

## Research Article

# Construction of Mobile Internet Financial Risk Cautioning Framework Based on BP Neural Network

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With the emergence of the 21st-century global economy, the international financial system faces economic risks. A competitive cautioning model for financial management is required to mitigate risks and losses in the financial sector. The financial losses of the banking industry have been categorized and analyzed using the Internet of Things (IoT) and big data technologies to minimize the economic risk of commercial banks in mobile internet finance (MIF). This article proposes a new financial risk cautioning framework (FRCF) based on the IoT, big data, and back propagation-neural network (BP-NN) to ensure steady growth of MIF in the long term. In this article, a big data technology-based approach for data recognition and mining has been suggested. A BP-NN-based method for risk identification and assessment in MIF is also presented. The BP-NN technique calculates each neural network (NN) layer's node count, transfer functions, learning rate, and other characteristics. The proposed FRCF has been developed through the proper construction, analysis, and testing of many information samples. A conceptual understanding of the use of IoT, big data, and artificial intelligence (AI) technologies through NN models in the financial industry has been described in the article. The proposed FRCF can predict the MIF risks associated with the MIF lending infrastructure with a 98.2% accuracy.

## 1. Introduction to Cautioning of MIF Risk in Financial Enterprises

The growth of Internet technology has aided socio-economic development, is now widely employed in many spheres of society, and has altered the financial sector's operations. The financial industry bases its action on Internet technology and leverages big data to move toward digitization. It achieves corporate change and undermines the conventional economic model [1]. A rational self is seen as a cohesive, noncontradictory whole in conventional economic theory. The financial survey of an organization has historically been a crucial resource for stakeholders. It is also an essential source for the general public, bankers, and trade partners to grasp the facts about the organization. When there are no longer any avenues for people to learn about an organization, they will seek for the organization's yearly report to study. They will base their investment choices on their own experiences [2]. Fitzpatrick matched samples of bankrupt and nonbankrupt firms in 1932, during the first economic

recession, and thus began the tradition of the statistical study of early financial cautioning. Fitzpatrick's 19 pairs of samples were split into two groups (bankrupt and nonbankrupt) using the single factor financial ratio index. Finally, it has been discovered that the value of capital, shareholders' assets, and debts were the three indices with the best potential to forecast the financial crisis [3].

Internet finance is an economic practice where various owners fulfill their demands for money by using digital technology like mobile computing [4]. Due to information asymmetry and other issues, China's banking system is not yet flawless. Banks frequently fail to get comprehensive financial information from lenders while expanding credit operations, which puts banks at risk for Internet finance [5]. An innovative financial business model called "Internet finance" uses the Internet and information and communication technologies to undertake financing, payments, capital, and informational intermediary services between established financial institutions and online businesses. The risks taken on by banks have developed along with the

financial concerns that have evolved as the globalization process of economic liberalization gains momentum. Given this context, banks are currently required to update the management mechanism for MIF risk assessment [6] using advancements in science and technology. The systematic process of identifying, measuring, monitoring, and managing the many risks that an organization faces is known as risk management. Risk management systems and capacity-building activities have mostly concentrated on financial and operational concerns inside microfinance institutions (MFIs).

The big data produced by the growth of mobile, Internet, and information systems have sparked a revolution and significantly influenced the advancement of many industries. A collection of data that can be quickly gathered, archived, maintained, and evaluated by a computer is what big data is, in essence [7]. The efficiency of data transport, retention, computing, and dissemination has increased in the big data era. Enterprise business information, financial information, and associated data may all be accessible simultaneously using big data. It offers a sizable data source for early cautioning of the risks related to MIF [8]. Big data analytics makes use of these vast amounts of data on MIF risk possible, enhancing the precision and objectivity of earlier detection and cautioning. Traditional risk assessment techniques, such as the multiple discriminant approach and logistic regression decision trees, may correctly estimate MIF risk. The drawback of these conventional approaches is that they depend too much on previous data and need a lot of actual data as the foundation, which limits their capacity to provide proactive cautioning [9].

Data management and development have been delayed in China. Many clients' financial and business information is not wholly disclosed, which presents unique challenges in predicting and evaluating financial risks [10]. Complex nonlinear issues can be resolved using the NN model. Therefore, early MIF risk may be easily assessed by using a BP-NN finance cautioning model to merge big data with MIF risk cautioning, and the steps to lower the danger of MIF are appropriate [11].

An early cautioning FRCF model to predict MIF risk using BP-NN has been constructed, and the NN is enhanced to boost the accuracy of cautioning of MIF risks. The FRCF accurately evaluates MIF risks and raises the financial sector's level of advancement. To identify, remove, and reduce risks, businesses utilize the risk management framework as a framework and guidance. The National Institute for Standards and Technology created it first in order to safeguard the American government's information systems. In addition, it serves as a guide for developing a risk cautioning system for banks' MIF operations. Thus, the main contributions of this article are as follows:

- (i) Big data and IoT technology are employed for MIF data recognition and mining to facilitate risk identification in the banking industry
- (ii) To examine the predicted gap value of risk evaluation and objectively examine the different MIF

risks faced by the banking sector, Risk Rate Model (RRM) and IoT have been used

- (iii) Construct an FRCF framework using the BP-NN to achieve compelling financial risk assessment and ensure steady growth of MIF
- (iv) The proposed FRCF has been developed through the proper construction, analysis, and testing of appropriate data samples from the rural financial institution in China

The remaining article has been ordered: Section 2 defines associated research on MIF risk and cautioning techniques. Section 3 gives a new financial risk cautioning framework (FRCF) based on the IoT, big data, and BP-NN. Experimental results and discussion have been given in Section 4. Finally, the conclusion, limitations, and scope for further research have been shown in Section 5.

