lin$L$. Using y as the measurement point, whose projection is $\emptyset(y)$in L, project $\emptyset(y)$ onto the eigenvectors of U_r^L that correspond to the nonlinear major components, equation (6).

$$(U_r^L.\emptyset(y)) = \sum_{j=1}^N \alpha_j^r(\emptyset(y_i).\emptyset(y_i)) \tag{6}$$

After the extraction of the key features, one uses the refined inputs to train the prediction model. The research suggests an IFSO-ECNN as a way to improve the predictive capacity and the accuracy of the system in detecting sudden financial calamities.

3.4 Intelligent fish swarm optimized ensemble convolutional neural network (IFSO-ECNN)

The goal would be to improve performance in tasks linked to image recognition, object identification, or other activities where ECNNs thrive by optimizing the training procedure and architecture of the ensemble of ECNNs using the improved optimization method. The suggested IFSO-ECNN system combines the IFSO algorithm with an ECNN. IFSO optimizes hyperparameters of each CNN model in the ensemble, for example, learning rate, convolutional filter numbers, and dropout value. A separate CNN is trained over another IFSO-adjusted configuration, and ensemble prediction is obtained through majority voting. Algorithm 1 illustrates the process of the IFSO-ECNN method.

Algorithm 1: Procedure of IFSO-ECNN

```
Input:
  D: Number of dimensions (hyperparameters like LR, dropout, filters, etc.)
  N: Number of artificial fish (population size)
  E: Number of CNNs in ensemble
  MaxIter: Maximum iterations for IFSO
  Dataset: Input image dataset with labels
Output:
  Final_ensemble_model: Ensemble of E CNNs optimized by IFSO
  Accuracy: Classification accuracy on validation/test set
Begin:
Initialize IFSO parameters:
  For each fish i in 1 to N:
    Randomly initialize hyperparameter vector Z_i in D dimensions
    Evaluate fitness FS_i = CNN_Train_Evaluate(Z_i, Dataset)
Set best_solution = Z_i with minimum FS_i
 Set best_fitness = FS_i of best_solution
Main Optimization Loop (for iter = 1 to MaxIter):
  For each fish Z_j in the population:
    Randomly select a neighbor Z_k ≠ Z_j
    Perform:
      a. Search behavior update
      b. Swarming behavior update
      c. Following behavior update
      d. Communication update
    Evaluate new position FS_j_new =
 CNN_Train_Evaluate(Z_j_new, Dataset)
    If FS_j_new < FS_j:
      Z_j = Z_j_new
      FS_j = FS_j_new
    If FS_j_new < best_fitness:
      best_solution = Z_j_new
      best_fitness = FS_j_new
Final Hyperparameter Selection:
  Select top E best solutions Z_1, Z_2, ..., Z_E from fish population
CNN Training:
  For i = 1 to E:
    Train CNN_i with hyperparameters Z_i
    Store model CNN_i
Ensemble Prediction:
  For each test sample x:
    Predict_i = CNN_i(x) for i in 1 to E
    Final_Prediction = MajorityVote(Predict_1 ... Predict_E)
Evaluate Ensemble Accuracy on Test Set
Return Final_ensemble_model and Accuracy
End
Function CNN_Train_Evaluate(Z, Dataset):
  Extract hyperparameters: learning_rate, dropout_rate, filter_size, etc. from Z
  Initialize CNN with these hyperparameters
  Train CNN on training set subset
  Validate on the validation set
  Return validation_loss or error as fitness
```

The combination of K-PCA, ECNN, and IFSO within the proposed IFSO-ECNN framework has been intentionally structured to solve the unique problems in predicting sudden financial disasters in the digital economy.

- K-PCA is a technique for nonlinear dimensionality reduction that is able to identify complex, high-order relationships among economic variables that linear methods, such as PCA, cannot discriminate.
- ECNN, chosen because of its ability to optimally learn hierarchical representations from structured economic datasets without being overfitted due to inherent ensemble diversity, as compared to sequential models like LSTM.

