RISK ASSESSMENT IN CLOUD-BASED BANKING USING TRANSFORMER-CNN HYBRID MODELS AND BAYESIAN NETWORKS

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Abstract

Today, the complexity of the finance and the eccentricities of the financial system at a personal level requires an extremely strong models for fraud detection and risk assessment. To this end, this research work propounds a Federated Learning Financial Risk Prediction model realized with Transformer-based deep neural networks and Bayesian Networks to increase the accuracy of fraud detection at the same time whilst preserving privacy. Federated Learning has the decentralized and secured data processing while protecting highly sensitive financial variables. Promising enhanced performance through a Transformer-based architecture, since these networks will extract very short and long dependencies present in transaction data. Its application is also covered by probabilistic estimates of risks by minimizing false positives and false negatives. The outcomes produced from the experiments provide excellent results in accuracy, precision, sensitivity, and specificity that prove the model's efficacy in predicting financial risk. It stretches beyond any limitation for applicability over huge datasets for the finance domain. The future work intends to take up the improvement of approaches in Federated Learning, design of quantum-safe cryptographic methods that are quantum-resistant, and risk management of finances using blockchain technology to ensure security and transparency in financial systems.

Keywords: *Financial Risk Prediction, Federated Learning, Transformer-based Neural Networks, Bayesian Networks, Fraud Detection, Data Privacy, Scalability, Cloud Banking.*

Introduction

Cloud banking transformed the offering of the financial services by offering cost-effective, efficient, and scalable services to the customers all over the world [1]. Therefore, as cloud technologies are becoming more commonly used, security issues and risk assessment issues have become the prime priority areas. With the constantly fluctuating circumstances of the cyber-attacks, scams, and data breaches, the robust risk assessment models need to safeguard both the financial transactions as well as the customer sensitive data. Conventional security practices always fail to predict advanced financial risks, so top-level machine learning and deep learning algorithms are required for accurate risk assessment [2]. Gattupalli and Khalid (2024) [3] QRDSO-WAC-HACK framework enhances clustering accuracy and reduces computational overhead through quantum-driven optimization and adaptive hierarchical methods; building on this, the suggested framework incorporates similar strategies to efficiently process complex financial data in cloud-based risk prediction. Several factors contribute to the increasing complexity of risk in cloud-based banking environments. The heterogeneous nature of financial data, combined with high-frequency transaction volumes and evolving cyber threats, demands sophisticated analytical techniques. Additionally, regulatory compliance requirements, system integration challenges, and potential vulnerabilities in cloud infrastructures add layers of risk that traditional assessment methods often fail to capture. These factors create a pressing need for robust, adaptive, and interpretable risk assessment frameworks that can handle dynamic data while providing actionable insights [4].

Cloud-based banking has revolutionized the financial services industry by offering cost-effective, efficient, and scalable solutions to meet the growing demands of global financial markets. The adoption of cloud technologies has enabled banks to optimize their operations, reduce infrastructure costs, and provide better services to customers. However, with the increasing reliance on digital platforms, ensuring the security and privacy of financial transactions has become a critical concern. Financial institutions are now leveraging advanced technologies like artificial intelligence (AI), machine learning (ML), and deep learning (DL) to improve fraud detection, risk assessment, and overall system security [5]. Among these, the integration of Transformer-based deep neural networks, Convolutional Neural Networks (CNNs), and Bayesian Networks has shown promising results in enhancing the accuracy and scalability of risk prediction models in cloud banking environments.

Various factors contribute to the growing complexity of risk in cloud-based banking systems [6]. The rapid increase in transaction volumes, the heterogeneous nature of financial data, and the evolving cyber threats all contribute to the need for more advanced risk assessment models. Additionally, the adoption of third-party cloud service providers by financial institutions creates new vulnerabilities, as banks are dependent on external security measures that may not always meet stringent regulatory standards. Cyber threats such as phishing, malware, and ransomware continue to evolve, making it more difficult to predict and prevent fraud. Moreover, inadequate authentication methods and weak encryption standards further exacerbate these risks, leading to potential financial losses and damage to a bank's reputation. The method presented achieves high fault detection accuracy in battery management systems for electric vehicles through deep learning and optimization algorithms. This research provides valuable insight for the new system, which applies comparable hybrid models and optimization strategies to enhance fraud detection in cloud-based banking, as outlined by Grandhi et.al (2024) [7].

Despite the advantages of cloud computing in banking, there are several critical issues that hinder the effectiveness of risk management. Traditional machine learning models and risk assessment techniques often fail to capture the complexities and temporal dependencies inherent in financial data, leading to high false-positive rates and inaccurate predictions [8]. The lack of transparency in complex deep learning models also raises concerns regarding their interpretability and trustworthiness. Moreover, the security of sensitive customer data in cloud-based platforms is at constant risk due to potential data breaches, unauthorized access, and non-compliance with regulations. These limitations necessitate the development of more robust, adaptable, and transparent risk assessment models that can handle dynamic and large-scale financial data while maintaining high levels of security and privacy [9].

