Enhancing Supply Chain Resilience: Application and Optimization of Blockchain Technology in Risk Management

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Abstract

This This paper introduces a novel solution to enhance supply chain risk management: the "Double Feedback Fuzzy Neural-based Blockchain Network (DF-BC)." This model is specifically designed to effectively mitigate risks for small- and medium-sized enterprises (SMEs) by integrating the advanced predictive capabilities of Double Feedback Fuzzy Neural Networks (DFFNN) with the security and transparency of blockchain technology. Utilizing blockchain, the model ensures a transparent and secure supply chain system by storing data in immutable blocks, thus guaranteeing data integrity and safety. Concurrently, the DFFNN processes this data, enabling precise risk management and accurate risk assessments. The foundation of this model is built on existing research, which provides effective techniques for addressing financial risks. However, the complexity of emerging risks, which can surpass traditional risk management methods, poses significant threats to the financial stability of supply chains. The DF-BC model offers a cutting-edge solution, guiding stakeholders toward anticipated outcomes, minimizing risks, and stabilizing the supply chain sector. Simulation results underscore the model's effectiveness, demonstrating improved risk prediction accuracy, enhanced processing efficiency, and overall better risk management practices within supply chain operations.

Keywords: Blockchain; DFFNN; Risk Management; Supply Chain ; Credit Risk; SME; Data Security; Predictive Analytics.

1. Introduction

1.1. Evolution of Supply Chain Finance and Its Impact

Since its inception in the 1970s, supply chain finance (SCF) has played a crucial role in global economic development. SCF focuses primarily on trade finance and bill discounting, which help companies manage cash flow more effectively[1]. Over time, the importance of integrating financial services with supply chain processes to optimize working capital has become increasingly recognized by businesses. This integration is particularly beneficial for small and medium-sized enterprises (SMEs)[2], which have historically struggled to secure traditional financing due to limited credit support. SCF provides SMEs with access to short-term loans and cash, enabling them to maintain operational stability and contribute to economic growth[3]. The economic benefits of SCF are significant, as it facilitates supply chain transactions, reduces financing costs, and enhances the efficiency of financial flows among customers, suppliers, and manufacturers. By linking financial institutions with SMEs and core businesses, SCF fosters the equitable distribution of resources, supporting the growth of smaller organizations that are vital to economic ecosystems[4]. Additionally, the increasing complexity of global supply chains has underscored the importance of SCF in mitigating risk and ensuring business survival, particularly in volatile market conditions[5]. As SCF continues to evolve, technological advancements are increasingly integrated into financial operations to enhance security and efficiency. These innovations promise to impact the economy by enabling real-time data sharing, reducing transaction times, and minimizing the risk of cyberattacks[6].

1.2. Emerging Challenges in Supply Chain Finance

As SCF has evolved, the banking industry faces several significant challenges in managing financial risks. One of the primary challenges is the growing credit risk associated with financing SMEs. Banks often find it difficult to assess and manage the risks inherent in SMEs, as these businesses typically lack the robust credit histories required for traditional loans. This instability can have immediate repercussions on the global market, leading to economic downturns and increasing the risk of defaults. Another major challenge is the integration of advanced technology into SCF systems. While technology offers substantial improvements in transparency, security, and efficiency, it also introduces vulnerabilities to sophisticated cyberattacks on sensitive financial data. Banks must navigate the complexities of implementing these technologies while ensuring compliance with legal requirements and protecting confidential customer information. The rapidly changing nature of technological advancements necessitates continuous updates and adaptations to maintain the effectiveness of SCF systems.

Additionally, modern global supply chains present challenges related to cross-border trade and regulatory compliance. Different countries have their own regulations governing trade activities, and banks must ensure that their SCF practices align with these diverse frameworks. The complexity of this task increases the risk of regulatory breaches, which can result in severe penalties and damage to the institution's reputation. Furthermore, the rise of fintech companies offering SCF solutions poses a competitive threat to traditional banks. To remain competitive, banks must continuously innovate, manage the risks associated with SCF, and strike a balance between financial stability and technological advancement. These challenges are summarized in Table 1.