- IFSO implements a biologically inspired evolutionary optimization model improved through communication mechanisms, as well as adaptive behavior mechanisms, balancing exploration and exploitation in fine-tuning CNN hyperparameters.

The hybrid architecture resolves three important problems: (i) the high-dimensional complexity of features, (ii) the necessity of achieving robustness in pattern extraction, and (iii) the necessary ability to learn adaptively in constant change environments. This hybrid approach takes advantage of the individual advantages of its components and delivers challenging predictive performance in the context of digital finance.

3.4.1 Ensemble Convolutional Neural Network (ECNN)

A common DL model for applications like picture segmentation, object detection, and classification is the ECNN. Due to its capacity to capture regional patterns and feature hierarchies, it is particularly useful for jobs involving grid-like data, such as photographs. ECNN was selected because it has the advantage of discovering the hierarchical structures within the high-dimensional data in the field of financial data. Ensemble promotes the generalization of the model and prevents over-fitting. The ECNN is also more effective with cross-sectional and structured economic input than the sequential models, such as LSTM.

3.4.1.1 Operation of convolution

Local information is extracted during the convolution process by dragging a small filter, also known as a kernel, over the input picture. The final characteristic map has just one value derived from the sum of the elements' separate processing. Equation (7) allows the convolution process to be expressed.

$$Q(j,i) = \sum_n \sum_m J(j+n, i+m) \times R(n,m) \tag{7}$$

where the value is located at (j,i) in the finalized feature map is denoted by $Q(j,i)$. The position value $(j+n, i+m)$ in the original image is represented by $J(j+m, i+m)$. $R(n,m)$ is the convolutions kernel's position value (n,m).

3.4.1.2 Function of activation

After the convolution procedure, each element is subjected to an activation function (commonly referred to as the Rectified Linear Unit, or ReLU), which adds non-linearity. The following describes the ReLU activation function as shown in equations (8 and 9):

$$ReLU(y) = \max(0, y) \tag{8}$$

$$Q(j,i) = {}^{max}_{n,m} J(j \times g + n, i \times g + m) \tag{9}$$

g is the stride of the pooling operation (the number of steps the pooling window moves). n, m are indices over the pooling window (for example, for 2×2 pooling, n, m $\in \{0,1\}$). J is the input feature map before pooling

3.4.1.3 Operating a pool

Pooling reduces the feature maps' spatial size while preserving important information. A popular pooling method is max pooling, and its formula for a certain location is:

3.4.1.4 Layer with full connectivity

The characteristics are often flattened and then passed through one or more fully connected layers after many convolutional and pooling layers to provide final predictions. Fully connected layers have bias furtherance and multiplication of matrix in their equations. These are the fundamental CNN components and formulae. Remember that there are many different sorts of CNN designs, such as normalization layers, skip connections, and other types of layers. To tune the hyperparameters of individual CNNs in an ensemble, it combines an IFSO algorithm. This is an evolutionary computing approach, which simulates the foraging of fish schools, enabling a fast search of the solution space.

3.4.2 Intelligent Fish Swarm Optimization (IFSO)

The optimality of IFSO can be explained by its better exploration-exploitation balance and its adaptive search behavior that enhances a more stable convergence. It has communication and local decision-making based on fish swarms, unlike PSO. This qualifies it as an appropriate algorithm in hyperparameter tuning of complex neural networks in dynamic financial settings. The IFSO is a novel population-based optimization technique inspired by fish's natural eating habits. Fish food satisfaction is represented as FS_i, and a fish is pictured by its D-dimensional position $Z_j = (Z_1, Z_2, \dots, Z_k, \dots, Z_d)$. The goal of this work is FS minimization. The Euclidean separation of two fish, $dij = |Z_i Z_j||$, indicates their relationship. Figure 2 depicts the IFSO algorithm workflow, showing relevant behaviors such as searching, swarming, following, and communication of fish agents in optimizing the hyperparameters of CNN.

