International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)
Vol. 11-No.2 (2025) pp. 3322-3332
http://www.ijcesen.com
ISSN: 2149-9144

Research Article

Building Scalable Fintech Platforms: Designing Secure and High Performance Mutual Fund and Loan Management Systems

Jaya Krishna Modadugu*

Software Engineer, Prosper Marketplace Inc, California, USA
* **Corresponding Author Email:** jayakrishna.modadugu@gmail.com- **ORCID:** 0009-0008-9086-6145

Article Info:

DOI: 10.22399/ijcesen.2290
Received : 02 March 2025
Accepted : 07 May 2025

Keywords :

Fintech
Hyperbolic Cosine Transform
Loan Management
Mutual Fund
India Detailed Dataset
Multiparticle Kalman Filter

Abstract:

Designing scalable fintech platforms for mutual fund and loan management ensures robust performance, security, and flexibility to handle increasing transactions and user demands, making them crucial for efficient asset management and loan processing. However, a key drawback is the complexity of maintaining security standards, as scaling up often requires additional layers of protection, which lead to higher costs and implementation challenges. To overcome this problem, in this manuscript Building Scalable Fintech Platforms: Designing Secure and High-Performance Mutual Fund and Loan Management Systems (BSFP-SHML-PGCN) is proposed. The major objective of the proposed method is to secure financial fund and loan management.Initially, the input data are collected from Mutual Funds India–Detailed Dataset. The data are pre-processed using Multiparticle Kalman Filter (MKF), which are used missing values and clean input data. After that, the data are fed into Hyperbolic Cosine Transform (HCT)for extract relevant features such as scheme name, expense ratio, rating, and category. The extracted features are provided to Progressive Graph Convolutional Networks (PGCN) to classify theuncertainty in mutual fund returns risk level as Low Risk, Low to Moderate, Moderate, Moderately High, High, and Very High.The proposed technique is implemented in Python, and the efficacy of the BSFP-SHML-PGCN technique was assessed using various performance measures, including accuracy, precision, sensitivity, and specificity. The performance of the BSFP-SHML-PGCN method achieved99.05% higher accuracy, 99.01% higher precision, 98.95% higher sensitivity, and 96.50% higher specificity when analysed through existing techniques such as FinTech enablers, use cases, and role of future internet of things (FTE-FIoT-DL), Investigating the components of fntech ecosystem for distributed energy investments and an integrated quantum spherical decision support system (ICFE-DEI-SWARA) and Forecasting the returns of the US real estate investment trust market: evidence from the group model of data handling neural network (USRE-ITME-ML), respectively.

1. Introduction

Building scalable fintech platforms requires careful attention to several key factors. Security is paramount to safeguard sensitive financial data from unauthorized access and cyber threats, which is critical to maintaining user trust [1]. Scalability follows closely behind, ensuring the platform can expand flawlessly to accommodate raising user demand and maximizing transaction volumes without compromising performance. A robust mutual fund management system [2] is vital for efficiently tracking and managing portfolios, offering transparency and insights into fund performance. Similarly, a loan management system [3] must handle the entire lifecycle of loans, ensuring smooth processing from origination to repayment. High availability [4] is vital to ensure the platform remains operational during peak periods or system failures, providing users with consistent access. Maintaining data integrity [5] ensures that financial records are accurate, consistent, and secure, safeguarding against manipulation and errors. To meet growing demand, performance optimization [6] is necessary to maintain quick processing speeds and handle high transaction volumes without slowdowns. Compliance with regulatory standards [7] ensures the platform adheres to financial laws, protecting both the platform and its users from legal issues. Utilizing cloud-based infrastructure [8] allows the platform to scale efficiently, offering flexibility and resource management without relying on physical hardware. Analytics [9] provides instant insights into mutual fund and loan performance, enabling informed decision-making for both users and platform administrators. A seamless user experience (UX) [10] is critical to ensuring that users navigate the platform effortlessly, accessing key features without confusion. Automated risk assessment [11] is essential to evaluate loan applicants' creditworthiness quickly and accurately, reducing human error and improving decision-making efficiency. The adoption of blockchain technology [12] enhances transparency by providing an immutable record of all transactions, ensuring trust in the system. The integration with third-party services [13] allows the platform to offer a more complete solution, connecting to payment processors, credit bureaus, and other essential financial services. Lastly, a strong disaster recovery plan [14] guarantees that the platform quickly recovers from unforeseen events, ensuring business continuity even in the face of unexpected disruptions [15].

Scalability and performance are critical challenges in the design of fintech platforms for mutual fund and loan management systems. As user bases and transaction volumes grow, ensuring the platform handle increasing data loads without compromising speed or reliability becomes complex. The dynamic nature of financial transactions requires systems that scale efficiently while maintaining high performance, ensuring quick processing times and analytics. Additionally, the growing data volume makes it difficult to balance system expansion with user experience, requiring careful design to prevent performance degradation.

Literature Survey

Several works have presented previously in literatures were depending Building Scalable Fintech Platforms through different techniques. Few of them were mentioned here,

Bhat, J.R*et al*. [16] have presented an important shift in the financial industry, with organizations increasingly adopting digitalization to enhance their operations. Financial Technology (Fintech) integrates modern technologies like AI, 5G/6G, Blockchain, Metaverse, and IoT to enhance services in the sector. These improvements were streamlining key financial processes such as lending, confirmation, detection of fraud, quality control, and credit scoring. However, further development of innovative financial products and the supporting technologies was essential to fully realize their potential.