Table 1. Existing techniques and their challenges.

Source	Challenges	Method used to address the challenges	Solution ideas to make the model more efficient
[7]	Credit Risk in SME Financing	Blockchain-driven credit risk assessment models	Use advanced blockchain to improve transparency and better assess the credit comfort of SME.
[8]	Lack of Credit Support for SME	Develop innovative SCF models and combine them with core enterprises	Design financing models where large firms help SMEs by providing guarantees and better credit terms
[9]	Technological Integration in SCF	Adopt advanced technologies like AI, blockchain, and fintech	Use AI and blockchain to automate and secure financial processes, reducing errors and fraud
[10]	Regulatory Compliance and Cross-border Transactions	Implement regulatory technology (RegTech) solutions	Make sure about compliance with international regulations through automated RegTech tools, simplifying global operations
[11]	Competition from Fintech Companies	Foster collaboration between traditional banks and fintech	Banks should collaborate with fintech firms to leverage their innovation and stay competitive

1.1. *Emerging Challenges in Supply Chain Finance*

SCF is a quickly developing field that is transforming financial operations through the combination of advanced technologies, which helps to transfer financial records [12] securely. These technologies effectively reduce the time and expenses of the transactions by allowing real-time data sharing and efficient communication between all participants. Their improved analytical skills make better risk assessment and decision-making possible [13] [14]. SMEs, particularly those who commonly struggle to obtain funding, can gain the most from this integration. Financial institutions can guarantee the protection of SMEs to maintain operational stability and contribute to economic growth by using the benefit of technology to provide more accessible financial services [15]. Moreover, implementing these technologies keeps organizations effective in a world that is digitizing quickly and conforming to ever- tougher regulatory rules.

1.2. *The Proposed System and its Motive*

In recent years, SCF has been one of the unavoidable domains in global financial operations, particularly in SME. By analysing all the above discussions, we finally present a novel solution to address the challenges in accessing financing. However, the development of SCF and the banking industry face several challenges. These challenges highlight the necessity for innovative solutions that can effectively manage and reduce financial risks within the supply chain; by considering these challenges as a main background, we develop the Double Feedback Fuzzy Neural Network based Blockchain system DF-BC system [16-18]. This approach combines the DFFNN predictive ability and blockchain technology's security and transparency capacity. The objectives of the DF-BC model are to improve risk assessment accuracy, allow real-time data processing, and create scalable solutions suitable for adjusting to different financial situations. By doing this, it aims to solve the drawbacks of the existing risk management techniques and guarantee that financial institutions can control risks and preserve the stability of supply chain financing activities.

2. Related Work

To support the healthy and rapid development of SCF, this paper [19] analyses recent research and highlights how blockchain can help to solve the problems in the field. With its decentralized and unchangeable features, blockchain technology has been observed as a game-changing innovation with various abilities to completely transform SCF. The study [20] highlights how integrating blockchain technology with SCF is essential to the field's further development. Using fuzzy cognitive maps and hierarchical analysis, it identifies and evaluates the significant risks connected to blockchain in SCF, such as operational and supply chain relationship risks, and demonstrates the risks that have the most effects on SCF. Traditional supply chain financing faces considerable issues as supply chains become more complicated. To increase supply chain financing efficiency and better risk management across various organizations, this study [21] proposes a double-chain management system that uses a blockchain-based risk assessment and behavior prediction algorithm. This study [22] uses a BP-GA model to improve a Credit Risk Evaluation (CRE) method to reduce risks in Internet-based SCF products. With its high prediction accuracy and error rate reduction ability, the model helps China's commercial banks handle SCF- oriented credit risks and improves its overall risk management system. SMEs are an important consideration under SCF during the COVID-19 epidemic. However, this quick growth has also led to more complicated credit risks, making effective risk management an important task. This study uses a lasso-logistic model to identify and predict key factors that impact SME credit risk, address these issues, and promote sustainable SCF (SSCF). It finds that administrative penalties, transaction credit, and reputation supervision are essential factors that affect SME credit risk, along with the variables of order data matching, contract enforcement, defaults, business concentration, and administrative penalties.