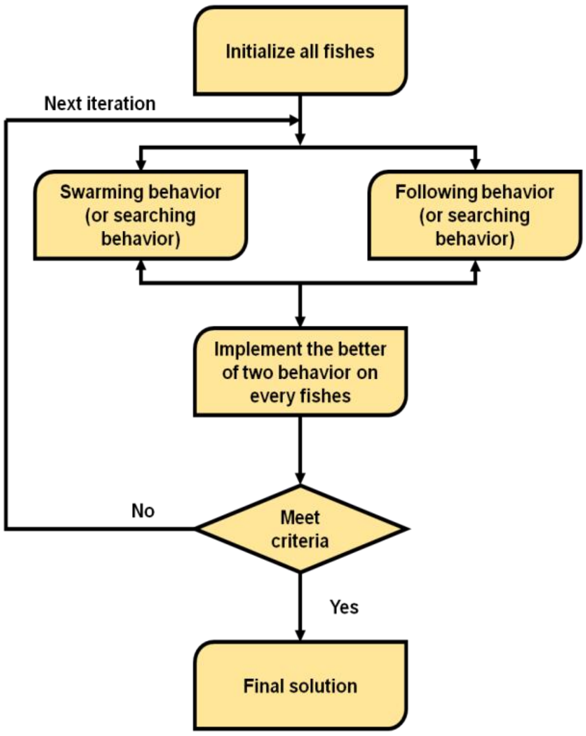

Figure 2: Architecture of IFSO

Fish population size is represented by the number n. All fish use three separate behaviors to search for areas where they can find food.

3.4.2.1 A search-related action

When searching for food, fish exhibit this behavior as a basic biological behavior. It is based on the random search principle and tends to concentrate on food. In mathematics, it is written as shown in equations (10 and 11):

$$\vec{Z}_{j+1}^{r} = \vec{Z}_{j}^{r} + K(G1)\frac{\vec{Z}_{i}^{r}-\vec{Z}_{j}^{r}}{\|Z_i - Z_j\|}, FS_i < FS_j \tag{10}$$

$$\vec{Z}_{j+1}^{r} = \vec{Z}_{j}^{r} + K(S2)\vec{1} \tag{11}$$

Where Z_j^r denotes fish location Z_j's rth element, for fish Z_j, choose a random place Z_j inside its image. After a certain number of trials, if FS_i is still unsatisfied, a random position within the step range will be immediately selected.

3.4.2.2 Swarming conduct

Fish congregate in a variety of swarms to reduce risk. All swarms share the same goals, which include supplying food intake requirements, amusing existing swarm members, and luring in new swarm members. Mathematically equation (12),

$$\vec{Z}_{j+1}^{r} = \vec{Z}_{j}^{r} + K(S2)\frac{\vec{Z}_{v}^{r}-\vec{Z}_{j}^{r}}{\|Z_v - Z_j\|}, FS_v < FS_j and \left(\frac{m_g}{m}\right) < \delta \tag{12}$$

A fish at Y_j has neighbors in its field of view. When describing the characteristics of the complete neighboring swarm, Yv is used to pinpoint the center position of those neighbors. The fish will travel from position Z_j to the next Z_{j+1} in the direction of Zv if the swarm center contains a higher concentration of food present at position Z_j. If a fish has an associated Yv, swarming behavior is carried out for it; otherwise, searching behavior ensures the fish's next position.

3.4.2.3 Adopting an action

Neighboring fish follow a fish that finds food, which is mentioned in Equation (13),

$$\vec{Z}_{j+1}^{r} = \vec{Z}_{j}^{r} + K(S2)\frac{\vec{Z}_{min}^{r}-\vec{Z}_{j}^{r}}{\|Z_{min} - Z_j\|}, FS_{min} < FS_j and \left(\frac{m_l}{m}\right) < \delta \tag{13}$$

To maximize enjoyment, a fish will naturally desire to follow the best fish (Z_{min}). This is due to the fish's perception; certain fish will be viewed as finding a larger amount of food than others, and these fish will try to follow the best one (Z_{min}). If a fish's following behavior is unable to predict its next place, searching behavior starts. Additionally, IFSO ought to offer a newsletter that documents the ideal condition and present performance of fish throughout iterations. It is difficult to get into deeper detail on IFSO because of parameter settings, notably for visuals and steps. To remove step influences, this work will introduce settings for these two parameters and use the PSO formulation for IFSO. Additionally, fake fish will also exhibit a communication behavior.

