Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Navigating Financial Hazards: An Innovative IoT-Driven Machine Learning Strategy for Big Data Analytics in Finance

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Introduction: The implementation of efficient risk management practices is essential in the constant environments of financial markets, as it facilitates sustainable business expansion and maintains prosperity in the long term. This research integrates the Internet of Things (IoT) with a Cat Swarm Optimized Bayesian Neural Network (CSO-BNN) to propose an innovative approach for financial risk assessment.
Objective: The intention of this investigation to analyze the suggested approach by utilizing data obtained from public sector banks (PSBs) in India.
Method: The proposed CSO-BNN demonstrates a significant measure of efficacy in adapting to evolving dynamics of the market, hence enhancing the adaptability and sensitivity of the risk management system. The efficacy of the proposed methodology is assessed through the utilization of a dataset obtained from public sector banks in India. The performance of the CSO-BNN technique is evaluated by applying requirements like accuracy, precision, recall, and f1-score.
Result: Based on the results of the analysis, it has been determined that the CSO-BNN technique exhibits the highest levels of accuracy (93,50 %), precision (91,70 %), recall (94,90 %), and f1-score (92,40 %). The findings provide evidence of the potential efficacy of the recommended technique in enhancing risk mitigation strategies for financial institutions and investors.
Conclusion: The connection of the “Internet of Things (IoT)” with the CSO-BNN model enables a novel and effective approach to handle risk administration problems in the dynamic financial

industry.

Keywords: Financial hazards; IoT; Big data; Cat Swarm Optimized Bayesian Neural Network (CSO-BNN).

1. Introduction

Financial risk is the possibility of suffering economic damage or unpredictability as a result of different circumstances that could affect an individual or organization's sustainability and productivity. These risks can take many different forms, such as developments in interest rates, market risks, operational risk, liquidity risks, credit risk, constraints of availability, and administrative alterations. (1) The financial threat variables are displayed in Figure 1.

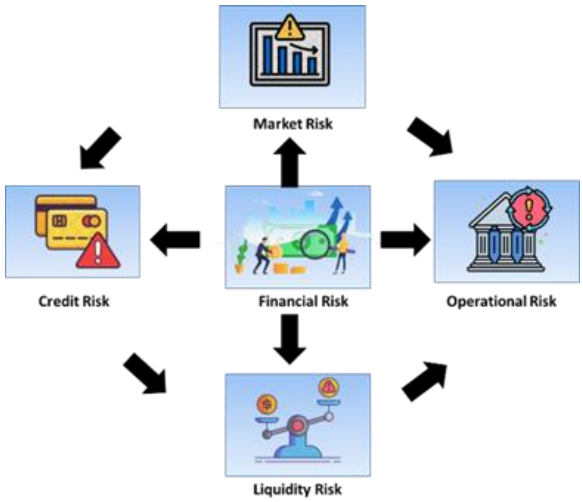

Figure 1. Variables of financial threat [Source: https://www.educba.com/financial-risk/]

To protect their resources, protect financial stability, and generate sustainable growth, firms and investors must recognize and manage financial risk efficiently. Effective risk management plans include a variety of financial tools, including insurance, trading, and derivatives, to reduce the negative consequences of financial fluctuations. (2)

Financial Risk Administration with IoT revolutionizes how companies navigate complicated financial environments by combining the efficiency of risk management techniques with the revolutionary potential of the Internet of Things (IoT) technology. (3) This creative method enables businesses to identify, evaluate, and mitigate possible financial hazards in real time by combining IoT devices, such as sensors, actuators, and data processing. This technology develops a preventive risk management environment by tracking market changes, operational weaknesses, and regulatory compliance through the use of the interconnected Internet of Things. (4) Businesses can improve operational resilience, predict changes in the market, and streamline decision-making processes by combining IoT with financial risk management. Furthermore, by taking a comprehensive approach, risk management procedures are improved while operational effectiveness is increased, costs are decreased, and resource allocation is optimized. [5]