3. Methodology

3.1. *Proposed Model Outline*

The model begins with supply chain participants and financial institutions-based transaction data and indicators. This data is securely stored and maintained within the blockchain ledger, which involves credit information, product transaction details, supply and consumption data and traceability information. The blockchain guarantees that the data is visible, unchangeable, and accessible and provides a strong foundation for further analysis. This data is again processed by DFFNN, which includes several interconnected modules; first, the data analysis module is performed to analyse the data and transfer it to the learning module. The learning module of DFFNN processes the input data by implementing fuzzy logic and neural network algorithms in a dual manner. Then, the processed data is sent to the feedback loop, which helps the model to improve its predicting abilities continuously. Finally, the data is again sent to the data analysis module for reanalyzing the refined data to adjust its parameters and learn from new information. This iterative process guarantees the model stability in the varying conditions of the supply chain process. The outcomes highlight the set of refined risk assessments that provide supply chain institutions with accurate and timely knowledge about potential risks and allow them to make informed decisions about credit allocation, investment and other financial operations of SMEs. Figure 1 shows the visual structure of the above words.

3.2. *Proposed Blockchain Process to Enhance Security in SCF*

All necessary information supply chain institutions and partners provide is collected and maintained through the blockchain facilities. This collected data is kept in a decentralized ledger comprising several blocks; each block has a specific type of information, such as supply and consumption info, credit information, transaction details of products and traceability information. Due to the decentralized nature of blockchain, there is less chance of unauthorized access because the blockchain guarantees that no entity has a right to control the data. Each block in the process is connected to the previous block through the cryptographic hash, which helps create secure surroundings for the confidential records. Additionally, institutions can follow the movement of goods, services, and payments more accurately with the help of its traceability benefit, which makes supply chain transactions easier. Identification of possible risks and guarantees the legal requirements is likely due to this traceability. Recent blockchain references made the foundation for proposed BC-based security enhancement under SCF. A study [24] highlights the effectiveness of BC techniques. Blockchain transactions are the foundation of SCF, which guarantees safe, transparent, and traceable data for products and financial transfers among many parties. The blockchain process securely handles all data related to financial transactions. This can effectively reduce inefficiencies and develop trust between parties. [25] demonstrate that BC-based smart contracts, which monitor the execution of processes, can be continuously integrated with other technologies. This process effectively reduces human errors, speeds up transaction times, and simplifies the process. Additionally, in [26], blockchain plays an important role in circular supply chains by improving the traceability and accountability of reverse logistics procedures like recycling and remanufacturing. Blockchain helps businesses to achieve their goals and secure operational efficiency to guarantee every step in the supply chain. This ability also supports environmental objectives.

3.3. *DFFNN to Improve the Prediction Ability*

The DFFNN, under the framework of our proposed model, is designed to improve quick prediction abilities, which are necessary for efficient risk management in SCF. By considering the complexity of financial transactions within a blockchain-based system, the DFFNN is used to improve prediction abilities by combining fuzzy logic and neural network processes. This network has four main layers: the input layer, the rule layer, the membership function layer, and the output layer.

Input Layer

The input to the DFNN is defined as a vector $xa = [xa1, xa2, \dots, xaK]^t \in \mathcal{R}^{K\times 1}$, where each component xa_K