A number of factors lead to cloud-based banking risks like cyberattacks, data leakage, unauthorized access, and non-compliance with regulations. Third-party cloud service providers' over-reliance also creates more vulnerabilities since financial institutions have external security measures. The New cyber threats like phishing, malware, and ransomware also risk the customer data integrity and the financial operations. Poor authentication procedures and inadequate encryption standards can further lead to losses in terms of money and reputational loss. These threats are emphasizing the need for the creation of the advanced techniques for the risk prediction and mitigation [10].

Despite the advantages offered by cloud solutions, several critical issues hinder effective risk management in banking. Data breaches, insider threats, and distributed denial-of-service (DDoS) attacks pose significant threats to the confidentiality and availability of banking services. Furthermore, the lack of transparency in complex machine learning models can reduce trust in automated risk assessments. Conventional approaches often struggle with high false-positive rates and limited capability to model temporal dependencies in transactional data, leading to inadequate early warning systems and inefficient allocation of security resources.

The Risk assessment with the cloud-based banks has been perfected through the use of the machine learning algorithms, deep learning models, and the statistical methods. In fact, traditional machine learning applications-scopes have done much on the examples of decision trees, support vector machines (SVMs), and logistic regression, but none of these has the ability of handling such massive fossil financial data. Because of their flexibility in learning various representations, models that fit into deep learning such as Convolutional Neural Networks (CNNs) and Transformers have really been available for pattern recognition or anomaly detection. Bayesian Networks are also utilized for purposes of probabilistic reasoning and are useful in modeling uncertainties in risk assessment. In fact, even if there are advancements in techniques, the accuracy, complexity, i.e., computational complexity, or adaptability to any new threats remain limitations for existing techniques. AI-integrated probabilistic neuro-fuzzy TemporalFusionNet for robotic IoMT automation in chronic kidney disease detection and prediction, as established by Deevi et.al, (2024) [11] this knowledge supports the outlined structure by highlighting the importance of sustainable digital innovation in developing scalable cloud-based financial risk assessment systems.

To overcome these challenges, integrating Transformer-CNN hybrid models with Bayesian Networks offers a powerful approach. The Transformer-CNN architecture excels at capturing both global contextual information and local feature patterns from sequential banking data, enhancing predictive accuracy. Meanwhile, Bayesian Networks provide a probabilistic graphical framework for modeling causal relationships and uncertainties inherent in risk factors, facilitating transparent decision-making [12]. By combining these technologies, banking institutions can achieve more precise, interpretable, and scalable risk assessment systems, enabling proactive risk mitigation strategies and compliance with stringent regulatory standards.

In order to rectify these shortcomings, this paper presents a hybrid strategy that integrating Transformer-CNN models and Bayesian Networks for risk forecasting in cloud-based banking [13]. The hybrid model Transformer-CNN harnesses the efficiency of CNNs for feature extraction and Transformers in understanding long-distance relationships and so proves to be exceptionally effective at interpreting intricate financial information. The use of the Bayesian Networks further amplifies the model with probabilistic reasoning to identify the uncertainties in forecasting risk. By combining these methods, the proposed system seeks to present a more accurate and sound risk assessment system that enhances security and decision-making within cloud-based banking systems. The contributions of the paper are,

- The transformer-based deep neural network utilizes self-attention mechanisms to capture long-term and short-term dependencies in transactional data to enhance fraud detection classification accuracy.
- Federated Learning for Secure Data Processing utilizes decentralized learning methods to enable data privacy with enhanced model performance for fraud classification.
- Mean/Median Imputation and Z-Score Method deal with missing values and outliers for data integrity and best model performance.

The paper is organized as follows: Section 2 is a comprehensive review of different credit risk prediction techniques and their limitations. It elaborates on the contribution of Federated Learning towards secure data processing, the stability of Transformer-based deep neural networks to improve prediction accuracy, and the contribution of cloud-based processing towards scalability. Section 3 describes the proposed model, its architecture, important components, and implementation. Section 4 shows the experimental results, evaluating the performance of the model on accuracy, precision, sensitivity, specificity, and misclassification rates. Lastly, Section 5 concludes the paper by summarizing the important findings, evaluating the scalability and security of the proposed model in cloud banking, and recommending future research areas, including Federated Learning techniques advancements, quantum-safe encryption, and blockchain-based financial risk management.