By using the IFSO visual, local search attributes are supplied. Due to its narrow viewing area, fish can only interact with a very small number of companions. The maximum step length for the IFSO step is limited, and a short step compels fish to search a smaller area and increases the probability of running out of time. Step values are dependent on IFSO performance and are determined using Euclidean distance computations. All of the original IFSO formulas have been altered:

Searching techniques

$$\vec{Z}_{j+1}^{r} = \vec{Z}_{j}^{r} + \varphi_{3r}\left(\vec{Z}_{i}^{r} + \vec{Z}_{j}^{r}\right), FS_i < FS_j \tag{14}$$

$$\vec{Z}_{j+1}^{r} = \vec{Z}_{j}^{r} + K(V1)\vec{1} \tag{15}$$

$$\varphi_3^r = v_3 k_3^r \tag{16}$$

Where equations (14-16), φ_3^r has a mean value of one and is a uniform random number, falling between $[0, 2]$. The uniform random number c3 is 2, falling between $[0, 1]$. The improved IFSO allows fish to swim farther than was allowed by the original IFSO when the step is less than visible. Modified search behavior can be used at any time.

Swarming actions

$$Z_{j+1}^r = \vec{Z}_j^r + \varphi_4^r(\vec{Z}_i^r - \vec{Z}_j^r), FS_v < FS_j and \left(\frac{m_g}{m}\right) < \delta \tag{17}$$

Where equation (17)φ_4^r is defined in the same way asφ_3^r, and $\vec{Z}_i^r$ is defined in the same way as FSA. Therefore, modified swarming behavior is allowed to step.

The subsequent actions

$$\vec{Z}_{j+1}^r = \vec{Z}_j^r + \varphi_5^r(\vec{Z}_{min}^r - \vec{Z}_j^r), FS_{min} < FS_j and \left(\frac{m_l}{m}\right) < \delta \tag{18}$$

Where equation (18) φ_5^r and φ_3^r are defined similarly, and Z_{min} is defined similarly it is used in FSA. Therefore, the modified following behavior allows for free stepping.

Only visual cues can determine the positions of Z_j, Z_i, Z_{min}, and the subsequent X_j.

Communication techniques

Artificial fish ought to possess greater skills than those present in real fish. The message enables fish to determine the optimal location of the entire swarm. Fish are allowed to reach the location if it is not already too crowded. In other words, this strategy guarantees that a specific number of fish will be actively seeking food around the global best position. The mathematical representation of this is as follows equation (19):

$$\vec{Z}_{j+1}^r = \vec{Z}_j^r + \varphi_6^r(\vec{Z}_{best}^r + \vec{Z}_j^r), \left(\frac{m_f}{m}\right) < \delta \tag{19}$$

If φ_6^r has the same definition as φ_3^r, $Zbest$ is the position with the maximum amount of achieved food satisfaction, and nb is the number of fish visible in the area around $Zbest$. Algorithm 2 illustrates the IFSO as follows:

Algorithm 2: Process of Intelligent Fish Swarm Optimization (IFSO)

```
1. Initialize fish positions randomly within the search space:
  For i = 1 to N:
  For j = 1 to num_dimensions:
 Randomly initialize fish[i][j] within bounds
2. Initialize fish fitness values:
  For i = 1 to N:
 fish_fitness[i] = calculate_fitness(fish[i])
3. Initialize the best solution and fitness:
  best_solution = fish[i]
  best_fitness = fish_fitness[i]
4. Main optimization loop:
  For iteration = 1 to max_iterations:
 For i = 1 to N:
For j = 1 to num_dimensions:
Select a random fish index k ≠ i
 Calculate new_position[j]
                 = fish[i][j] + (fish[i][j]
                 − fish[k][j]) * rand()
 Clip new_position[j] within bounds
  new_fitness = calculate_fitness(new_position)
  If new_fitness < fish_fitness[i]:
 Update fish[i] with new_position
 fish_fitness[i] = new_fitness
 If new_fitness < best_fitness:
 Update best_solution with new_position
 best_fitness = new_fitness
5. Output best_solution and best_fitness
6. End
```