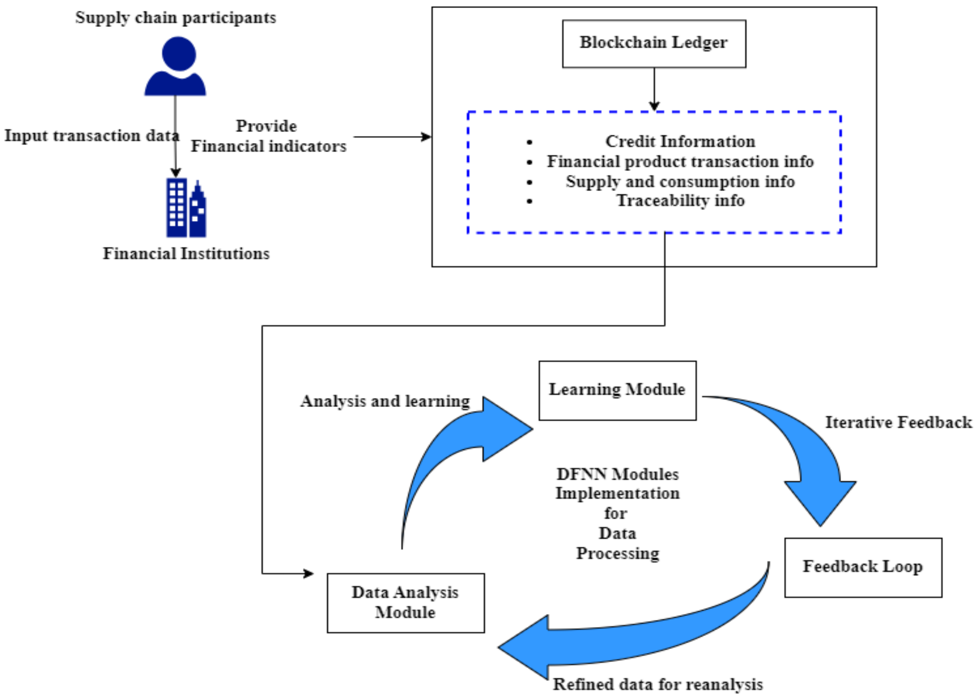

Fig. 1. Proposed DF-BC Implementation

denotes a key financial indicator from the blockchain ledger. The output from this layer is defined as

$$\vartheta_K = xa_K \cdot wa_{roK} \cdot esxy \quad (1)$$

Here wa_{roK} denotes the weight matrix connected to the input layer to the output layer and exy denotes feedback from the output layer.

Membership function layer

This layer is made up of nodes; each node represents a Gaussian function-based membership function. The output of the layer μ impact the center vector c_v, base width b_w and the feedback connection weight r_w. The output μ_{Ki} for the ith membership function of xa_K is expressed as

$$\mu_{ki} = exp^{\left[\frac{(\theta k + rkiesk - cki)2}{baki^2}\right]} \dots \dots \dots \dots \dots \dots \dots (2) \quad \dots..$$

Here the layer's feedback signal is defined as $esx_{\mu_{Ki}}$, μ_{Ki} is the ith membership function of xa_K.

Rule Layer

Each node output ol_j in this layer is calculated as the result of all the input signals corresponding to a particular rule. This layer can be expressed as

$$ol_j = \prod_{K=1}^{2} \mu_{Kj} \quad (3)$$

The output vector ol denotes the strength of every rule in the fuzzy logic system.

Output Layer

Finally, the last layer produces the output ya_t, which calculates the upper bound of uncertainties in the financial data related to the supply chain. It performs this by adding up the contributions of each rule and weighting them according to wa_t. The output is expressed as

$$ya_t = wa^t ol = wa_1 ol_1 + wa_2 ol_2 + \cdots .. + wa_m ol_m \quad (4)$$

To ensure the continuous adjustment of the network and the improvement of risk assessment abilities within the dynamic context of blockchain-based SCF, this output is then fed back into the input layer to improve future forecasts.

3.3.1. *Implementation of DFFNN*

The DFFNN model is effectively designed to adaptively learn and predict the upper bound of uncertainties in SCF. We can implement the procedure here, particularly within a blockchain environment. According to the Lyapunov stability theory, this solution is based on fuzzy logic and neural network learning, which are improved by adaptive rules.

