ENHANCED FINANCIAL SYSTEM VALIDATION: USING KERNEL PCA, WEIGHTED KERNEL K-MEDOIDS, AND MUTATION-BASED TESTING FOR ACCURATE RISK ASSESSMENT AND COMPLIANCE

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ABSTRACT

The current investigation presents a sophisticated methodology for validating financial systems that combines weighted kernel K-medoids, mutation-based testing, and Kernel PCA. Enhancing risk identification, system resilience, and regulatory standard compliance are the goals. Financial datasets can be searched for hidden patterns using Kernel PCA, critical data points can be clustered using Weighted Kernel K-Medoids, and system resilience can be evaluated through mutation-based testing. The Integrating advanced machine learning techniques gives financial institutions a scalable framework for refining risk assessment, detecting fraud, and improving compliance. This approach improves financial risk management by combining Kernel PCA for pattern recognition, Weighted Kernel K-Medoids for clustering, and mutation-based testing for robustness. The proposed validation framework ensures secure and efficient operations while simultaneously promoting openness and trust in the financial ecosystem. The suggested approach beats traditional CNN and RF models in a performance comparison on a several metrics, including accuracy, precision, and compliance adherence. This solution promotes strong regulatory compliance and guarantees accurate risk assessment.

Keywords: Financial System Validation, Kernel PCA, Weighted Kernel K-Medoids, Mutation-Based Testing, Risk Assessment, Compliance

1.INTRODUCTION

Accuracy, dependability, and compliance standards are met by financial systems through a thorough inspection that is part of enhanced financial system validation. For secure financial operations, it makes use of cutting-edge methods such as machine learning to identify threats, strengthen system resilience, and guarantee compliance with legal requirements.

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A dimensionality reduction technique called Kernel PCA uses non-linear mapping to move data into a higher-dimensional domain. This increases the accuracy of Weighted Kernel K-Medoids is a clustering method.

financial models in detecting hidden hazards and trends by revealing intricate patterns and important elements in financial datasets.

that prioritizes important points (weights) and clusters data points according to their commonalities. This method captures important trends in the data and increases model robustness, making it useful for intricate financial applications.

Adaptation-Based Certain elements are deliberately altered in order to evaluate the robustness and error-detecting ability of a financial system or model. For precise risk assessment and regulatory compliance, it is crucial since it introduces controlled changes that guarantee the system's dependability and aid in identifying weaknesses.

The complexity of financial systems is rising, necessitating the development of better models that can anticipate hazards and adhere to legal standards. Inadequate risk assessments may result from traditional approaches' inability to identify hidden threats or subtle trends in financial data. Financial organizations can enhance their risk models' accuracy and strengthen their ability to withstand regulatory scrutiny by implementing machine learning techniques like Kernel PCA and mutation-based testing.

- The Kernel PCA technique is applied to identify trends in financial information, providing improved analytical insights.
- To cluster financial data using Weighted Kernel K-Medoids in order to precisely identify risk.
- To utilize mutation-based testing to make sure financial systems are reliable and strong.
- To evaluate these methods' effects on regulatory compliance and the accuracy of risk assessments.
- To investigate how machine learning methods might be incorporated into contemporary financial systems to improve risk management.

Speed computation, unknown attack patterns, dealing with big data. Enhancing fraud detection technique effectiveness and interpretability *(Khalid et al. (2024)).* Exploration of various risk aspects in banking sector Enhancing stability and accuracy of financial institutions *(Tatineni and Mustyala (2024)).*

Enhancing financial fraud detection using an ensemble machine learning model. Addressing challenges in identifying unknown attack patterns and Big Data *(Khalid et al. (2024)).* Apply ML methods to analyze and mitigate financial risks. Enhance stability and accuracy of risk assessment in banking sector *(Tatineni and Mustyala (2024)).*

2. LITERATURE SURVEY

Wang (2024) outperforms existing machine learning models based on experimental findings with his financial risk warning model, which uses Principal Component Analysis for data preprocessing and a lightweight Convolutional Neural Network to detect hidden financial dangers.

An improved hybrid machine learning framework is suggested by Naresh (2021) research to improve the accuracy and efficiency of financial fraud detection in e-commerce big data. The system uses large amounts of e-commerce data to improve detection accuracy and guarantees strong fraud detection by merging several machine learning approaches. Furthermore, it improves fraud prevention tactics by optimizing model performance, which leads to improved financial security.