## 2. Related Works on MIF Risk and Cautioning Techniques

Structured risk is an exogenous, non-diversifiable risk that threatens the macroeconomic environment instead of just a few banking firms. Non-diversifiable risk results from variables that have an impact on the entire market, such as overseas investment policy, financial policies, changing socio-economic parameters, changing taxation provisions, and threats to and actions taken in relation to global security. Systematic risk is a type of market risk that cannot be diversified. Economic, political, and social considerations, for example, are outside the control of the company or investor. Unsystematic risks, meantime, are microeconomic issues that have an impact on businesses. Nevertheless, the worldwide financial crisis of 2008 made regulatory agencies and academia realize that structured risk has several degrees of impact on the actual economy. As a result, a new notion for systemic risk has emerged, known as contagion risk, which states that one banking institution's failure will cause other banking firms' failure [12]. Systemic financial hazards have received much attention from governmental bodies and academics ever since the global financial crisis of 2008. Systemic risk "induces a significant amount of market players to experience substantial losses simultaneously and swiftly propagate the loss into the whole economic system" [13].

Authors in [14] examined the primary factors of loan loss provision (LLP), which are categorized as either voluntary (revenue flattening, investment management, and communication) or nonvoluntary using information from a group of more than 410 Italian banks for the years 2002 to 2016 (based on the business loop). An item on the income statement called a loan loss provision is set aside to cover unpaid loans and loan payments. To offer a realistic picture of their overall financial health, banks must take into consideration prospective loan defaults and expenditures. According to the findings, LLP in Italian banks appears to be contractionary, with nonvoluntary factors and socio-economic disruptions exerting a substantial influence. Additionally, because regional banks' liabilities are better secured

and their conduct is more heavily influenced by adequate supervision, LLP is less cyclical in this circumstance [14].

The “Fractional Predicted Loss Method,” Conditional Risk-at-Value Method (*CoVaR*), and specific other novel risk evaluation techniques are proposed to characterize the general level of systemic risk further. These techniques also quantify the contribution of individual banking firms to more comprehensive economic risk when the financial sector is unstable. However, because *CoVaR* and  $\Delta CoVaR$  only take into account correlation into account, two companies with the same connection to the market but different turbulence levels will be evaluated equally by *CoVaR*, even if one is almost secure and has turbulence of zero [15].

The median estimated shortcomings (MES) measuring approach does not consider the size of banking firms, liquidity ratio, or solvency ratio. Still, it does show the capital that businesses would need to augment in the case of a financial crisis [16]. As a result, the process of determining risk factors may be biased.

Due to their nonlinear correlations among variables that may significantly boost the effectiveness of MIF early cautioning, nonlinear models have increasingly supplanted the usage of linear models, such as time-series data, in financial forecasting, and cautioning systems. Zou et al. suggested a multiscale NN model predict the risk of selling crude oil [17]. These risk projections were combined as the ensemble members using the convolutional neural network (C-NN)-based nonlinear ensemble model, which results in the best ensemble predictions. The suggested model’s effectiveness has been empirically evaluated using a large dataset built using daily price records from the leading crude oil markets.

Ensemble approaches have been effective in predicting financial distress. Gradient boosting was employed to forecast bankruptcy accurately among the other ensemble approaches. Shares of ordinary stock will stop yielding dividends and effectively lose all value. When a corporation files for bankruptcy, the stock may be delisted from the main stock exchanges and the symbol may be changed to Q. In [18], the authors developed CatBoost, a unique method for categorizing attribute values using gradient boosting decision trees. Initially, they started by looking into the significance of the characteristics found in the CatBoost model. CatBoost is a technique for decision trees that uses gradient boosting. It was created by Yandex engineers and researchers and used for weather prediction, personal assistance, self-driving automobiles, and search. Second, the suggested technique was compared to eight baseline machine learning models employed between one and three years before failure. Compared to other cutting-edge techniques, the model shows a significant enhancement in the ability of classification results.

Deep learning has advanced in recent years, and specifically, deep learning techniques, including the LSTM NN, have been increasingly integrated into MIF risk forecasting. Yang and Wang (2019) discovered that the accuracy rate was much better than the BP when using the LSTM NN to study the prediction of three different maturities of 30 international stock indices. Deep learning techniques have the edge over conventional machine learning since they can handle

complex, high-dimensional, unpredictable data more efficiently. With limited cognitive resources in a small sample set, the attention-LSTM network further presents a learning algorithm based on the LSTM network that can swiftly filter out critical data from a massive amount of available data [19].

The effectiveness of data processing has significantly increased with the introduction of big data technologies and machine learning. Risk management has become increasingly digital and loaded with information due to the novel correlation analysis of several algorithms and big data technologies [20]. Zhang developed an intelligent fuzzy neural network-based financial investment risk model. This study provides reliable assessments of the cautioning signs of MIF risk for a sample of businesses from an economic standpoint, derives inferences from empirical comparison research, and recommends appropriate regulatory changes [21].

The NN can suit nonlinear problems without depending on the job configuration to provide an effective prediction result, allowing it to assess the FRCF’s prediction impact more precisely. In essence, the article builds a BPNN-based FRCF using big data and IoT technology to identify and evaluate the financial hazards associated with the MIF. Then, the real MIF platforms are selected for investigation based on the early risk prediction research conducted on the recently established MIF application. This study aims to offer a crucial source of information for the steady growth of MIF.

### 3. Financial Risk Cautioning Framework (FRCF) for MIF in the Banking Sector

The banking industry collaborates with the Internet, mobile computing, IoT, and other technologies to develop MIF. MIF has seen a significant change in governance, procedures, and technology compared to conventional financial approaches. The MIF model that is expanding is Internet credit financing due to its easy implementation and high returns on investment.

**3.1. MIF Credit Risk.** MIF credit is obtaining and lending loans to individuals and between individuals and businesses on a digital site. This borrowing strategy departs from conventional banking in the implementation process. The borrowing strategy calculator uses different interest rates and repayment plans to demonstrate the fundamentals of banking borrowing and repayment. Your clients will gain from careful examination of their mortgage and payment alternatives in order to make choices that enable their funds to work harder for them. People have preferred it since it is based on digital technologies and relatively cheap but has a comparatively high return on investment.