Neural Network Structure and Initialization

First, the DFFNN initializes its structure, which consists of layers for rule processing, output, fuzzy membership functions, and input. A vector $xa = (q\dot{q})^t$, where q and $\dot{q}$ are measurable signals (financial indicators) from the blockchain ledger, serves as the neural network's input.

The network aims to define the collected uncertainty p in the system's upper bound $\hat{p}$, . This can be stated as

$$\hat{p} = \hat{w}a^t \hat{ol} \quad (5)$$

Here $\hat{w}at$ denotes weight vector of the fuzzy neural network and $\hat{ol}$ is the function of the input xa, the center vector $\hat{c}_t$, $\hat{b}_t$ base width and the feedback weights $\hat{r_t}$ and the outer weights $\hat{w}a_{ro}$.

Adaptive Learning and Parameter Updates

Adaptive principles developed from the Lyapunov stability theory are used to modify the weights and parameters of the neural network in real time. These adaptive rules aim to reduce the difference $\tilde{p}$ between the estimated value $\hat{p}$ and the true value p. The deviation is defined as

$$\tilde{p} = p - \hat{p} = wa{*}tol{*} - \hat{w}\, at\hat{ol} + \in \quad (6)$$

Here (6) $wa^{*} and\ tol^{*}$ denotes the optimal weights and functions, and $\in$ denotes the approximation error.

Adaptive Laws for Parameter Adjustments

In real time, adaptive laws are employed to adjust the parameters of d, K, wa, ct, $bt\ rt$, $waro$ in real time. These laws guarantee that the DFFNN learns and improves better at making predictions over time. The Lyapunov function is defined to ensure system stability and tracking error convergence. The Lyapunov function is expressed as

$$v_1 = \frac{1}{2}\sigma^t\sigma + \frac{1}{2}t_k(d^t d) + \frac{1}{2}t_{R}(\bar{k}t_{\bar{k}}) + \frac{1}{2}l(\tau^t\tau), + \frac{1}{2}\eta_1 tr(wa^t wa) \ldots\ldots\ldots\ldots\ldots (7)$$

Here σ denotes the error in tracking the sliding surface, whereas $\tilde{d}, \hat{K}, \zeta, \tilde{w}a$ denotes the error in estimating parameters d, K, ζ, wa.

Sliding Model Control Integration

To make the DFFNN more adaptable to uncertainties and disturbances, it is integrated with a dynamic fractional order sliding mode controller. This control law is expressed as

$$\mu_0 = -\frac{1}{c+\leftthreetimes 1}(\psi + \dot{\mu}_0 \ddot{-} \cdots) \quad (8)$$

In (8), ψ *and* $\leftthreetimes 1$are the system parameters and $\hat{p}$ is the estimated uncertainty. The adaptive laws for the unknown parameters are created to ensure that the system output more closely resembles the original reference model. These laws provide good dynamic features and are easier to implement.

Final Output and Feedback

In SCF, the figure 2 DFFNN final output, represented as $\hat{p}$ is important for defining the control action which need to preserve system stability. By including the estimated uncertainty $\hat{p}$ into the dynamic control law, the control action μ_0 is obtained. This can be expressed as

$$= \frac{1}{c+\leftthreetimes 1}\left(\psi + \dot{\mu}0 - qr + (c+\leftthreetimes 1)\psi - (c+\leftthreetimes 1)\ddot{q}_r + \leftthreetimes 1c\ddot{e} + \leftthreetimes 2d^a e + \hat{p}\frac{\sigma}{K\sigma K}\right) \quad (9)$$

In (9) ψ *and* $\leftthreetimes 1$, are the system parameters, and qr is the reference model acceleration e denotes the error derivative and $d^a e$ is the fractional derivative of the error.

Convergence and stability

The Lyapunov function V_f is carefully designed to guarantee the system's stability. The system reaches maximum stability by assuring that the derivative of the Lyapunov function V_f is non-increasing. Ensuring the tracking error σ and fractional sliding surface $\sigma 0$ converge to zero is essential for upholding exact and dependable forecasts in real-time.