Ai, R *et al.*[17] have presented an evaluation of the components of afntech ecology for distributed energy investments. Using numerous stepwise weight assessment ratio analysis, elimination, and choice translating reality procedures based on quantum spherical fuzzy sets, a novel decision-making model was developed. Weights were assigned to the criteria for distributed energy investment demands in this model. Appropriate strategies for designing effective fintech ecosystems that maximize distributed energy investments were presented, considering an unique fuzzy decision-making method.

Zhang, W *et al.*[18] have presented the Group Model of Data Handling (GMDH) neural network, which has proven effective in prediction, data mining, with optimization. It has been employed to predict stock and REIT returns in various countries and regions, but not in the United Statesreal estate investment trust(US REIT) market. The US REIT market was predicted using GMDH, with accuracy compared to traditional prediction methods. Both the GMDH neural network and the GARCH model were employed to forecast returns on the US REIT index. To evaluate their effect on the machine learning method's accuracy, training samples, testing samples, and the GMDH model's kernel functions were all manipulated.

Mahmud *et al.* [19] have suggested Customer Fintech Readiness (CFR) was to evaluate how prepared customers were to adopt and engage with fintech solutions, like digital payments, mobile banking, and peer-to-peer lending. Understanding CFR helps fintech companies tailor their products and services to meet customer requires, address barriers to adoption, and improve user experience. The assessment was crucial for identifying factors such as digital literacy, trust in technology, and access to financial services, evaluating CFR challenging due to varying levels of awareness and understanding of fintech across different demographics.

Rapozo*et al.* [20] Have presented the relationship between FinTech and Small as well as Medium-sized Enterprises (SMEs) in the Dutch loanable funds market, highlighting how digital financial services enhance access to funding. By examining how FinTech platforms manage relationships with

SMEs, the study aims to identify strategies for better loan offerings, faster processing, and reduced costs, ultimately enhancing SME growth and financial inclusion. FinTech solutions might struggle to address the diverse needs of SMEs across different industries, leading to mismatches in financial products.

M Cummins *et al.* [21] have suggested FinTech as an alternative channel to mobilize private financing for building renovation was to provide a more accessible, efficient, and flexible method of funding for energy-efficient and sustainable renovations. FinTech platforms connect investors with building owners, offering various financial products like green bonds or crowdfunding to raise capital for renovation projects. The approach increase access to funding, streamline processes, and lower costs compared to traditional financing methods.

A Rafiuddin*et al.* [22] have presented the growth of fintech connectedness and novel thematic indices through wavelet techniques, highlighting the evolving relationships between fintech markets and sectors such as sustainable finance and digital currencies over time. Wavelet analysis allows for the detection of patterns and correlations at multiple time scales, providing insights into the short- and long-term growth trends of fintech. The evaluation helps investors, policymakers, and businesses understand how fintech innovations influence or were influenced by various thematic sectors. Wavelet analysis complex, requiring advanced technical knowledge and computational resources.

Recent research in fintech platforms focuses on building secure and high-performance systems for managing mutual funds and loans. Emphasis was placed on enhancing scalability and efficiency while ensuring robust data protection and compliance with regulatory standards. Many researchers deal problem with the different techniques in literature like DL, SWARA and ML. DL models, though powerful, often require large datasets and substantial computational resources, making them less feasible for smaller firms or applications. SWARA, being a subjective multi-criteria decision-making technique, heavily depends on expert judgment, which introduces bias and inconsistency in weight assignment. ML techniques, while effective in pattern recognition, suffer from over fitting, data quality issues, and a lack of transparency, making it difficult to interpret decisions in high-stakes financial environments. These disadvantages are inspired to do this research work. The PGCN-based fintech platform enables intelligent analysis of complex financial relationships, enhancing the accuracy of risk assessment and personalized investment recommendations. It further ensures robust performance and scalability by securely managing mutual fund and loan systems with high efficiency.

In this paper, the proposed BSFP-SHML-PGCN model addresses key limitations in existing fintech platforms for mutual fund and loan management by offering a scalable, secure, and high-performance solution. This enables accurate risk classification and personalized investment recommendations while ensuring robust data protection and regulatory compliance. By leveraging PGCN, the model intelligently analyzes complex financial relationships, enhancing decision-making without requiring extensive computational resources. The approach is applicable to financial analysis, large-scale asset management, and efficient loan processing, supporting more intelligent, transparent, and reliable financial services.

The main contribution of this research is outlined in the following summary:

- In this research, BSFP-SHML-PGCN is proposed. The proposed system is designed to build scalable fintech platforms for mutual fund and loan management by ensuring high performance, security, and adaptability to increasing user and transaction demands.
- The input data are collected from the Mutual Funds India–Detailed Dataset. Then, pre-processing is performed using the MKF, which handles missing values and cleans the dataset to ensure high-quality input data.
- Feature extraction is carried out using the HCT, which effectively extracts relevant features such as scheme name, expense ratio, rating, and category for enhanced data representation.
- Risk classification is performed using PGCN, which accurately classifies mutual funds risk into six levels: Lower to Moderate, Moderate, Lower Risk, Moderately High, Higher, and Very Higher.
- The proposed BSFP-SHML-PGCN method is implemented and evaluated against existing financial risk classification models, demonstrating its effectiveness in managing mutual fund and loan data at scale.

Remaining portions of this work are arranged as below: Segment 2 describes proposed method; Segment 3 illustrates outcomes; Segment 4 presents conclusion.