Figure 1 depicts the two MIF credit operation modes in the banking sector. Figure 1(a) demonstrates how the online mode of MIF operation may accomplish all credit and financial operations using the Internet framework and IoT technologies. Still, it can also produce a very high default probability, necessitating the acceptance of the associated risk. As shown in Figure 1(b), the second mode blends

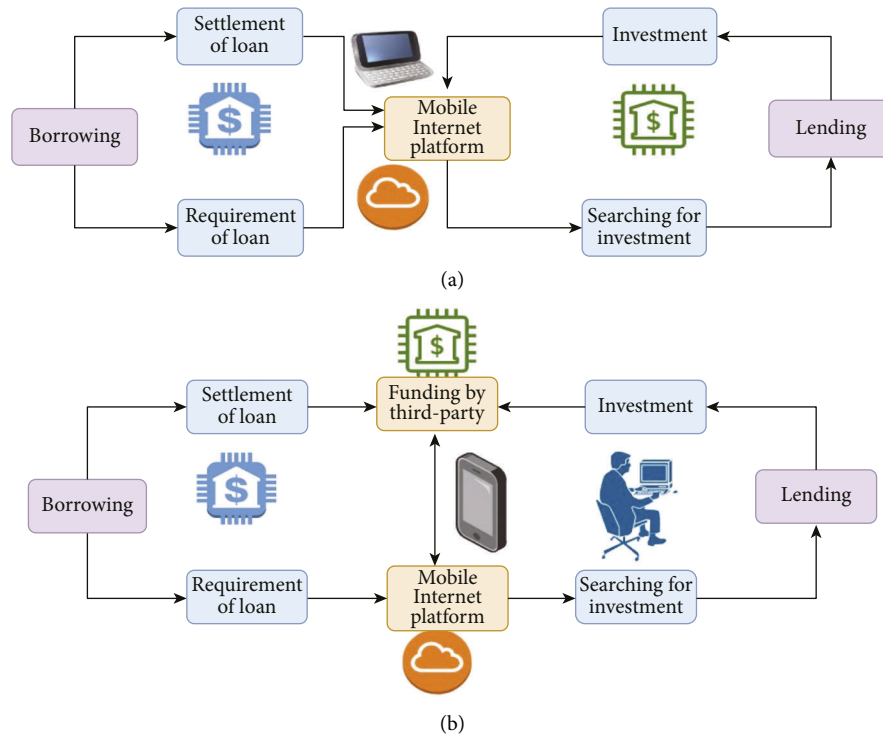


FIGURE 1: Modes of operation of MIF credit in the banking sector. (a) Online mode of operation of MIF. (b) Combined (online and offline) mode of operation of MIF.

online and offline transactions; while the loan may be raised online, “searching for investment,” and evaluations must be completed offline. Information dependability may improve as a result, but running expenses will increase. Despite the differences in their features, these two operational modes will produce some credit risks for MIF.

**3.2. Data Recognition and Mining of MIF Data Using Big Data and IoT Technology.** The big data technique refers to the concept of data mining with the advent of specific unstructured multimedia data, such as images and audio files—the fast expansion of such unstructured information results from the development of storage technologies. In order to uncover hidden patterns and forecast upcoming trends and behaviors in the financial markets, data-gathering techniques have been applied. Mining such data, particularly high-frequency financial data, often requires advanced statistical, mathematical, and artificial intelligence approaches. The proliferation of distributed programming and cloud-based systems in the IoT age has led to a change in the research focus of big data technologies to fog computing and distributed processing architectures. Mobile data now has the features of dispersion and fragmentation due to the ongoing popularity of smartphones and the exponential increase of data in social media-based networks. These qualities make storing and analyzing the banking sector’s mobile data related to IF a challenging process.

Figure 2 shows the data recognition and mining of mobile MIF data using big data. Big data technology is used to handle a significant volume of mobile data. As shown in

Figure 2, certain vital technologies related to big data and the IoT extract combine and store various types of MIF data. The MIF data has been analyzed through analogous computation and deep learning algorithms. The analog deep learning method includes hurling incredibly fast protons through materials. The device’s electrical conductivity is modulated by electrochemically inserting the proton, the smallest ion, into an insulating oxide. RapidMiner, a rather sophisticated data mining system, may offer some assistance with extensive data analytics via a graphical user interface to display the output MIF data [22]. Data transformation, modeling, analysis, assessment, and information processing are just a few of the many operations found in RapidMiner. Data loading and transformation (ETL), data preparation and visualization, data modeling and statistical modeling, assessment, and deployment are just a few of the data mining and machine learning processes that RapidMiner offers. RapidMiner is a potent data mining program that supports model deployment, model operations, and data mining. All the specific loading and machine learning skills required to make a significant effect throughout your business are provided by our end-to-end data science platform. It has been widely utilized because of its strong data mining skills, extensive algorithm functionality, and advanced analytics. The analyzed MIF data can be processed through deep learning algorithms to predict the risk involved through appropriate computation and human-machine interaction to get the desired output for MIF risk prediction. HMIs may be utilized for both straightforward and intricate tasks. An HMI’s user interface can be customized by the user to meet their needs.

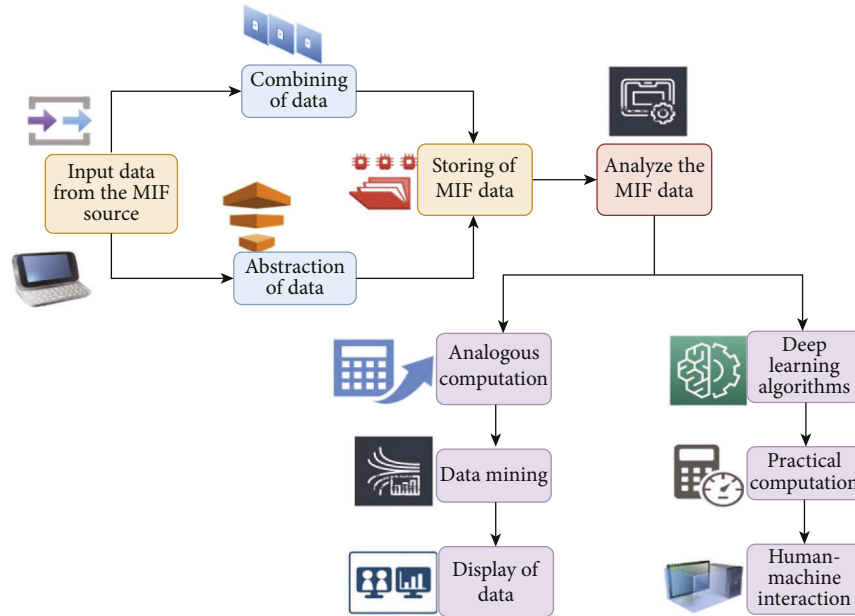


FIGURE 2: Data recognition and mining of mobile MIF data using big data.