Here f_g denotes the estimated feedback gain and $\epsilon_0$is any residual approximation errors. To provide a reliable and effective risk management solution for blockchain-based SCF, Barbalat's Lemma is used to further analyze the system's stability by guaranteeing that the tracking error and the fractional sliding surface will gradually converge to zero.

$$V_f \le \sigma_0^t\left(f_g + (c+\leftthreetimes 1)f_g - \hat{\psi} - (c+\leftthreetimes 1)\hat{\psi} - p\right) + \sigma_0(w\hat{a}\,to\hat{l} + \epsilon_0)\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

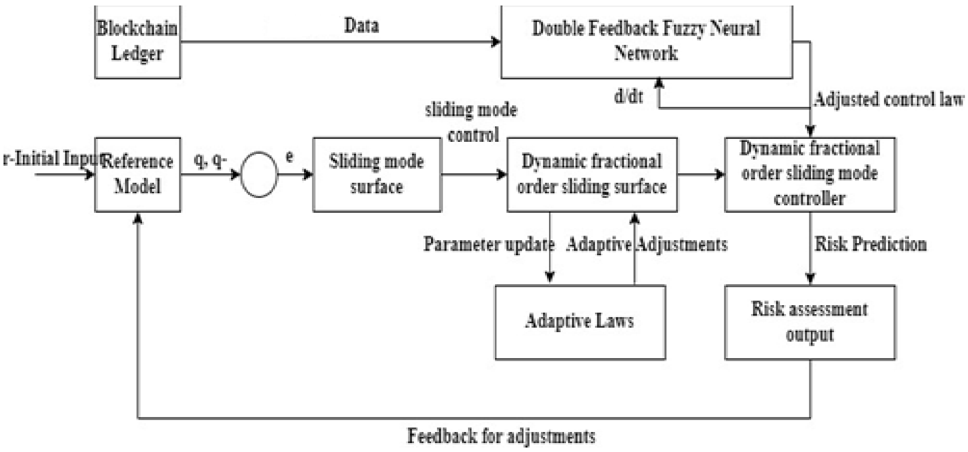

Fig. 2. Implementation of proposed DFFNN

4. Experiments

4.1. *Simulation Setup*

The suggested model is assessed using the SCF risk assessment dataset, which was inspired by [18]. Based on the study, we clearly provide the features of the dataset in Table 2.

Table 2. Dataset Description.

Features	Description	Processing
Total Samples	5000 samples in the dataset	Sample count for training and testing
Training samples	3300 samples for training and Fuzzy Neural Network	Subset used for model training
Test Samples	1700 Samples for testing and validation	Used for validation
Correlation Coefficient Filter	Features with a correlation coefficient ≥ 0.7 are filtered out.	SPSS 25.0 used for correlation filtering.
Normalization	Fuzzy adaptive data-based normalization	To train the neural network
Financial Indicators	Extracted from blockchain ledger, financial indicators based on transactions	Risk Assessment input
Robustness Training	10 Different sets of training and testing data	To ensure model stability
DFFNN output	Credit classification for SME	Final model output for risk prediction

4.2. *Evaluation Criteria*

The present study is compared with the existing research of [18] Fuzzy Neural Networks in terms of risk prediction. The current method highlights its effectiveness in their simulations, based on the same procedures we perform the experiments of proposed; according to the same procedure ,it compare the accuracy of suggested DF-BC with existing FNN. Finally, the prediction output of both models highlights the effectiveness of risk prediction. The main goal of the existing FNN method is to effectively classify financial data by removing indicators that show a high correlation to improve data separation and system processing effectiveness. The technique involves preprocessing the data to ignore related indications before classifying the training sample set using FNN. Using this method, we can effectively identify the patterns and make effective decisions using financial indicators to achieve maximum classification accuracy. However, the suggested model outperforms the existing FNN with its double-loop architecture. By applying the suggested DF-BC to the same dataset, it shows notable improvement in classification accuracy across various test cases; this can be visually shown in Figure 3.