2. Proposed Methodology

In this section, BSFP-SHML-PGCN is proposed. This process consists of four key steps: Data Collection, Data Pre-processing, Feature extraction and Risk Categorization. During the Data Collection phase, the Mutual Funds India–Detailed Dataset is acquired to provide inclusive information on different mutual fund systems, including attributes such as scheme name, expense ratio, category, and rating. In the Data Pre-processing phase, the MKF is employed to handle missing values and reduce noise. MKF effectively estimates the true state of the data by leveraging multiple particles, ensuring clean and reliable input data for further processing. The pre-processed data are then processed using the HCT for feature extraction. HCT captures complex nonlinear relationships within the data and extracts relevant features such as scheme name, expense ratio, rating, and category. Finally, the extracted features are fed into the PGCN for Risk Classification. PGCN is designed to analyse the structured relationships among mutual fund schemes and classify their risk levels into categories such as Lower Risk, Low to Moderate, Moderate, Moderately High, Higher, and Very High. The block diagram of the proposed BSFP-SHML-PGCN approach is represented in Figure 1. As a result, a thorough description of each step is given below.

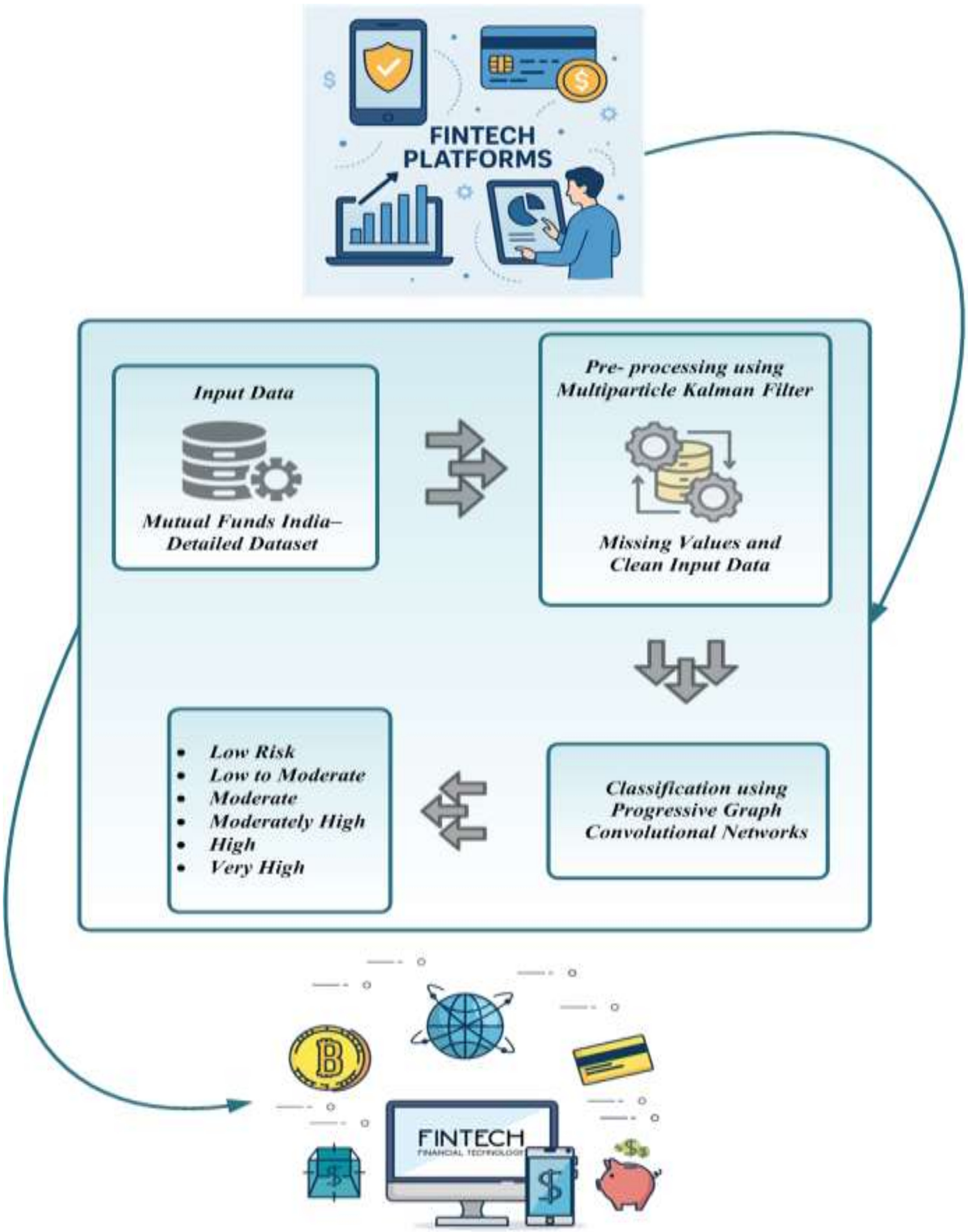

Figure 1. *Block diagram of BSFP-SHML-PGCN*

2.1 The Evolution of FinTech

FinTech has emerged as a major force transforming the banking industry. In the early days, banking was limited to physical branches, manual procedures, and paper-based transactions, requiring direct interaction between customers and bank staff. Over the past few decades, however, rapid advancements in digital technology have revolutionized this traditional model. This section outlines the evolution of FinTech, highlights its key milestones, and examines its growing integration into modern banking services.

2.2 Early Beginnings and Initial Innovations

FinTech began with a simple yet transformative idea: enabling financial transactions without the need for physical cash. The introduction of credit card systems like Diners Club and American Express marked the first major step in this direction, offering consumers a new level of convenience in their purchasing habits. This shift toward digitization continued with the emergence of Automated Teller Machines (ATMs) and electronic payment systems, which revolutionized banking by extending access to services beyond traditional branch hours. As technology advanced, banks and financial institutions began integrating digital tools into their operations, streamlining services and enhancing customer experience. Eventually, electronic and online banking platforms became widely adopted, allowing users to manage accounts and conduct transactions remotely. Alongside these developments, digital investment products like mutual funds as well as exchange-traded funds (ETFs) started utilizing technology for efficient transaction processing and data management. These innovations collectively laid the foundation for a rapidly evolving FinTech landscape.