The financial industry has experienced a revolution due to the integration of Internet of Things (IoT) technologies with financial risk management. Businesses can make data-driven decisions in real-time, reducing risks and improving security as a consequence of the combination of IoT and machine learning. [6] Through the processing of this data, Machine learning techniques provide the capability to identify instances of fraudulent conduct with a high level of efficiency, determine prospective risk factors, and estimate market changes. Financial organizations can improve customer's confidence and ensure better regulatory compliance by using prediction intelligence to analyze and manage possible hazards.[7, 8] The study [9] developed machine learning in business, an operation that was growing in importance, and the movement was anticipated to extend to other industries. Machine-learning technologies possess the potential to decrease expenses and enhance efficiency. Research [10] categorized the loan-related elements, the financial elements, the reputation components, and the particular factors that influence the repayments of "Peer-to-peer (P2P)" online debtors into four groups. Regarding consideration of the determining variables of the default amount, recommended improvements for the Loan organization and various P2P platforms are presented as the advised path of other countries' advancement in the industry. Article [11] presented a deep learning method for the banking sector, and academic organizations were established to recognize the advantages. Paper [12] presented an augmented hybrid ensembles Machine Learning strategy termed “RSMultiBoosting” by merging two traditional ensembles ML strategies, “random subspace (RS)” and Multi-Boosting, to increase the efficiency of predicting inadequate as well as “small and medium-sized enterprises (SMEs')” financial risk. The prediction outcome demonstrates that RS-MultiBoosting performs well even with constrained information collection. The study [13] developed ML techniques in banking industries have motivated considerable investigation efforts into their potential use in the area of bankruptcy predictions. Paper [14] presented a deep learning algorithm for the credit scoring problem, which allowed examining it from a different perspective. Compared to other techniques, “deep belief networks (DBN)” utilising Restricted Boltzmann Machines performed better in the experiments. The DBN model's superior performance persists beyond the several dimensions of assessment reliability that were examined. Research [15] developed a model-free convolutional neural network that receives as input the previous markets of a financial property investment and outputs the weights of individual commodities in the investment.Article[16] developed an ML technique, including adaptive component identification and categorization to determine if particular characteristics generated by the financial statistics and yearly reports might be combined to create an enhanced financial fraud-detecting instrument. The study [17] presented a deep Learning methodology on extensive records comprising numerous market quotations operations for US equities and discovered empirical evidence that supports the presence of a consistent as well as unchanging relationship between the historical order movement and the subsequent orientation of price movements. Their findings demonstrate the effectiveness and practicality of Deep Learning techniques for simulating the momentary activities of financial institutions. Research [18] employed six data mining techniques, namely "support vector machine (SVM), classification and regression tree (CART), back propagation neural network (BP-NN), logistic regression

(LR), Bayes classifier (Bayes) and K-nearest neighbor (KNN).”An effective strategy for identifying fraudulent financial documents is a combination of SVM and the progressive regression complexity reduction technique. Article [19] presented a particle swarm optimization–based SVM combination model to predict a consumer's financial hazards. The prediction categorization impact of the strategy recommended in this investigation is demonstrated empirically. Paper [20] developed a “Bayesian neural network (BP)” neural network-based financial statement identification system measures for detecting fraudulent financial reports of generally traded businesses. The findings indicated that among the 20 judgment measures, the top five in terms of significance were total properties net profit, revenues for each share, capital reinvested rate, operational sales revenue, and initial proportion of profitability to debts.

By strengthening financial organizations' adaptability and promoting more effective risk control systems, this innovative method aim to optimize risk management tactics and contribute to a more sustainable as well as secured financial environment.

2. Methods

In this research, we present Cat Swarm Optimized Bayesian Neural Network (CSO-BNN), a novel technique for predicting financial risk. Data was collected regarding the performance of failing and maintaining commercial and public sector banks in India from Jan 2000 to Dec 2020.

Dataset

Data were gathered pertaining to failing and surviving banks, specifically focusing on public sector banks in India, throughout the time duration comprising from Jan 2000 to Dec 2020. Data were gathered for banks that had available data over a period of four years subsequent to their potential expiration. Similarly to the banks that managed to endure, the sample encompassed the data from the past four years. In the final sample, consisting of 59 banks, it was observed that 42 banks were classified as surviving banks, while the remaining 17 banks were categorized as failed banks. Twenty-five attributes and financial measures were computed for a period of four years for each individual bank. In the given example, the total number of variables per bank was calculated by multiplying 25 by 4, resulting in a sum of 100 variables. [21]

Cat Swarm Optimized Bayesian Neural Network (CSO-BNN)

By utilizing Bayesian neural networks for statistical simulation and cooperative decision-making is to imitate the coordination exhibited in cat swarms. The different technique improves risk assessment by reacting to dynamic financial data from IoT devices, providing a solid solution for real-time risk administration in the complicated as well as associated environment of finance technology and the Internet of Things.