4 Results and discussion

The evaluation metrics of sensitivity, specificity, accuracy, and F1-Score are used in the part where we examine how well our suggested approach performs in comparison to current approaches. To demonstrate how successful a given method is, its dependability and effectiveness are compared to those of more established techniques like hybrid hunter–prey optimization with a deep learning-based financial crisis prediction (HHPODL-FCP) [25], quantum artificial butterfly optimization- long short-term memory- long short-term memory (QABO-LSTM-RNN) [26], Ant colony optimization (ACO model) [25].

Sensitivity is the percentage of real positive cases properly recognized by a prediction model. In terms of financial catastrophe risk avoidance, high sensitivity indicates that the system is capable of identifying possible risks or abnormalities in the digital economy. When comparing our proposed method with existing methods. Figure 3 and Table 2 illustrate the sensitivity values. Our proposed method, IFSO-ECNN- 95.23%, outperforms existing models, including HHPODL-FCP (93.51%), QABO-LSTM-RNN (85.89%), and the ACO model (78.27%), demonstrating superior sensitivity values in the digital economy's intelligent emergency risk during sudden financial disasters. Sensitivity (95.23%) is the model's power to identify actual early warning symptoms of financial crises, which is important in order to initiate timely interventions that will halt mass disturbance of the economy.

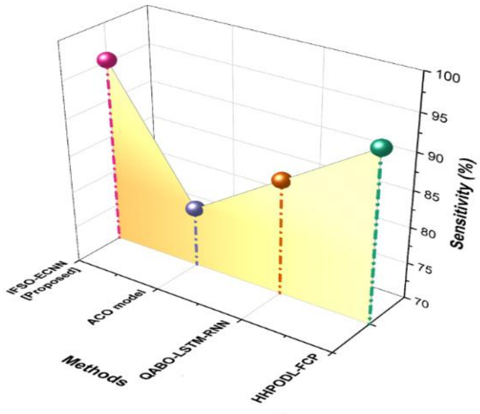

Figure 3: Sensitivity outcome

Table 2: Sensitivity values

Method	Sensitivity (%)
HHPODL-FCP	93.51
QABO-LSTM-RNN	85.89
ACO model	78.27
IFSO-ECNN [proposed]	95.23

Specificity refers to the fraction of real negative situations properly detected by a prediction model. Specificity is necessary to reduce false alarms. In the financial industry, a high specificity suggests that the system can accurately recognize circumstances when there is no immediate financial crisis, eliminating unneeded fear or actions. Figure 4 and Table 3 illustrate specificity values, affirming the superiority of our proposed IFSO-ECNN-96.25% over established methods like HHPODL-FCP (93.97%), QABO-LSTM-RNN (92.65%), and the ACO model (69.25%). Our approach signifies significant advancements in navigating sudden financial disasters and intelligent emergency risk avoidance in the digital economy. Specificity (96.25%) is all about invoking minimal false alarms to avert overreacting with alarm or ineffective policy measures.