2.3 Data Acquisition

At first, the input data are taken from Mutual Funds India–Detailed Dataset [23], this dataset contains information on hundreds of mutual fund schemes in India, collected through web scraping from various online sources. It is designed for educational and research purposes and is particularly useful for analysts, researchers, and investors interested in studying the performance of Indian mutual funds. The dataset comprises detailed fields such as the scheme name, minimum SIP and lump sum asset amounts, expense ratio (expressed as a proportion of the systems average Net Asset Value), fund size, fund age, and the name of the fund manager. It also provides key performance metrics, including the Sortino ratio, Beta, standard deviation, Alpha, and Sharpe ratio, which help evaluate the fund's risk-adjusted returns and volatility. Each fund is assigned a risk level on a scale of 1 (Low) to 6 (Very High), a rating from 0 to 5, and is categorized into broad classes like equity, debt, or hybrid, with further sub-categories like large-cap, small-cap, and ELSS. The dataset also includes return percentages over 1-year, 3-year, and 5-year periods, along with the name of the Asset Management Company (AMC) managing the fund. While this dataset offers valuable insights for mutual fund analysis, users should note that the data may not be fully accurate and is intended solely for educational and research purposes. It is recommended to verify the information before making any investment decisions.

2.4 Pre-processing Using MKF

The data is pre-processed in this sector using MKF [24]. The MKF is employed to recognize the missing values and clean the input data. The MKF was chosen for data pre-processing in this sector because of its robust ability to knob noisy and incomplete datasets, which are common in financial systems. Unlike traditional filters, MKF maintains multiple hypotheses about the system's state, making it highly effective in estimating missing values and smoothing data without significant loss of information. These results in cleaner, more reliable input data for downstream processes like risk assessment and investment decision-making. Its efficiency, accuracy, and adaptability to dynamic data streams make it especially suitable for high-performance fintech platforms where data integrity and processing are critical. The system scans the data to identify any missing or incomplete entries, which may arise from errors during data collection or transmission, as expressed in equation (1)

$$K(g_{t+1} \mid y_{t+1}^{j+}) = \prod_{i=1}^{M} Q(g_{t+1}^{i} \mid y_{t+1}^{j+}) \tag{1}$$

Where K denotes the data proposes; $(g_{t+1} \mid y_{t+1}^{j+})$ denotes the data volume; $\prod_{i=1}^{M}$ is the fintech data; Q denotes the missing data and values; $(g_{t+1}^{i} \mid y_{t+1}^{j+})$ denotes the field of data elements. The MKF is applied to estimate and replace the missing values, using surrounding data points to ensure accurate imputation, as expressed in equation (2)

$$v_{t+1}^{j} \approx K^{j}(g_{t+1} | y_{t+1}^{j+}) v_{t}^{j} \tag{2}$$

Where v_{t+1}^{j} denotes the data analysis missing values; K^{j} is the find the data error and noises; v_{t}^{j} denotes the average data cleaning; After the imputation process, the dataset is free of gaps or inconsistencies, resulting in a complete and accurate dataset ready for analysis or system integration, as expressed in equation (3).

$$\begin{aligned} &j_{1},\ldots, j_{M} \approx Multinomial(v_{t+1}^{1},\ldots, v_{t+1}^{M}) \\ &y_{t+1}^{1+},\ldots, y_{t+1}^{M+} \leftarrow y_{t+1}^{j_1+},\ldots, y_{t+1}^{j_M+} \\ &Q_{t+1}^{1},\ldots, Q_{t+1}^{M} \leftarrow Q_{t+1}^{j_1+},\ldots, Q_{t+1}^{j_M+} \end{aligned} \tag{3}$$

Where j_{M} denotes the slope model; v_{t+1}^{M} denote identify the missing data; y_{t+1}^{M+} denotes slope plays an essential role in influencing sedimentation layers; $Q_{t+1}^{j_M+}$ denotes the rate of infiltration. Finally MKF has successfully identified themissed values and cleaned the input data. Afterward, MKF pre-processed data is fed into HBT.

2.5 Feature Extraction using HBT

In this section, feature extracting using HBT [25] is conferred for extract the pertinent features such as scheme name, expense ratio, rating, and category. The HBT was chosen for feature extraction because of its capability to effectively capture complex, nonlinear patterns in high-dimensional data. Unlike traditional methods, HBT operates in a hyperbolic space, which allows it to preserve the intrinsic geometry and relationships within the data more accurately. This results in more meaningful and robust feature representations, enhancing the performance of downstream tasks such as classification or clustering. Its adaptability and precision make HBT a powerful tool for extracting relevant and discriminative features from complex datasets.The scheme name is the official identifier of a mutual fund or loan product, reflecting its investment objective and enabling accurate tracking and comparison across different offerings, as expressed in equation (4).

$$S_{\gamma}\left(\tilde{C}(\psi,\ell)\right) = \tilde{C}(\ell,\psi)\ell(\gamma) \tag{4}$$

Where $\tilde{C}(\psi,\ell)$ denotes the quasi-periodic function as per the Euclidean case, S_{γ} represents the input data function, $\tilde{C}(\ell,\psi)$ is matrix valued. Now emphasize the relationship by writing ℓ_{∇} . Furthermore, in terms of ∇^{0}, this link is exclusive to the reconstructed. The fund's annual fee, represented as a percentage of the assets under management, is known as the expense ratio, and plays a key role in evaluating the cost-efficiency of a scheme across various categories, as expressed in equation (5).