3.3. *Detection of MIF Risks Using Big Data Techniques.* Big data expertise has been employed to determine the risks associated with MIF. When RapidMiner is used for risk modeling and examination of MIF, the web crawler technique is employed to gather information [23]. An Internet bot that routinely browses the Internet and is primarily run by browsers for the sake of Web indexing is known as a Web crawler, sometimes known as a spider or spiderbot and frequently abbreviated to crawler (web spidering). There is simply too much information at times. It is simple to deceive the crawler. Websites include secret information that may be used to trick users into thinking they are seeing something they are not. The required preprocessing is accomplished in RapidMiner to obtain the correct MIF information module and enable the use of big data technologies for information assessment.

Figure 3 depicts the detection of MIF risks using big data techniques. The following stages are often used to segment data mining and detect MIF risk: initially, the web crawler’s data is selected to obtain the relevant statistical information and progressive information regarding MIF. Following the analysis and preprocessing to detect data anomalies and incompleteness, the data set’s features have been determined, and data conversion and cleaning are carried out. The processed information is used as modeling data for the random forest (RF) algorithm and logistic regression model [24] for MIF data classification to detect and evaluate MIF risks and provide analysis findings. Random forest has a greater true and false positive predictive value as the number of explanatory factors in a dataset rise, but regression analysis performs better in general when the number of noisy variables is less or equal to the total of explanatory variables.

The RF algorithm must be implemented, which necessitates the creation of different data sets. Subsequently, the information has been trained, and the decision tree for

classification may be retrieved. The data not retrieved throughout the collection process will make up the unbiased data set. During feature extraction, these decision trees must be categorized according to their classification capacities. Then a recursive function may be used to acquire the whole classification decision tree, and an optimization model has been used to detect the MIF risks. Without supervision, the decision tree may grow to the maximum, reducing error and enabling many decision trees to grow together to build an RF.

3.4. *MIF Risk Analysis Using IoT Technology.* IoT technology advancement offers financial firms substantial and practical technological assistance in managing risk management. IoT risk management is a collection of procedures and techniques used to find and assist in removing possible threats and detrimental effects of IoT vulnerabilities. IoT risk management employs risk management procedures and controls the associated business risk depending on all parts of that firm’s usage of technology. Modern technical frameworks do, however, also carry with them several new operational dangers like MIF. Depending on the fundamental logical framework of IoT, the operational risks may be divided into the following three types. Threats from the data detection layer are within the first group. Bar codes, Quick Response (QR) codes, different sensors, and sensing technology like satellite location are the key components of the detection layer. Banking firms usually use these sensors to gather and analyze the MIF data. Various sensors often have varying degrees of precision, leading to inconsistent operational risk awareness.

Multiple levels of functioning risks in the perceptual layer will also originate from terminal failures, information source failures, or denial of QR codes. Risks from the

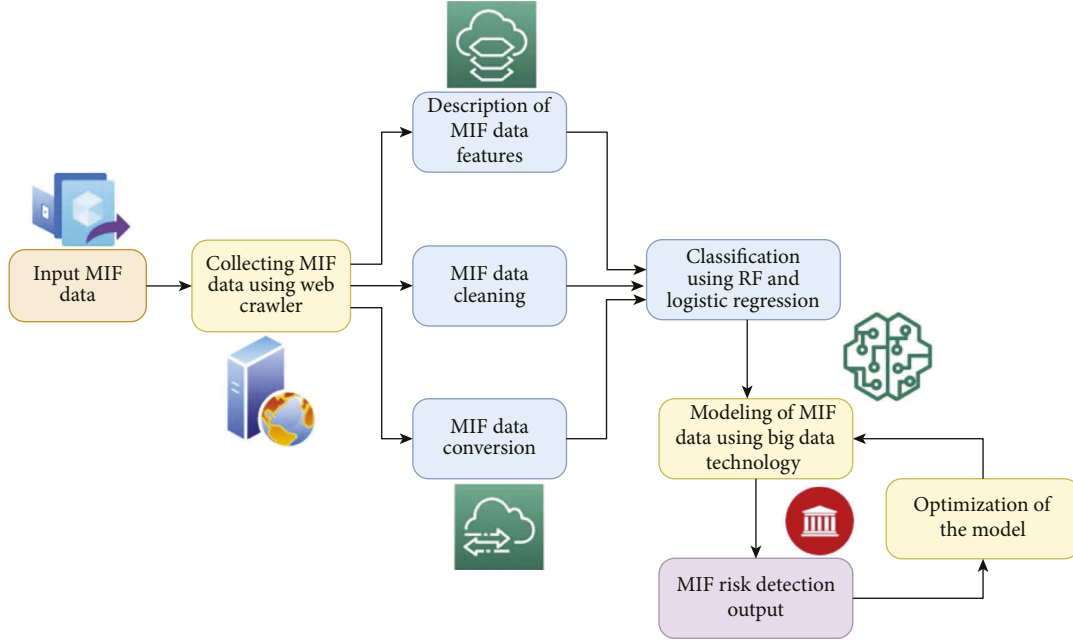


FIGURE 3: Detection of MIF risks using big data techniques.

network and transport layer are under the classification. MIF data is primarily sent and received by the network and transport layer across the broadband Internet. Once this layer delivers and analyses data collected at the perceptual layer, operational risks might arise due to imperfect technology and guidelines. The physical layer, or perception layer, contains sensors for perceiving and collecting environmental data. It detects certain physical factors or locates other intelligent devices in the surrounding area. MIF data exposure, breach, communication latency, data encryption, asymmetric information, and hostile intrusion are the primary hazards the network and transport layer must overcome.