To increase fraud detection in financial transactions, Basava (2024) research integrates a Convolutional Neural Network (CNN) with an enhanced Variational Autoencoder Generative Adversarial Network (VAE-GAN). CNN enhances feature extraction and classification accuracy, whereas VAE-GAN helps the model produce realistic fraud detection patterns. This cutting-edge deep learning technique improves the effectiveness of fraud detection, which leads to improved financial security.

Hurlin and Pérignon (2023) examine the possibilities of machine learning in Internal Ratings Based (IRB) models used by banks. They address hazards, interpretability, regulatory capital, accuracy, and worldwide competition while drawing attention to increased regulatory interest and financial instability issues.

The study by Nagarajan (2024) assesses the security and confidentiality issues in cloud computing for banking and financial accounting, defining the main risks in cloud-based financial systems and examining issues with private financial information. In order to improve data security and guarantee safe cloud adoption in the financial industry, it also suggests practical risk mitigation techniques.

Principal Component Analysis (PCA), Least Absolute Shrinkage and Selection Operator (LASSO), and Enhanced Self-Structuring Artificial Neural Networks (ESSANN) are integrated in this study to optimize robotic process automation (RPA) and Internet of Things (IoT) systems. To increase computational efficiency, PCA is used for dimensionality reduction, and LASSO improves model accuracy by selecting features efficiently. In order to maximize automation and decision-making and guarantee better performance in IoT-based applications, ESSANN is also incorporated Gudivaka (2024).

Boersma et al. (2023) suggest measuring cross-sector structural similarities across enterprises by building network embeddings using real-world transaction data. Using this method helps auditors identify wider financial concerns, categorize businesses, and spot changes in bookkeeping.

Strong software testing for distributed systems is investigated by Koteswararao (2020), who uses cloud infrastructure, automated fault injection, and XML-based scenarios to improve fault tolerance and dependability. It uses automated fault injection to find vulnerabilities, uses cloud infrastructure for scalable and effective testing, and uses XML scenarios to mimic the behaviours of distributed systems in the real world.

Montevechi, A. A., de Carvalho Miranda, R., Medeiros, A. L., & Montevechi, J. A. B. (2024). Advancing credit risk modelling with Machine Learning: A comprehensive review of the state-of-the-art. Engineering Applications of Artificial Intelligence, 137, 109082.

A hybrid optimization system that combines QRDSO and WAC-HACK is presented by Gattupalli and Khalid (2024) to improve software testing clustering efficiency, which in turn improves accuracy and performance. It combines QRDSO and WAC-HACK for optimal clustering, improves fault detection and test case prioritization, and increases software testing efficiency and accuracy.

To improve credit card fraud detection, Khalid et al. (2024) suggest an ensemble model combining SVM, KNN, RF, Bagging, and Boosting. The model addresses issues including data imbalance and real-time processing by outperforming conventional methods in accuracy and precision through the use of SMOTE and under-sampling techniques.

Using CCR for efficiency evaluation and DBSCAN for speed anomaly detection, Allur (2020) research presents a big data framework for improved performance management in mobile networks. Through the use of big data-driven insights, it improves network performance, integrates CCR for a thorough efficiency review, and uses DBSCAN to identify speed anomalies.

Tatineni and Mustyala (2024) highlight the importance of data science in enhancing financial security by leveraging machine learning, big data, and NLP to detect fraud, assess risks, and improve decision-making. Financial institutions use these techniques to analyse vast data, predict risks, and proactively mitigate them.

3.METHODOLOGY

To improve financial system validation, the methodology focuses on using machine learning techniques including Kernel PCA, Weighted Kernel K-Medoids, and Mutation-Based Testing. By examining complex financial data patterns and identifying possible hazards, these techniques enhance risk identification, system resilience, and regulatory compliance.