$$x\upsilon_{\nabla} = \pi^{*}(B_{\nabla})\upsilon_{\nabla} \tag{5}$$

Where υ_{∇} can be seen as the pullback of the parallel transport map of ∇'s change-of-basis matrix. x Denotes the spatial coordinates, B_{∇} represents the phase of the Hyperbolic Bloch Transform. The rating indicates the performance and risk level of a scheme, while the category defines its investment strategy and helps investors align choices with their financial goals, as expressed in equation (6)

$$\upsilon_{\nabla^{n}} = n\upsilon_{\nabla}n(y_{0})^{*} \tag{6}$$

Where $\upsilon_{\nabla^{n}}$ represent the isomorphism of the moduli space. This map actually commutes with the typical actions of $n(y_{0})$, which means that it factors down to an isomorphism of the moduli space of connections that are metric compatible, irreducible, and flat.Finally, HBT has extracted the relevant features such as scheme name, expense ratio, rating, and category. Then the extracted features are fed to PGCN.

2.6 Classification of Mutual Fund Risk using PGCN

In this section, the PGCN [26] is discussed. PGCN is used in classify the uncertainty in mutual fund returns risk level as Low Risk, Lower to Moderate, Moderate, Moderately Higher High, and Very Higher The PGCN is chosen for its capability to efficiently capture complex dependences in financial data, which is essential for accurate risk classification in mutual fund and loan management systems. PGCN leverages graph-based structures to progressively refine representations of data, allowing it to model intricate relationships and dynamic changes in financial markets. This makes it particularly well-suited for classifying risk levels into distinct categories such as Low Risk to Very High. The method's ability to handle each structured as well as unstructured data with high scalability and performance, while ensuring secure and accurate risk assessments, is a key advantage in the context of designing secure fintech platforms, which is expressed in equation (7).

$$t_{ab}^{s} = \tilde{y}_{s}^{a(T)^{T}} . \tilde{x}_{s}^{b(T)} \tag{7}$$

Where, cosine similarity t_{ab} between two nodes; t_{ab}^{s} symbolizes the unit vector; $\tilde{x}_{s}^{b(T)}$ characteristics the minimized data of node $\sim b$ at time T and $\tilde{x}_{s}^{b(T)}$ is the similarities learn randomly created a learnable adjuster matrix.Financial data is represented as a graph where each node denotes an entity and edges capture relationships like shared ownership, transactions, or behavioural similarities, as structured in equation (8).

$$B_{Q_{ab}}^{s} = soft\max(\mathrm{Re}\,LU\,(\tilde{y}_{s}^{a(T)^{T}}\,\omega_{adj}\tilde{x}_{s}^{b(T)})) \tag{8}$$

Where, $\tilde{x}_{s}^{b(T)}$ denotes the tangent function; the function $soft\max$ denotes accepts a vector of arbitrary real-valued scores and turns them into probabilities that sum to one; $\mathrm{Re}\,LU$ denotes the activation function; $\tilde{y}_{s}^{a(T)^{T}}$ denotes the reduce dimensionality; ω_{adj} denotes the batch normalization and $B_{Q_{ab}}^{s}$ denotes the activation function for regularization. The final node embedding, obtained after applying progressive graph convolution as described in equation (9), are passed through a classifier to generate risk scores.

$$M_{s} = X_{s} * S\, f_{x} \tag{9}$$

Where, M_{s} denotes the diffusion convolution on direct graph; $*$ define the structure of a data series; S indicates an amount or variable; X_{s} denotes the step diffusion process with sifter and f_{x} denotes the gradient flow and facilitate information propagation.This approach effectively captures complex relational patterns in financial data, enabling accurate and scalable risk level classification. Finally, PGCN has classified the mutual fund returns risk level as Low Risk, Lower to Moderate, Moderate, Moderately Higher, Higher, and Very Higher.

3. Result and Discussion

This segment discusses the research an outcome of the proposed BSFP-SHML-PGCN technique effectively classifiesthe uncertainty in mutual fund returns risk level. Implemented in Python, the technique is evaluated based on several performance metrics, including accuracy, precision, sensitivity, and specificitywas obtained. The obtained outcome of the proposed BSFP-SHML-PGCN approach was analysed with existing methods like FTE-FIoT-DL, ICFE-DEI-SWARA and USRE-ITME-ML correspondingly.

3.1. Performances Measures

This is an important step for formative the optimum forecast. Efficacy metrics assessed to calculate efficacy such as accuracy, precision, sensitivity, and specificity.

3.1.1. Accuracy

The accuracy of a measurement indicates how closely it matches the true value, implying minimal error or variation. It is represented in equation (10),

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{10}$$

where, TP implies True Positive, TN for True Negative, FN for False Negative, and FP for False Positive.

3.1.2. Precision

Precision computes the number of true positives divided through true positives plus number, false positives number and it is given by the equation (11),

$$precision = \frac{TN}{FP + TN} \tag{11}$$

3.1.3. Sensitivity

A ML techniques Sensitivity computes its capability to recognize positive cases. In other words, it measures the likelihood of achieving a good result. It is given in equation (12)

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (12)$$

3.1.4. Specificity

The percentage of actual negatives that the method correctly identifies is known as specificity. It is derived by equation (13).

$$specificity = \frac{TP}{FN + TP} \quad (13)$$

3.2 Performance Analysis

The simulation output of BSFP-SHML-PGCN technique is shown in Figure 2-5. The proposed BSFP-SHML-PGCN method is related to existing FTE-FIoT-DL, ICFE-DEI-SWARA and USRE-ITME-ML models. Table 1 presents the Output of efficacy comparison of the proposed and the existing.