The application layer presents risks in the third category. The application layer is primarily used to analyze the information and data transmitted by other levels of the IoT network, send them to financial institutions for processing, and offer workable mobile applications for banking activities, including economic decision-making and status monitoring. The risks in the application layer nest vulnerabilities in other levels that are further complicated, such as the risks of securing intellectual property and coordinating with stakeholders because the application layer comprises a diverse variety of businesses and individuals.

**3.4.1. RRM and IoT to Examine MIF Risks.** The RRM and IoT have been used to examine the predicted gap value of risk evaluation and objectively construct the different MIF risks faced by the banking sector. MIF's IoT-based mathematical risk formulation is built on the RRM as the basis for its operational risk assessment. (1) shows the mathematical model of MIF risk based on RRM. A vital tool for making loan choices and managing and building portfolios is a risk rating model. They provide lenders, analysts, and asset managers with a fairly objective method of classifying

borrowers or particular assets according to their trustworthiness and default risk. Value at risk (VaR) is a metric that measures how much money might be lost by a company, investment, or position over a certain period of time. The Value at Risk (VaR) at a threshold value  $x$  for MIF in the banking sector is given as

$$VaR^x = \begin{cases} \frac{x}{(zy)} \left[ \frac{q}{p} (1 + \beta) \right]^{-y} - 1, & y < 0, \\ x + z \ln \left[ \frac{q}{p} (1 + \beta) \right], & y = 0, \\ \frac{x}{(zy)} \left[ \frac{q}{p} (1 + \beta) \right]^{-y} + 1, & y > 0, \end{cases} \quad (1)$$

where  $x$  is the threshold value for MIF in the banking sector,  $p$  is the MIF data samples higher than  $x$ .  $q$  is the MIF data samples lower than the threshold  $x$ .  $y$  and  $z$  are MIF risk factors.  $\beta$  is the survival rate of the banking sector, despite MIF risks. The mathematical computation of high MIF risks using  $VaR^x$  has been carried out using the expected shortcomings (ES) value and is given as

$$ES_x = \left[ \frac{VaR^x}{1 + z} \right] - \left[ \frac{(y - xz)}{(1 + z)} \right], \quad (2)$$

where  $VaR^x$  is the value at risk at a threshold value  $x$  for MIF in the banking sector,  $y$  and  $z$  are MIF risk factors. National financial institutions now lack a comprehensive database for operating MIF risks and losses. A MIF risk analysis model may be created based on the findings of the developed mathematical model, which can compute and identify various forms of financial business risk loss value.



3.4.2. *FRCF Using BP-NN to Detect MIF Risks.* Huge quantity, cross diversity, quick creation, and fragmented value are the four components of big data which broadens its valuation arena. The most effective technique for extensive data processing is the NN, a calculating method that mimics the comprehensive data analysis techniques of the nervous system. The BP-NN aims to simulate and represent the issue from the network's point of view. The interlinked transmission topology of every neuron in the network has been stored and identified. More variables can be controlled, and versatility can be improved. The recent data must be entered again into the NN for the calculation to provide updated values for risk prediction. The adaptive development and each neuron's link weight can be adjusted to influence this procedure.

Figure 4 depicts the structure of BP-NN used in FRCF to predict the MIF risks in the banking sector. The neuron is a part of the NN that has a typical configuration, as illustrated in Figure 4, with many input terminals and one output terminal. The input values given to NN are denoted as  $\{A1, A2, \dots, An\}$  for  $i^{\text{th}}$  neuron and the corresponding weights are given as  $\{W_{i1}, W_{i2}, \dots, W_{in}\}$ . The limiting value of the NN is provided by  $\alpha$ . The most popular converter or transfer function is the sigmoid function, which has been used to alter the magnitude of the NN model output. One of the sigmoid units of a neural network. It is a given that the output of a unit will always fall between 0 and 1 when the activation function of a neuron is a sigmoid function. The purpose of the transfer function is to obtain the output  $B_i$  for neuron  $i$  to attain the limiting value of  $\alpha$  based on the input values  $\{A1, A2, \dots, An\}$ . As seen in Figure 4, the BP-NN has three layers: an input layer, an output layer, and a hidden layer, with  $M$ , 1, and  $N$  nodes, correspondingly. Each input node's link weight value to each hidden state node is  $M_{ki}$ . Similarly, each output node's link weight value to each hidden state node is  $M_{kj}$ .

Figure 5 shows the flow diagram of the BP-NN process. The NN parameters have been set at the beginning, including defining the quantity of input and output nodes. The input vector and the expected outcome of the algorithmic process will be fed to the NN. The following are the design principles for neuron models: the BP-NN employs a multiple-layer feedforward NN with reinforced learning and a fault backpropagation algorithm to match the correlation between input and output and the widely applicable structure. For the chain rule method's neural network training, backpropagation is performed. To put it simply, this technique does the backward pass after each feedforward run through a network in order to modify the model's parameters depending on weights and biases. Backpropagation is sluggish and unstable since each authority is only used for a small number of input instances. Furthermore, the assortment of experts is unable to swiftly modify its parsing when new situations emerge. Existing blends of specialists cannot add a new type of specialty if a situation calls for it. For reinforcement methods of artificial networks employing gradient descent, backpropagation—short for “rewinding of errors”—is a method. The approach determines the grade of the error function in relation to the weights of the artificial

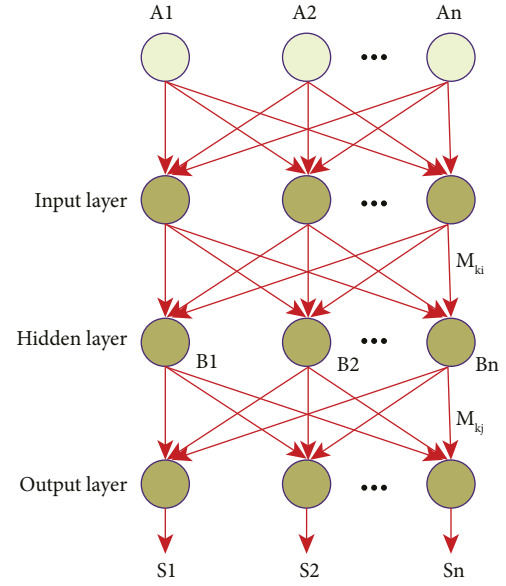


FIGURE 4: Structure of BP-NN used in FRCF to predict the MIF risks.

neural network given an error function and an artificial neural network. The weighting factor is adjusted following the feedback mechanism at the output based on the learning function of NN. The fault value in the learning outcome is given as  $f = I - h$  if the intended output and the definite output value is given as  $h$ .