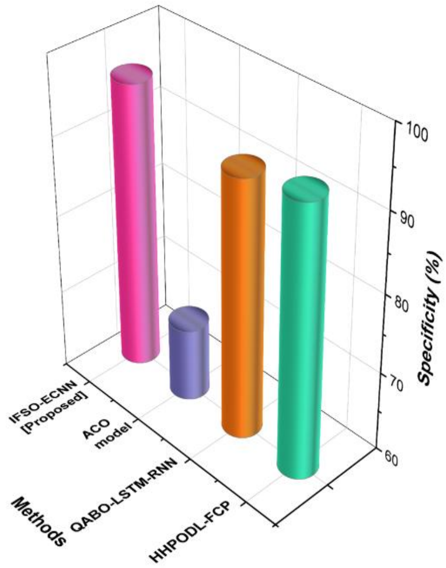

Figure 4: Specificity outcome

Table 3: Specificity values

Methods	Specificity (%)
HHPODL-FCP	93.97
QABO-LSTM-RNN	92.65
ACO model	69.25
IFSO-ECNN [proposed]	96.25

Accuracy assesses the model's overall accuracy, taking into account both true positives and true negatives. In the context of financial crises, high accuracy indicates that the system is generating generally right forecasts. Figure 5 and Table 4 illustrate the accuracy values. When evaluating the suggested method's performance against that of other approaches, such as HHPODL-FCP-94.87%, QABO-LSTM-RNN- 90.78%, and ACO model-75.72%. Specifically, our suggested method, IFSO-ECNN-97.14%, substantially improves its ability to predict sudden financial crises in the digital economy through smart risk avoidance during disasters. Accuracy (97.14%) is a measure of the general dependability of the model for predicting crisis and stability conditions, allowing proper planning and trust in automated decision support.

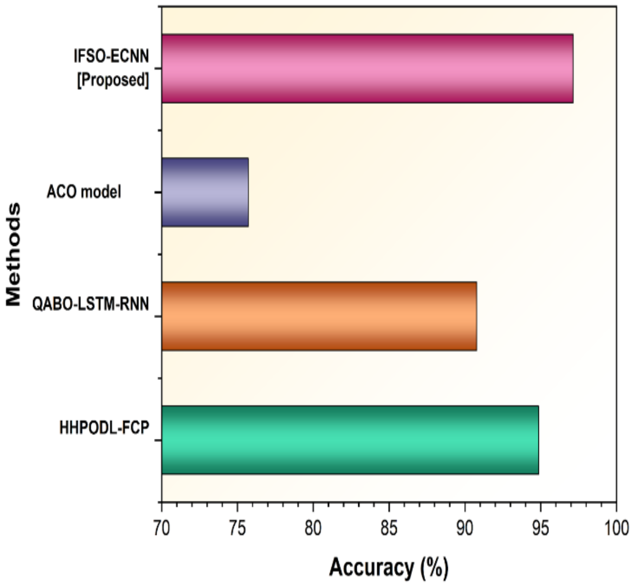

Figure 5: Accuracy outcome

Table 4: Accuracy values

Methods	Accuracy (%)
HHPODL-FCP	94.87
QABO-LSTM-RNN	90.78
ACO model	75.72
IFSO-ECNN [proposed]	97.14

F1-Score, a harmonic mean of accuracy and recall, strikes a balance between precision and sensitivity, which is crucial in the digital economy. Its equilibrium ensures accuracy while detecting a significant number of true positives. Figure 6 and Table 5 illustrate F1 score values. In contrast, the suggested approach is different from the current approach. The suggested approach shows a higher value of IFSO-ECNN -95.51% than the existing methods, such as HHPODL-FCP-93.67%, QABO-LSTM-RNN-89.08 %, and ACO model-85.35%. It demonstrates that our proposed method, IFSO-ECNN, achieves a success rate of 95.51% in estimating the digital economy of sudden financial disaster intelligent emergency risk avoidance. F1-Score (95.51%) is the balance of precision and recall because the system performs well even if partial risk indicators or imbalanced data are involved.