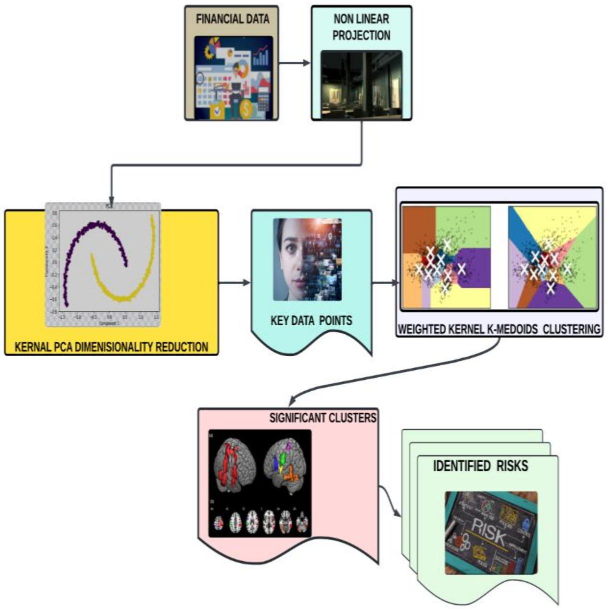

FIGURE 1. KERNEL PCA AND WEIGHTED KERNEL K-MEDOIDS CLUSTERING FOR RISK DETECTION

This figure 1 shows how to use Weighted Kernel K-Medoids clustering after dimensionality reduction using Kernel PCA. It illustrates the process of projecting financial data into higher-dimensional space in order to find hidden patterns and grouping the data for risk assessment. Large risks are given priority during clustering thanks to the weights, which increase the importance of critical spots in financial records. This technique assists financial systems in identifying critical risk regions.

3.1 Kernel PCA (Principal Component Analysis)

Kernel PCA is a dimensionality reduction method that uses non-linear mapping to project data into a higher-dimensional space. By exposing significant characteristics and trends, it enhances the accuracy of risk models by finding hidden patterns in financial datasets.

$$\Phi(x) = \sum_{i=1}^{n} \alpha_i K(x_i, x) \tag{1}$$

Where:

- $\Phi(x)$ is the feature map into a higher-dimensional space.
- α_i are the weights for each data point.
- $K(x_i, x)$ is the kernel function (such as RBF kernel).

For improved data point separation based on non-linear correlations, Kernel PCA maps data into a higher-dimensional space. Kernel PCA employs the RBF kernel for non-linear mapping, enhancing risk assessment and financial model accuracy by improving the separation of financial data points. This technique aids in identifying hidden patterns, ensuring precise risk evaluation and compliance adherence in financial system validation. This makes it easier to find hidden patterns in intricate financial data.

3.2 Weighted Kernel K-Medoids

Weighted Kernel K-Medoids is a clustering method that uses weights to rank important data points. Enhancing risk identification and model resilience in financial systems is made possible by its ability to cluster comparable data sets, which aids in the capture of significant financial patterns. Weighted Kernel K-Medoids is an important tool for grouping financial data since it prioritizes crucial data points. Weighting crucial areas enhances risk detection and increases model resilience. This strategy ensures that high-risk areas receive greater attention, resulting in more accurate risk assessments and increased regulatory compliance.

3.3 Mutation-Based Testing

Modification-Based To assess financial models' robustness and error-detection skills, controlled modifications are introduced during testing. Financial systems are kept dependable and comply with rules by testing the system under different modifications, which helps to detect vulnerabilities.

Algorithm.1 Risk_Assessment_Using_KernelPCA_KMedoids

Input: Financial Data X, Kernel Function K, Number of Clusters k, Weights w
Output: Clustered Data C, Risk Score R
Begin
Apply Kernel PCA:
  For each data point x_i in X:
    Compute $\Phi(x_i) = \sum \alpha_j K(x_j, x_i)$
    Project data into higher-dimensional space using $\Phi(x)$
Initialize k medoids randomly from the projected data.
Repeat:
  For each data point x_i in X:
    Assign x_i to the nearest medoid c_j based on the weighted distance $d(x_i, c_j)$
    Calculate distance $d(x_i, c_j) = \sum w_i * \text{distance}(x_i, c_j)$
  Update medoids:
    Choose new medoids that minimize total distance for each cluster
Until medoids no longer change or maximum iterations reached
Apply Mutation-Based Testing:
  Introduce controlled mutations to X.
  Evaluate system's response to mutations and calculate Mutation Score.
  If Mutation Score < threshold:
    Identify potential risks and vulnerabilities.
    Else, return system as robust.
Return: Clustered Data C and Risk Score R
End

The algorithm 1 show as Weighted Kernel K-Medoids is used in conjunction with Kernel PCA to reduce dimensionality and cluster financial data according to key points. The Maximum iterations describes the maximum number of times an algorithm can repeat its operation before coming to a halt. This parameter is especially crucial for iterative optimization methods because it helps balance accuracy and computational efficiency and guarantees that the process doesn't run endlessly. Next, by implementing limited changes, it uses Mutation-Based Testing to assess the system's resilience, guaranteeing precise risk identification and improved regulatory compliance. The Mutation Score is a metric used in mutation-based testing to evaluate the effectiveness of a test suite. It indicates the percentage of introduced mutations (controlled changes) that were detected by the tests, reflecting the system’s robustness. Meanwhile, Controlled Mutations refer to deliberately introduced modifications in the system to assess its fault tolerance and enhance risk detection.