The learning procedure is split into two parts in the BP-NN algorithm's flowchart given above: the onward transmission of the operational data and the BP of the fault value. The resulting value of the  $i^{\text{th}}$  neuron located in the hidden level corresponds to the feedforward transmission of the operational data and is given as

$$B_i = Fn \left[ \sum_{i=1}^I M_{ki} A_i + \alpha_i \right], \quad (3)$$

where  $B_i$  is the value of the  $i^{\text{th}}$  neuron located in the hidden level. The intended output is, and the value of the  $i^{\text{th}}$  neuron located in the input level is given as  $A_i$ . The limiting value of the  $i^{\text{th}}$  neuron is given by  $\alpha_i$ . Each input node's link weight value to each hidden state node is  $M_{ki}$ .

The resulting value of the  $j^{\text{th}}$  neuron located in the output level corresponds to the BP of the fault value and is given as

$$S_j = Fn \left[ \sum_{j=1}^N M_{kj} B_j + \alpha_j \right], \quad (4)$$

where  $S_j$  is the value of the  $j^{\text{th}}$  neuron located in the output level that determines the FRCF value. The number of nodes in the hidden group is, and the value of the  $j^{\text{th}}$  neuron located in the output level is given as  $B_j$ . The limiting value of the  $j^{\text{th}}$  neuron is given by  $\alpha_j$ . Each output node's link weight value to each hidden state node is  $M_{kj}$ .

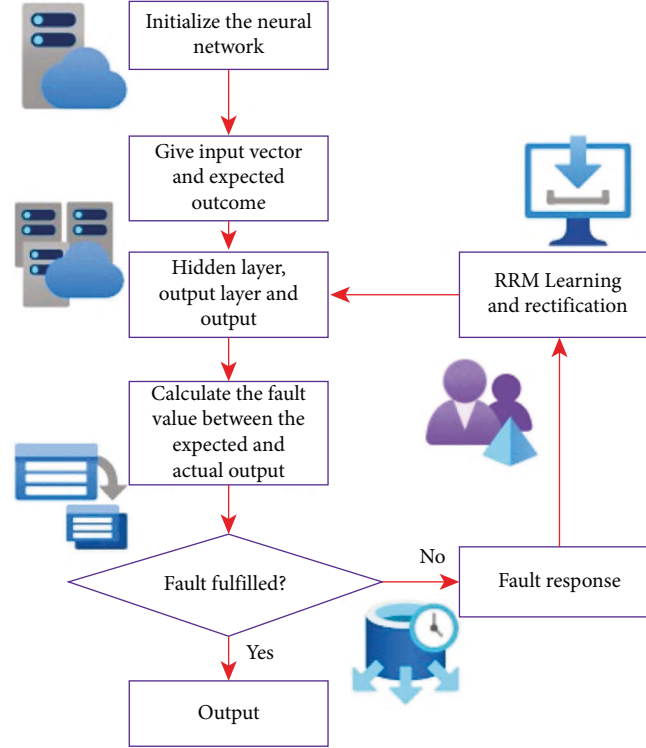


FIGURE 5: Flow diagram of the BP-NN process.

The fault value of BP-NN is given as

$$f(n) = 0.5 \left[ \sum_{j=1}^N (I_j - h_j)^2 \right], \quad (5)$$

where  $f(n)$  is the fault value of a node  $j$  in NN. The quantity of nodes in the hidden level is  $N$ . The intended output of node  $j$  is, and the actual output value is given as  $h_j$ . Finding optimal filter coefficients that produce the smallest average square of the process variable is how least mean square (LMS) algorithms, a kind of adaptive filter, imitate the desired filter. The corresponding weight values of BP-NN have been adjusted based on the least mean square (LMS) error algorithm for  $i^{\text{th}}$  and  $j^{\text{th}}$  neurons and are given as follows:

$$\begin{aligned} \delta M_{kj} &= \rho (I_j - h_j) B_i, \\ \delta M_{ki} &= \rho \sum_{j=1}^N (I_j - h_j) M_{kj} A_i, \end{aligned} \quad (6)$$

where  $\delta$  is the weight adjusting factor.  $\rho$  is the effectiveness of the RRM learning process. The number of nodes in the hidden level is  $N$ . The intended output of node  $j$  is, and the actual output value is given as  $h_j$ . Each input node's link weight value to each hidden state node is  $M_{ki}$ . Each output

node's link weight value to each hidden state node is  $M_{kj}$ .  $A_i$  and  $B_i$  are the values of  $i^{\text{th}}$  neuron in the input and hidden level.

Standardized metrics include the nonfinancial metric  $S_o$ , and the four comprehensive metrics (bank stability score, bank operational capacity score, capital adequacy score, and bank-scale possible score) have been chosen for FRCF using BP-NN. The data is then used as the input, with five input nodes ( $N = 5$ ). The complete FRCF value falls inside the one output node, which is the MIF risk prediction based on,  $S_j = Fn[\sum_{j=1}^N M_{kj} B_j + \alpha j]$ .

The suggested FRCF performs well in forecasting and classification when employing BP-NN, big data, and IoT. The proposed FRCF is crucial to categorizing and managing banks in IF with similar risk profiles. Considering the link between the financial metrics, ecological indicators, and MIF risk level of relevant banks, BP-NN can determine the coherency and discrepancy between banks and relevant indicators. This coherency allows it to retrieve pertinent, helpful information relating to the chosen research banks based on the corresponding function correlation. The FRCF can be studied and assessed using the procedures mentioned above. The high learning effectiveness of BP-NN, particularly its incredible performance in fault BP and weight adjustment, can assist in controlling the fault for evaluating MIF and risk within the permissible range. This effectiveness of BP-NN can improve the accuracy of the FRCF evaluation result compared to other



mathematical methods. Thus, the BP-NN is chosen as the evaluation instrument to evaluate banks' MIF and FRCF based on the analysis mentioned above.