Proposed technique

This combined technique for managing financial risks can make use of data streams from Internet of Things (IoT) devices, such as market sensors and transaction records, to generate real-time updates to risk assessments. The CSO feature adjusts the hyperparameters of the

Bayesian Neural Network to enhance the model's capacity for making appropriate predictions]. To effectively anticipate market fluctuations and financial measures, integrating IoT elements provides the collection of large volumes of information from a wide number of resources. This provides the way for immediate assessment of threats and action. Furthermore, the CSO-BNN is well-suited to the ever-changing environment of financial markets because of its adaptable nature, which allows it to respond to financial circumstances. Algorithm1 shows the pseudo-code for (CSO-BNN).

Algorithm 1: pseudo-code for Cat Swarm Optimized Bayesian Neural Network (CSO-BNN)

```
import cat_swarm_optimization
import bayesian_neural_network
import IoT_data_acquisition
import financial_risk_metrics
num_cats = 100
num_iterations = 100
learning_rate = 0.001
def create_bayesian_neural_network():
  bayesian_nn = BayesianNeuralNetwork()
return bayesian_nn
cats = initialize_cats(num_cats)
IoT_data = IoT_data_acquisition. collect_data()
for iteration in range(num_iterations):
  for cat in cats:
 parameters = cat. position
    bayesian_nn. update(parameters)
  financial_metrics = evaluate_risk(bayesian_nn, IoT_data)
 cats = cat_swarm_optimization. update_cats(cats, financial_metrics, learning_rate)
best_cat = select_best_cat(cats)
final_risk_prediction = bayesian_nn. predict(IoT_data)
print("Final risk prediction: ", final_risk_prediction)
```

3. Results

The proposed approach has been implemented employing the Python 3.11 platform, Tensor Flow version 1.14.0, and Anaconda version 2019.07. The laptop is equipped with the OS- 10, with a Ryzen 5 processor and 6 GB of RAM. The performance of the proposed method is analyzed in terms of various parameters, including Precision (%), F1-score (%), Accuracy (%), and Recall (%), to evaluate the efficacy of the proposed methodology in relation to existing techniques. Such as "Support vector machine (SVM) [18], "Particle swarm optimization-support vector machine (PSO-SVM) [19], and Improved back propagation (IBP) [20].

This statistic quantifies the efficiency of risk event predictions, thereby enhancing the dependability of investment decision-making processes and minimizing the possibility of financial damages. Figure 2 shows the accuracy comparison. The performance of the existing approaches in terms of accuracy are SVM (80,63 %), PSO-SVM (85,5 %), and IBP (92,44 %). While our proposed approach has (93,5 %).The outcomes indicate that our proposed method has a much higher accuracy compared to the existing approach for predicting financial risk as shown in Equation (1).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

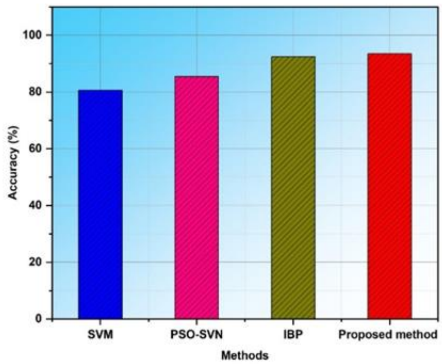

Figure 2. Result of accuracy [Source: author]

The indicator evaluates the ratio of correctly identified optimistic predictions to the total number of anticipated positive instances, hence evaluating the reliability of accepting financially risky events, which is essential for the sustainable management of risk. Figure 3 provides the precision comparison. The performance of the existing approaches, SVM (82,48 %), PSO-SVM (89,9 %), and IBP (90,54 %) in terms of precision. While our proposed approach has (91,70 %).The findings indicate that the proposed method exhibits a greater level of precision in comparison to the existing methods for financial hazards as shown in Equation (2).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

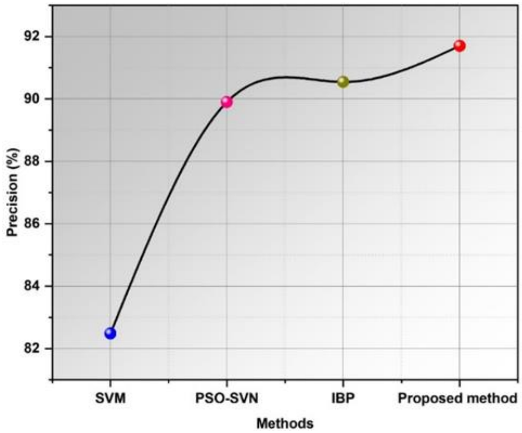

Figure 3. Result of precision [Source: author]

Evaluates the efficiency of identifying actual financial risk events, with an emphasis on limiting the occurrence of false negatives to achieve complete risk recognition and prevention. Figure 4 displays the comparative evaluation of recall. When comparing the proposed approach (94,90 %) with the existing method SVM (94,17 %), PSO-SVM (91,6 %), and IBP (91,78 %), As a result, in each instance, the efficacy of our proposed technique offers a greater advantage for financial risk as shown in Equation (3).