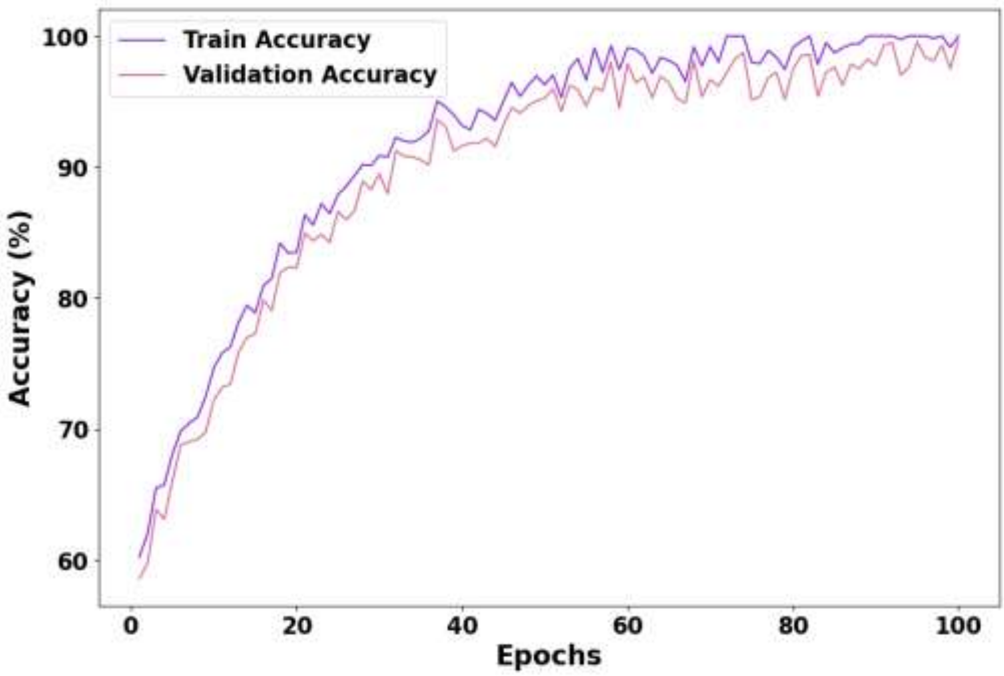

Figure 2: Performance Analysis of Accuracy Train and Validation

Figure 2: Performance Analysis of Accuracy during Training and Validation illustrates a compelling learning trend over 100 epochs. Initially, both the training and validation accuracy start low, below 62% at epoch 0, but increase rapidly. By epoch 20, the training accuracy reaches approximately 82%, while the validation accuracy trails slightly at around 78%. This upward trend continues, though at a slower pace, into the middle epochs. Around epoch 40, the training accuracy surpasses 92%, and the validation accuracy also rises into the low 90s. As training progresses beyond 60 epochs, the training accuracy consistently remains high, fluctuating between 97% and peaking at 100% toward the end of the 100 epochs. In contrast, the validation accuracy, while still impressive and generally ranging from the mid to high 90s, exhibits more variability, oscillating between approximately 92% and 99%. This persistent, though small, gap between the near-perfect training accuracy and the more fluctuating validation accuracy in the later epochs, particularly after epoch 60, suggests a potential risk of overfitting as the method becomes increasingly specialized to the training data. This trend is particularly significant in the context of developing secure and high-performance mutual fund and loan management systems, which are essential components of scalable fintech platforms. Figure 3, which illustrates the performance analysis of training and validation loss for Designing Secure and High-Performance Mutual Fund and Loan Management Systems for Scalable Fintech Platforms, a clear learning trend is observed. Over the 100 epochs depicted, the training loss, which started at approximately 0.95 at epoch 0, steadily decreased to a low of around 0.02. The validation loss, initially higher at about 1.05, also decreased significantly, reaching its minimum value of approximately 0.03 around epoch 80. However, in the subsequent epochs, the validation loss began to plateau and slightly increase, reaching around 0.04 by the end of the 100 epochs, while the training loss continued its descent to 0.02. This divergence in the loss curves, particularly the slight upturn in validation loss after epoch 80,