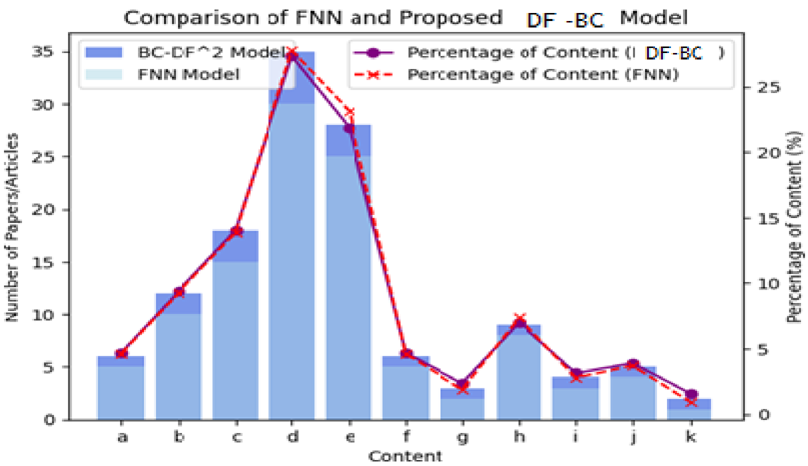

Fig. 3. Proposed DFFNN training results

Figure 4 highlights the improvement of suggested DF -BC under different environmental scenarios which is labeled as A, B, C, and D. This indicates market levels variations, credit risk and external economic conditions. In this scenario the FNN get struggle to maintain the exactness across diverse environments. But the suggested model consistently achieved highest detection indexes across all tested environments.

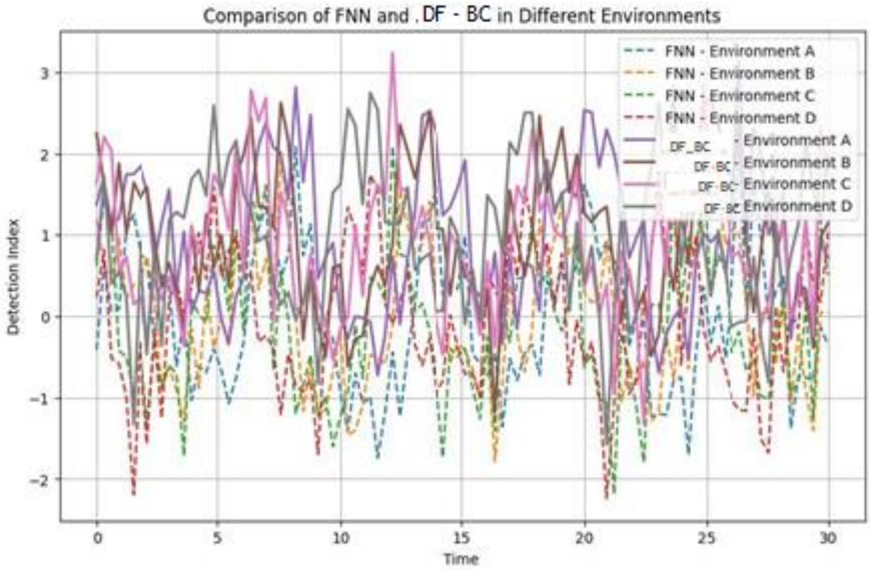

Fig. 4. Distribution of Neural Networks across various scenarios

Figure 5 aims to evaluate 5000 data points; this can be separated as 3300 for training and 1700 for testing. This process can involve 10 different extractions of the sample set. Across various index systems, the suggested model significantly outperforms the existing FNN model with increased classification accuracy rates. When compared with the existing FNN, the suggested model achieves the average of 3-5 % points of higher accuracy.