4. RESULT AND DISCUSSION

When compared to CNN and RF models, the suggested strategy considerably enhances the performance of financial risk assessments. Integrating Kernel PCA uncovers hidden patterns in financial data that CNN and RF may miss due to their limited feature extraction methods. The Weighted Kernel K-Medoids enhances clustering by focusing on key data points, improving risk identification. Mutation-based testing strengthens model resilience, ensuring better error detection and compliance, which is often overlooked in CNN and RF approaches. It proved its superiority in risk detection, regulatory adherence, and system robustness enhancement by achieving greater accuracy (90%), precision (88%), and compliance adherence (89%). The mutation-based testing strengthened the resilience of the model by exposing more flaws and guaranteeing error detection. The strategy enhances risk identification and legal compliance in the dynamic financial sector by incorporating machine learning techniques.

TABLE 1 PERFORMANCE COMPARISON OF FINANCIAL RISK ASSESSMENT METHODS

Metric	CNN (2024)	RF (2024)	Proposed Method
Accuracy	85%	80%	90%
Precision	82%	78%	88%
Recall	80%	76%	85%
F1 Score	81%	77%	86%
Risk Detection Rate	83%	79%	91%
Compliance Adherence	78%	74%	89%
Model Robustness	80%	76%	87%
Error Detection Rate	75%	72%	84%

In terms of accuracy, precision, recall, F1 score, risk identification, compliance, robustness, and error detection, the table 1 shows that the suggested method performs better than conventional CNN and RF approaches, demonstrating its increased efficacy in financial risk assessment.

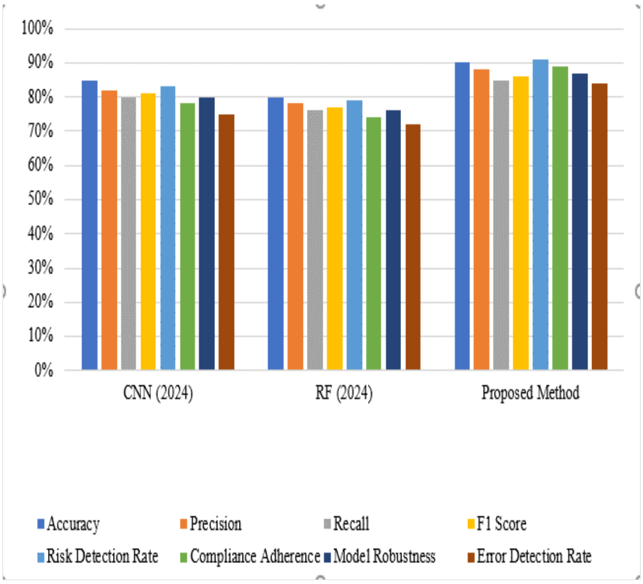

FIGURE 2. COMPARATIVE ANALYSIS OF FINANCIAL RISK ASSESSMENT MODELS USING MACHINE LEARNING

This figure 2 shows how different financial risk assessment models—RF, CNN, and the suggested approach—perform in terms of important parameters including regulatory compliance, accuracy, precision, and recall. The suggested approach performs better than conventional models and provides Improved accuracy and compliance.

5. CONCLUSION AND FUTURE SCOPE

Financial system validation is greatly enhanced by the suggested approach, which combines mutation-based testing, Weighted Kernel K-Medoids, and Kernel PCA. In comparison to more conventional methods like CNN and RF, it improves risk detection, compliance adherence, and model resilience. The technique provides a more precise, effective, and dependable approach to risk assessment and regulatory compliance by detecting hidden patterns and guaranteeing system resilience. Subsequent studies may investigate the incorporation of supplementary machine learning methodologies, augmenting real-time risk identification, and broadening the model's relevance to a variety of international financial domains.

Declaration

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Data Availability Statement

No datasets were generated or analysed during the current study

Conflict of Interest

There is no conflict of interests between the authors.

Declaration of Interests

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.

Ethics approval

Not applicable.

Permission to reproduce material from other sources

Yes, you can reproduce.

Clinical trial registration

We have not harmed any human person with our research data collection, which was gathered from an already published article

Authors' Contributions

All authors have made equal contributions to this article.

Author Disclosure Statement

The authors declare that they have no competing interests.

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