#### 4. Results and Discussion

Rural Financial Institution (RFI) in China [25] has been chosen as the research entity. The organization statistics coherent with the trivial and medium-level businesses from multiple areas and having an account with RFI are selected. This analysis looks at the impact of the FRCF model based on BP-NN to predict MIF risk levels. Regarding the information sources, the loans that have been granted but still pose a risk of MIF risks have essentially been the primary focus. Under ordinary situations, the risk assessment of the MIF loan typically relates to the pertinent debtor data. It determines the likelihood of nonpayment based on the bank managers' consuming ideology and credibility. Big data technologies may be used to find relevant details, and the web-crawler technique has been used in this article to collect and archive the information [23]. Three years' worth of statistics are examined, assessed, and to create records, a sample of the data that appears in the event window is randomly picked. The sample data for testing is chosen from 25% of the total data samples, while the training dataset is selected from the remaining 75%. RapidMiner uses SplitData to determine the MIF risk levels and grading functions on the training and test samples [22].

The MIF risk levels have been classified based on the "3sigma" rule [26]. The statistical term used to determine the Degree of Deviation (DoD) in data samples is the "3sigma" criterion. This probability interval's definition is a foundation for the progressive grading of MIF risks. Implementing this rule enables the systematic grading of nonpayment rates to be quantified, allowing for a more logical examination and assessment of MIF risks.

Table 1 shows the MIF risk level identification using the "3sigma" criterion in FRCF. Standardized metrics in FRCF include the nonfinancial metric  $S_0$ , and the four comprehensive metrics (bank stability score, bank operational capacity score, capital adequacy score, and bank-scale potential score) have been chosen as input for BP-NN to find the risk level ( $S_j = Fn[\sum_{j=1}^N M_{kj} B_j + \alpha_j]$ ). After data preprocessing, the average value of  $S_j$  is found to be  $Avg = 0.512$  and  $DoD = 0.399$ . The output of FRCF using BP-NN is the five MIF levels classified as "Highly secure, Secure, Caution, Risky, and Highly risky" based on the "3sigma" criterion.

A total of 1000 samples have been considered for FRCF analysis, and 750 samples have been used in the training set. The remaining 250 samples from the data sample are included in the test set. The MIF risk levels and rate of nonpayment for training samples have been displayed in Figure 6. Calculations of the actual nonpayment percentage and predicted nonpayment percentage of different samples are used to assess whether IoT, mobile computing, and big data can effectively identify MIF risks. The fraction of debtors to the total quantity of samples in the dataset is the actual nonpayment rate. The mean number obtained after

TABLE 1: Identification of MIF risk levels using the "3sigma" criterion in FRCF.

"3sigma" period	Value	MIF risk levels
$[(Avg-DoD), (Avg + DoD)]$	[0.113, 0.911]	Highly secure
$[(Avg + DoD), (Avg+3DoD)]$	[0.911, 1.709]	Secure
$[(Avg+3DoD), +\infty]$	[1.709, $+\infty$ ]	Caution
$[(Avg-3DoD), (Avg-DoD)]$	[0.685, 0.113]	Risky
$[-\infty, (Avg-3DoD)]$	$[-\infty, 0.685]$	Highly risky

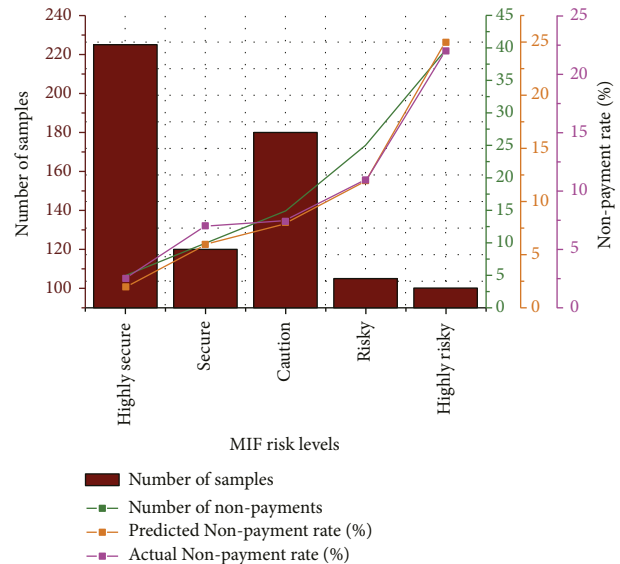


FIGURE 6: Comparison between MIF risk levels and nonpayment rate for various training samples in FRCF.

forecasting the nonpayment rate in the sample dataset is the predicted nonpayment rate. The training set contains 75% of the data sample chosen from the dataset [25]. The sample size and nonpayment rate of each MIF risk level may be obtained using the FRCF calculating technique based on IoT and big data technologies. It has been observed from Figure 6 that the actual and predicted nonpayment rate has increased with the decrease of MIF risk levels.

Figure 7 compares MIF risk levels and nonpayment rates for various test samples. The test set's sample data has an aggregate nonpayment rate of roughly 10.1%. The nonpayment rate for samples with MIF risk at the level "highly risky" is 32.9%, increasing as MIF risk levels decline. The actual nonpayment percentage and predicted nonpayment percentage of various data samples are determined to assess the viability of IoT, mobile computing, and big data technologies in recognizing MIF risks. According to Figure 7, there is a positive link between the actual and expected nonpayment rates, which means that both rise when MIF risk levels fall.