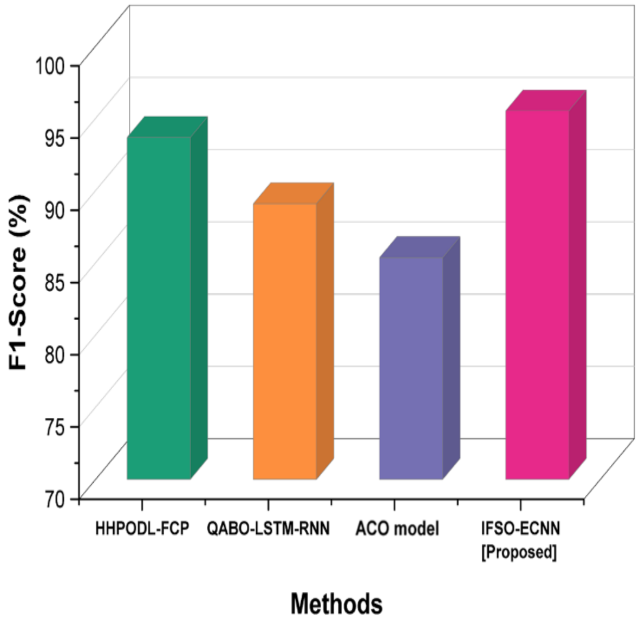

Figure 6: F1-Score outcome

Table 5: F1-Score values

Methods	FI-Score (%)
HHPODL-FCP	93.67
QABO-LSTM-RNN	89.08
ACO model	85.35
IFSO-ECNN [proposed]	95.51

4.1 Discussion

Utilizing existing approaches like QABO-LSTM-RNN [26], ACO model [25], and Hybrid Hunter-Prey Optimization with HHPODL-FCP [25] assists in accomplishing the goal of preventing sudden financial disasters in the digital economy through intelligent emergency risk avoidance. While QABO-LSTM-RNN combines optimization inspired by quantum computing with long short-term memory networks, it is also plagued by computational complexity and temporal inefficiency, and therefore, is less applicable to real-time crisis forecasting. HHPODL-FCP combines hybrid optimization and deep learning for efficient crisis prediction. Although effective, it is not generalizable in the face of shifting financial signals or unseen risk patterns.

Furthermore, the ACO model makes use of methods inspired by ants. ACO-based models are highly sensitive to parameter settings and have the tendency to converge too quickly in dynamic situations. These approaches have drawbacks that could impact their efficiency and practical usefulness in real-world situations, despite their potential. Examples of these drawbacks are the sensitivity of ACO to parameter decisions and the computational complexity of quantum algorithms in QABO-LSTM-RNN.

In contrast to previous methods that often depend on severe structures or a single optimization step, IFSO-ECNN makes a novel technical impact in incorporating a stable fish swarm optimization algorithm with an ensemble of CNNs. This adaptive tuning process greatly enhances generalizability and flexibility, representing a new financial crisis prediction model breakthrough. This provides hyperparameter optimization, improved exploration-exploitation trade-offs, and significantly high noise tolerance to financial data streams. The outcome is a smart emergency risk avoidance system that is reliable, accurate, and reactive.

5 Conclusion

Disasters like natural disasters and unforeseen mishaps have been happening more frequently lately, which has negatively impacted a particular region's usual development of financial business. The theoretical underpinnings of the ECNN and IFSO algorithms are comprehensively explained in this study, along with some of their benefits and drawbacks. The IFSO-ECNN prediction model is then created by merging these two algorithms, and it is used to predict sudden financial disasters with successful outcomes. The proposed technique's sensitivity was 95.23%, specificity was 96.25%, accuracy was 97.14%, and F1-score was 95.51%, based on the previously published results. Although the IFSO-ECNN model did quite well in this piece, this area of research is still in its early stages. There are still more forecasting-related applications that need to be carefully examined. Thus, additional study is needed in the following areas: improved indicator and sample data selection, improved parameter selection, and tuning. Although the IFSO-ECNN model has demonstrated greater effectiveness, further effort are needed to establish theoretical convergence assurances, as well as evaluating other model fusions with distinct dimensionality reduction or optimization routines. The work on further development of a fully adaptive hybrid learning framework will be suggested, and the chosen model will dynamically select the most effective preprocessing and optimization strategy regarding the changing character of financial input data.

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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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