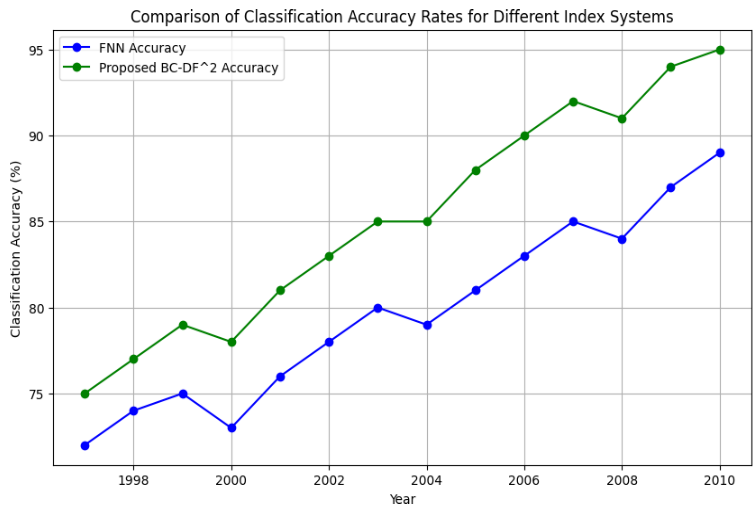

Fig. 5. Classification Accuracy Comparison

Figure 6 highlights the suggested model's ability to capture difficult patterns in SCF. This is visually shown in a smoother, more accurate reconstruction of the attribute values, closely matching expected trends. Also, the proposed model's effective mechanism can notably reduce the error margins when compared with existing FNN.

5. Conclusion

The present study uses the effective combinations of blockchain with fuzzy neural networks. The existing neural networks still have the major drawback within their logic rules, according to that, we introduce the DFFNN which effectively handle complexities of SCF under SMEs with its double layer architecture. Credit assessment in the SCF sector is one of the challenging zones. Most of techniques are assessed in this domain and shows considerable improvements. But the proposed is possible

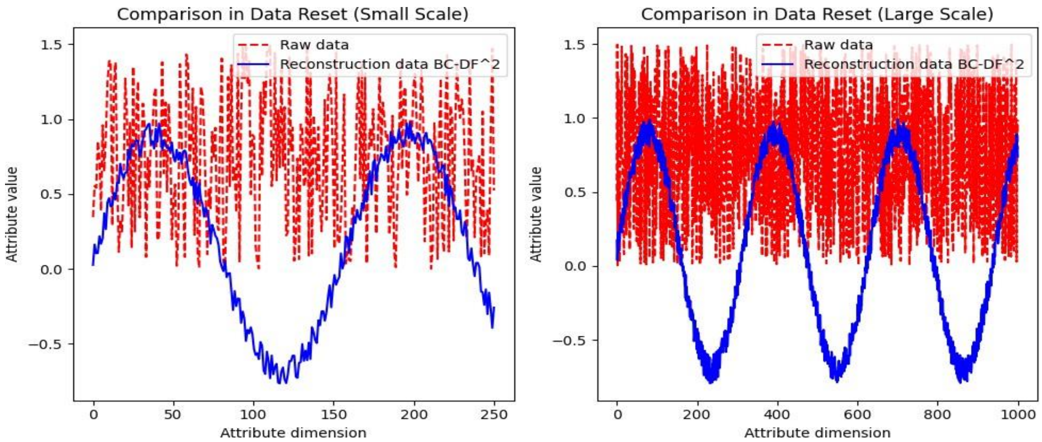

Fig. 6. Data Rest Comparison

solution which includes the blockchain technology for improving security enhancement, as well as combine the strength of DFFNN for risk prediction. The suggested model is simulated using SCF based dataset. Additionally, the model is an effective extension of the existing FNN techniques, by using the foundation of FNN we can effectively introduce DFFNN. Combining with blockchain technology is one of the notable ideas, which helps to effectively handle the large volumes of confidential information's. Through the experiments, we observed that the suggested model proves its improvement over existing FNN under credit risk management in SMEs. Overall, the suggested model is rich in risk prediction also maintains the confidentiality of financial sector and acts as effective contribution in this domain.

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Competing interests
The authors declare no competing interests

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