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

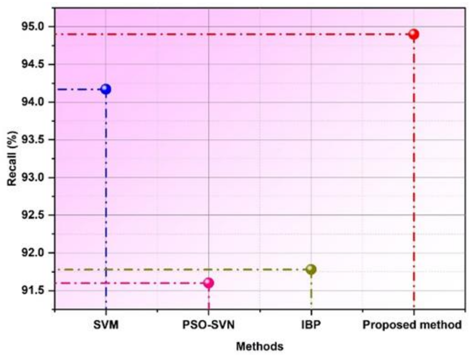

Figure 4. Result of recall [Source: author]

It balances the potential consequences of both accurately recognizing financial reservations and reducing false alarms. In Figure 5, when comparing the proposed method (92,40 %) with the existing method SVM (87,94 %), PSO-SVM (90,7 %), and IBP (91,16 %), it shows that our suggested approach is better than the existing approach. This indicates that our suggested strategy is more effective for financial hazards as shown in Equation (4). Table 1 provides the overall result comparison.

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision}*\text{recall}}{\text{Precision}+\text{recall}} \tag{4}$$

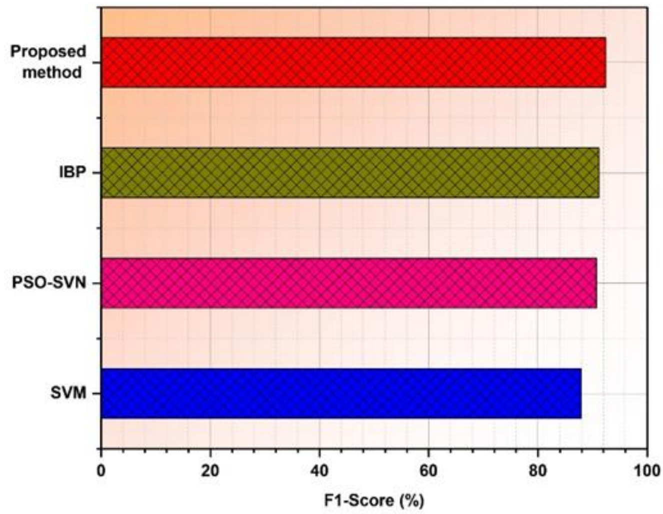

Figure 5. Result of f1- score [Source: author]

Table 1. Overall result comparison [Source: author]

Methods	Accuracy %	Precision %	Recall %	F1-score %
SVM	80,63 %	82,48 %	94,17 %	87,94 %
PSO-SVM	85,5 %	89,9 %	91,6 %	90,7 %
IBP	92,44 %	90,54 %	91,78 %	91,16 %
Proposed method	93,5 %	91,7 %	94,90 %	92,40 %

4. Conclusion

This research emphasizes the critical relevance of proficient risk administration in the dynamic world of financial markets for business growth and economic stability. The revolutionary combination of the Internet of Things (IoT) and a Cat Swarm Optimized Bayesian Neural Network (CSO-BNN) provides an innovative method for financial risk assessment. The application of this strategy, as demonstrated by data from Indian public sector banks, indicates its dynamic flexibility to changing market conditions, resulting in a more reactive and adaptable risk management strategy. The CSO-BNN model outperforms existing risk management strategies in terms of accuracy (93,50 %), precision (91,70 %), recall (94,90 %), and f1-score (92,40 %). These findings highlight the potential to improve risk-mitigation techniques for financial organizations and consumers. The suggested CSO-BNN model, with its adaptation, reliability, and productivity, emerges as a significant resource in understanding the complexities of modern financial systems. Its adoption carries the potential of improved decision-making, eventually assisting in the reduction of financial hazards and promoting a more reliable financial environment. The limitation is critical to ensure that this particular technique is applicable and reliable in a variety of financial circumstances. Additional improvements in data quality, computing features, and real-time analysis might improve the model's adaptability and expand its effectiveness in financial environments.

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