In this article, we aim to review five types of neural networks for binary classification problems. These are back propagation-neural network (BP-NN) [8], radial basis function-neural network (RBF-NN) [9], general regression-neural network (GR-NN) [10], probabilistic-neural network

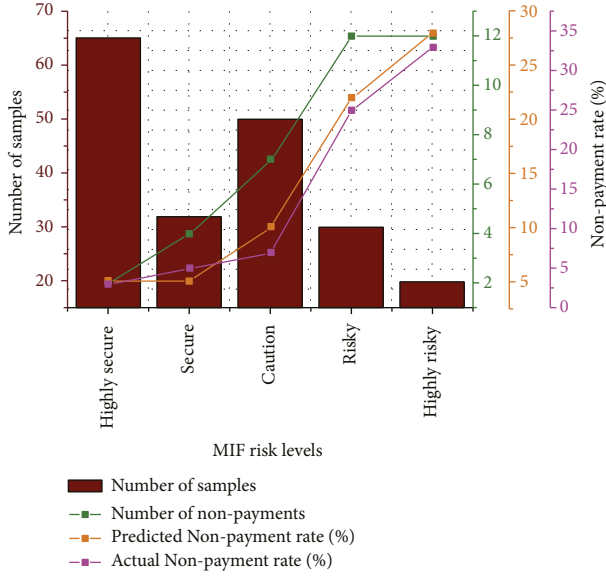


FIGURE 7: Comparison between MIF risk levels and nonpayment rate for various test samples in FRCF.

(PNN) [11], and complementary-neural network (CMTNN) [12].

In this article, prediction accuracy and mean square error (MSE) of MIF risk levels for the proposed FRCF using BP-NN have been compared with other NNs [27]: radial basis function-neural network (RBF-NN), general regression-neural network (GR-NN), probabilistic-neural network (PB-NN), and complementary-neural network (C-NN).

Figure 8 depicts the prediction accuracy (%) and MSE value for various NN schemes in FRCF. The prediction accuracy of MIF risks for the proposed FRCF is given by

$$\text{prediction accuracy (\%)} = \left[ \frac{\text{true positive}}{\text{true positive} + \text{false negative}} \right] * 100. \quad (7)$$

True positive is the figure of correctly identified MIF risks in FRCF. False negative is the figure of correctly identified MIF security. The MSE has been calculated as

$$\text{MSE or prediction error} = \frac{1}{DS} \sum_{j=1}^{DS} (\hat{S}_j - S_j)^2, \quad (8)$$

where  $DS$  is the total amount of information samples,  $\hat{S}_j$  and  $S_j$  are the predicted and actual values of MIF risks in FRCF, respectively. The FRCF is accurate if it can predict the MIF risks with low prediction error values. Among the NN schemes for FRCF, the proposed BP-NN can predict the MIF risk levels with the highest accuracy of 98.2% and the least MSE of 0.028 due to its optimized fault response mechanism. GR-NN has the highest prediction error and the lowest accuracy among NN schemes.

This article examines the effectiveness of the BP-NN-based FRCF model in predicting MIF risk levels. The loans that have been approved but still have a risk of MIF hazards

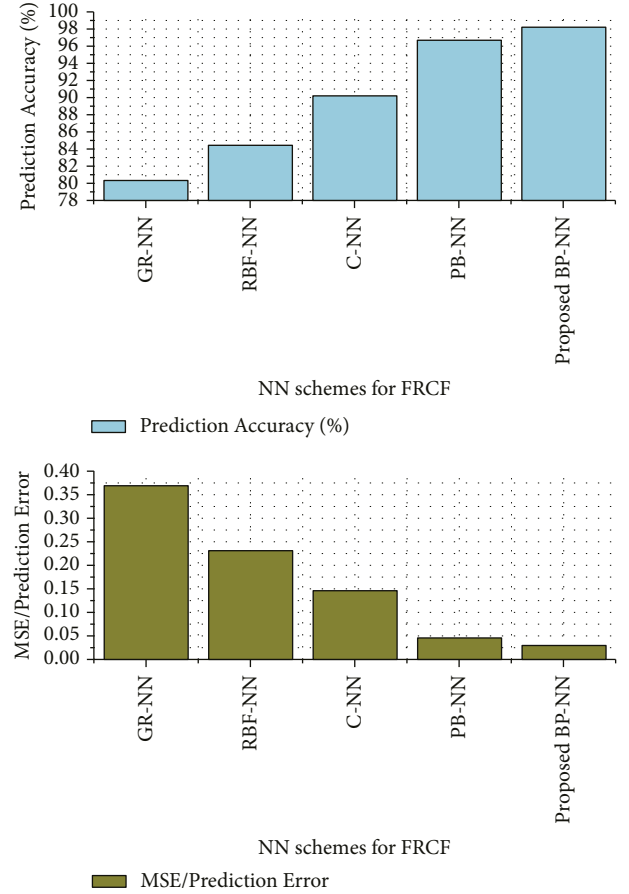


FIGURE 8: Prediction accuracy (%) and prediction error value for various NN schemes in FRCF.

have essentially been the main emphasis in terms of the data sources. The MIF risk levels have been classified based on the “3sigma” rule using one nonfinancial and four comprehensive metrics.

## 5. Conclusion, Limitations, and Future Study

This study suggests a novel financial risk cautioning framework (FRCF) based on IoT, mobile computing, and big data technologies, and BP-NN to ensure a significant rise in MIF. This article proposes a big data technology-based data mining and recognition strategy. A BP-NN-based method for identifying and evaluating risks in MIF is also provided. The node count, transfer functions, learning rate, and other properties of each NN layer are calculated using the BP-NN approach. The proper training and testing of numerous information samples led to the development of the suggested FRCF. The output of FRCF using BP-NN is the five MIF levels classified as “Highly secure, Secure, Caution, Risky, and Highly risky” based on the “3sigma” criterion. Due to its optimized fault response mechanism, the suggested BP-NN among the NN schemes for FRCF can forecast the MIF risk levels with the most remarkable accuracy of 98.2% and the least MSE of 0.028.

Nevertheless, there are still certain restrictions on this research work. It primarily concentrates on risk assessment of the newly emergent credit structure, which is insufficient for MIF. Uniting a few other representative sectors is necessary to make future study findings more compelling. A specific volume of data samples must be needed to analyze the BP-NN model. The quantity and reliability of the data samples significantly impact how well NN models learn and function in the end. Consequently, to assure the correctness and applicability of the results obtained, the datasets' legitimacy, dependability, and diversity should be guaranteed as feasible in future research.

## Data Availability

All data generated or analyzed during this study are included in the manuscript.

## Conflicts of Interest

The author declares no conflicts of interest.

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