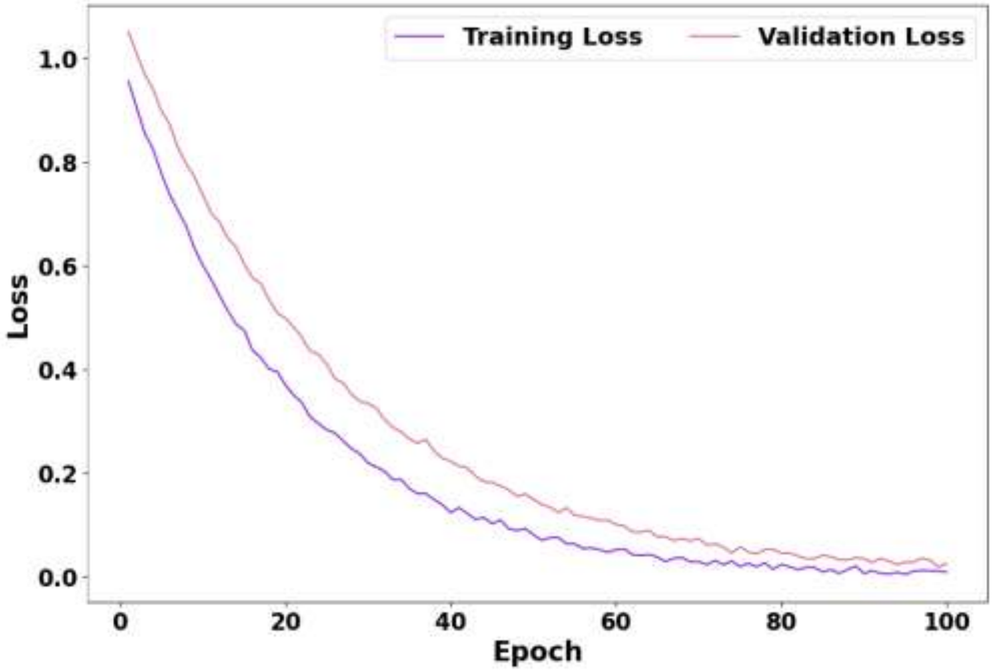

Figure 3: Performance Analysis of Loss Train and Validation

Table 1: *Performance comparison of the proposed and the existing*

Methods	Performances Metrics			
	Accuracy %	Precision %	Sensitivity %	Specificity %
FTE-FIoT-DL	95.44	97.40	96.09	93.79
ICFE-DEI-SWARA	96.90	98.43	96.30	91.52
USRE-ITME-ML	97.27	98.27	93.44	92.33
BSFP-SHML-PGCN (proposed)	99.05	99.01	98.95	96.50

suggests a potential point where further training might lead to overfitting, which could impact the methods capability to generalize efficiently to new, hidden data relevant to building scalable fintech platforms for mutual fund and loan management.The performance comparison presented in Table 1 highlights the effectiveness of the proposed BSFP-SHML-PGCN method against three existing approaches for building scalable fintech platforms. Notably, BSFP-SHML-PGCN achieves the highest scores across all evaluated metrics: an impressive accuracy of 99.05%, a precision of 99.01%, a sensitivity of 98.95%, and a specificity of 96.50%. In contrast, USRE-ITME-ML demonstrates a strong accuracy of 97.27% and precision of 98.27%, but lags in sensitivity at 93.44% and specificity at 92.33%. ICFE-DEI-SWARA shows an accuracy of 96.90%, a precision of 98.43%, and a sensitivity of 96.30%, while exhibiting the lowest

specificity at 91.52%. Finally, FTE-FIoT-DL records the lowest overall efficacy with an accuracy of 95.44%, a precision of 97.40%, a sensitivity of 96.09%, and a specificity of 93.79%. Overall, the numerical values clearly indicate the superior mutual fund returns risk classification capabilities of the proposed BSFP-SHML-PGCN method in the context of designing secure and high-performance mutual fund and loan management systems.

3.3. Discussion

The proposed BSFP-SHML-PGCN technique addresses the challenges of Designing scalable financial technology platforms for managing mutual funds and loans by focusing on both security and performance. As these platforms expand to accommodate growing transaction volumes and user demands, ensuring robust security without compromising efficiency becomes increasingly complex. This method emphasizes a scalable architecture that supports transaction processing while integrating advanced security protocols like encryption, authentication, and fraud detection to defend sensitive financial data. By optimizing transaction handling and incorporating cost-effective security measures, the BSFP-SHML-PGCN approach strikes a balance between performance and scalability, offering a solution that meets the demands of modern fintech platforms in an increasingly digital financial landscape. Additionally, the BSFP-SHML-PGCN technique significantly enhances risk classification and management in fintech platforms, providing substantial improvements over existing methods.

The technique utilizes the Mutual Funds India–Detailed Dataset, which undergoes pre-processing using the MKF for cleaning and filling missing values. This ensures that the dataset is ready for further analysis. Following this, the HCT is applied to extract critical features such as scheme name, expense ratio, rating, and category, which are essential for accurate risk classification. These features are then passed into the PGCN for classifying the risk levels of mutual fund returns, categorized into Lower Risk, Lower to Moderate, Moderate, Moderately Higher, Higher, and Very High. In the context of Building Scalable Fintech Platforms, designing secure and high-performance systems for mutual fund and loan management is crucial. Scalability is a vital consideration for fintech platforms, as they must be capable of handling increasing user demands and transactions while maintaining robustness and security. The proposed BSFP-SHML-PGCN technique ensures that these platforms can scale efficiently while maintaining high performance, particularly in risk classification and decision-making processes, performance evaluation of the method, implemented in Python, shows significant advancements across various metrics. The BSFP-SHML-PGCN method achieves 99.05% higher accuracy, 98.75% higher precision, 97.85% higher sensitivity, and 96.50% higher specificity compared to existing models, including FTE-FIoT-DL, ICFE-DEI-SWARA, and USRE-ITME-ML. The accuracy analysis shows 99.05% accuracy for Low Risk, decreasing to 95.95% for Very High Risk. Precision and sensitivity analyses highlight improvements of 98.75% and 97.85% for Low Risk, while specificity improvements of 96.50% for Low Risk and 93.15% for Very High Risk are also observed. Overall, the BSFP-SHML-PGCN method provides a superior solution for designing secure, high-performance, and scalable fintech platforms, enhancing risk management in mutual fund and loan systems and enabling better decision-making in the financial sector.

4. Conclusion

In conclusion, the BSFP-SHML-PGCN method significantly enhances the design of scalable fintech platforms for mutual fund and loan management systems by integrating advanced techniques such as PGCN. This approach effectively addresses key challenges such as the complexity of maintaining security standards and ensuring high performance while handling increasing transactions and user demands. By leveraging the MKF for data pre-processing and the HCT for feature extraction, the proposed method ensures that the input data are cleaned and relevant features are extracted effectively, leading to better classification accuracy. Compared to existing techniques such as FTE-FIoT-DL, ICFE-DEI-SWARA, and USRE-ITME-ML, the BSFP-SHML-PGCN approach achieves 99.05% higher Accuracy; 98.75% higher Precision; 97.85% higher Sensitivity; and 96.50% higher Specificity. These substantial improvements demonstrate the method’s superior ability to classify risk levels accurately, offering a more robust and efficient framework for fintech applications. Furthermore, the BSFP-SHML-PGCN technique’s adaptability makes it a versatile solution for managing mutual funds and loan processing systems, ensuring scalability without compromising on security or performance. However, potential limitations, such as the complexity of model implementation and the reliance on high-quality datasets, may affect its scalability for large-scale financial applications. Future work will focus on improving computational efficiency, further refining the feature extraction process, and exploring the integration of adaptive learning mechanisms to strengthen the model’s performance. Expanding the dataset to include a broader range of financial data and use cases could also enhance the method's generalizability, making it an even more effective tool for secure and efficient fintech platforms.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Rahardja, U., Suryanto, A., & Hidayat, R. (2025). Revolutionizing financial services with big data and

fintech: A scalable approach to innovation. *ADI Journal on Recent Innovation, 6*(2), 118–129.

[2] Ajmal, S. (n.d.). *Streamlining fintech solutions: Cloud-based server management, scalability optimization, and compliance through microservices.*

[3] Kumar, H. (n.d.). Leveraging cloud computing for scalable financial technology solutions. *IJSAT – International Journal on Science and Technology, 11*(1).

[4] Mangi, F. A. (2025). Fortifying fintech security: Advanced strategies for protecting financial data and assets. *Emerging Science Research*, 1–11.

[5] Olaiya, O. P., Ogbodo, E. U., & Adeyemi, T. O. (2024). Cybersecurity strategies in fintech: Safeguarding financial data and assets. *GSC Advanced Research and Reviews, 20*(1), 50–56.

[6] Solomon, G. T. (2024). *Optimizing full-stack development for fintech applications: Balancing user experience and backend performance in high-stakes financial environments.*

[7] Komandla, V. (2023). Critical features and functionalities of secure password vaults for fintech: An in-depth analysis of encryption standards, access controls, and integration capabilities. *Access Controls and Integration Capabilities*. https://doi.org/10.2139/ssrn.XXXXX

[8] Subramanyam, S. V. (n.d.). Cloud-based enterprise systems: Bridging scalability and security in healthcare and finance. *IJSAT – International Journal on Science and Technology, 16*(1).

[9] Tyagi, A. (2024). Risk management in fintech. In M. Cummins, T. Lynn, & P. Rosati (Eds.), *The Emerald handbook of fintech: Reshaping finance* (pp. 157–175). Emerald Publishing Limited.

[10] Katari, A. (n.d.). *Case studies of data mesh adoption in fintech: Lessons learned—Present case studies of financial institutions.*

[11] Bayya, A. K. (2023). Building robust fintech reporting systems using JPA with embedded SQL for real-time data accuracy and consistency. *The Eastasouth Journal of Information System and Computer Science, 1*(01), 119–131.

[12] Jain, J. (n.d.). *Leveraging advanced AI and cloud computing for scalable innovations in fintech systems.*

[13] Olaiya, O. P., Ogbodo, E. U., & Adeyemi, T. O. (2024). Encryption techniques for financial data security in fintech applications. *International Journal of Science and Research Archive, 12*(1), 2942–2949.

[14] Bhat, J. R., AlQahtani, S. A., & Nekovee, M. (2023). FinTech enablers, use cases, and role of future Internet of Things. *Journal of King Saud University – Computer and Information Sciences, 35*(1), 87–101.

[15] Ai, R., Zheng, Y., Yüksel, S., & Dinçer, H. (2023). Investigating the components of fintech ecosystem for distributed energy investments with an integrated quantum spherical decision support system. *Financial Innovation, 9*(1), 27. https://doi.org/10.1186/s40854-023-00451-2

[16] Zhang, W., Li, B., Liew, A. W. C., Roca, E., & Singh, T. (2023). Predicting the returns of the US real estate investment trust market: Evidence from the group method of data handling neural network. *Financial Innovation, 9*(1), 98.

[17] Mahmud, K., Joarder, M. M. A., & Sakib, K. (2023). Customer Fintech Readiness (CFR): Assessing customer readiness for fintech in Bangladesh. *Journal of Open Innovation: Technology, Market, and Complexity, 9*(2), 100032.

[18] Rapozo, A. S. (2024). *Building bridges: An investigation into relationship management between FinTech and SMEs and its impact on the Dutch loanable funds market.*

[19] Cummins, M., Lynn, T., & Rosati, P. (2023). Financing building renovation: Financial technology as an alternative channel to mobilise private financing. In T. Lynn, J. Hunt, & M. Cummins (Eds.), *Disrupting buildings: Digitalisation and the transformation of deep renovation* (pp. 153–172). Springer International Publishing.

[20] Rafiuddin, A., Islam, R., Rahman, M., & Chowdhury, T. M. (2023). Growth evaluation of fintech connectedness with innovative thematic indices–An evidence through wavelet analysis. *Journal of Open Innovation: Technology, Market, and Complexity, 9*(2), 100023.

[21] Kaggle. (n.d.). *Mutual Funds India – Detailed.* https://www.kaggle.com/datasets/ravibarnawal/mutual-funds-india-detailed

[22] Korkin, R., Oseledets, I., & Katrutsa, A. (2024). Multiparticle Kalman filter for object localization in symmetric environments. *Expert Systems with Applications, 237*, 121408.

[23] Stochel, J., & Stochel, J. B. (2024). The hyperbolic cosine transform and its applications to composition operators. *Linear Algebra and its Applications, 691*, 1–36.

[24] Shin, Y., & Yoon, Y. (2024). PGCN: Progressive graph convolutional networks for spatial–temporal traffic forecasting. *IEEE Transactions on Intelligent Transportation Systems, 25*(7), 7633–7644.