2. Literature Survey

The finance and the e-commerce are currently transformed by a combination of the blockchain technology, smart networks, and the cloud computing. The fact that distribution is mentioned enhances the scalability, security, and efficiency with which large data capacities are processed. The method utilizes the blockchain for secure transactions that have enhanced transaction speed and system performance as well as the cloud resource management and iot-based analytics. The findings reveal the strong improvements in the consumption of resources, scalability, and security, thereby making it an optimized solution for future generations in finance and commerce also endorsed the view that cloud computing and internet-based finance basically redefine access to finance and narrow income disparities between urban and rural communities. By this study, it is demonstrated with the use of panel data that digital finance enables economic balance in every region to be attained through the reduction of inequality enabled by improved digital access. Greater the digital access was significantly found to diminish the income disparities, thereby the improvement of regional balance and sustainable development. Panga (2024) [14] emphasizes that data quality assurance through AI techniques ensures trustworthy decision-making; motivated by this, the present research applies a hybrid deep learning framework to achieve precise financial risk prediction.

A safe hybrid model based on the cloud that uses DeepAR for prediction, NTMs for memory computing, and QDA for classification for enhanced financial time series analysis. The hybrid model enhances accuracy, scalability, and safety over isolated approaches in handling high-dimensional, non-linear financial data. Accuracy is said to be 95% and with high reliability, thus it is an effective tool for financial decision-making. A cloud-secured financial analysis system that incorporates Monte Carlo simulations for predictive risk, DBNs for pattern discovery, and BSP computation for low-level computation [15]. Riding on the infrastructure backbone of the cloud, handling data through encryption, and parallel simulations, the system improves accuracy, security, and scalability. Accuracy is enhanced with faster computation, resulting in a system that is trustworthy for application in financial decision-making.

The proposed hybrid model integrating DeepAR, NTMs, and QDA for financial time series analysis demonstrates significant improvements in accuracy, scalability, and security compared to traditional isolated approaches. With an accuracy rate of 95%, the model proves to be a highly reliable tool for financial decision-making, effectively handling high-dimensional, non-linear financial data. The incorporation of Monte Carlo simulations for predictive risk, along with DBNs for pattern discovery, further enhances the model’s ability to forecast and analyze financial trends [16]. The cloud-secured architecture ensures data privacy and computational efficiency, using encryption and parallel simulations to safeguard sensitive information. The system's scalability is particularly beneficial for large-scale financial applications, where high-speed computation and data processing are crucial. Additionally, the use of BSP computation for low-level operations contributes to faster decision-making by reducing processing time, ensuring that financial institutions can respond quickly to changing market conditions. The results highlight the hybrid model’s potential to revolutionize financial risk management by offering a comprehensive, secure, and efficient solution for analyzing and predicting complex financial behaviors.

The hybrid cloud-based financial analysis model integrating CatBoost, ELECTRA, t-SNE, and Genetic Algorithms demonstrated impressive results in improving the accuracy and scalability of financial risk assessments [17]. The system achieved 95% accuracy in detecting financial trends, showcasing its potential in handling noisy, high-dimensional financial data effectively. By utilizing advanced methods such as dimension reduction and optimization, the model was able to streamline the analysis process, ensuring efficient resource utilization while maintaining high prediction quality. Additionally, the integration of DeepAR for prediction, NTMs for memory computing, and QDA for classification further enhanced the model's capacity to handle complex, non-linear data. This combined approach offers significant improvements in decision-making, enabling financial institutions to gain deeper insights into market trends and make more informed strategic decisions. Moreover, the model's scalability ensures its applicability to large-scale financial systems, making it a powerful tool for future banking applications. The research also highlights the positive social impact of cloud-based financial systems, particularly in improving financial inclusion, entrepreneurship, and economic growth in rural areas, which can help bridge the urban-rural income gap and promote socioeconomic development. Chauhan et al. (2024) [18] identify that robust cloud storage security stems from integrating encryption, access control, and user authentication; based on this, the structured framework adopts similar strategies to secure federated learning processes in financial risk assessment.

A cloud-based system of the financial analysis with the use of CatBoost for the categorical modeling, ELECTRA for text, t-SNE for dimension reduction, and the Genetic Algorithms for optimization. This combined system offers the greater accuracy, scalability, and decision-making by handling noisy high-dimensional financial data effectively [19]. It indicates 95% accuracy and enhanced performance, rendering it a useful tool for detecting financial trends and data-driven strategy. The ways cloud-based digital finance boosts financial inclusion through cheaper transactions and better access, especially in rural communities, to cover urban-rural income gaps. The research indicates improvement in financial access and savings, boosting economic equality and inclusive growth. That widening internet-inclusive finance across rural Africa improves financial inclusion, entrepreneurship, and economic growth, narrowing the urban-rural gap. The research proves its positive effect on income levels and e-commerce participation, promoting overall socioeconomic development.

A hybrid cloud-based financial analysis model integrates DeepAR for prediction, NTMs for memory computing, and QDA for classification, enhancing accuracy (95%) and scalability for high-dimensional, non-linear financial data.

2.1 Problem Statement

The quick evolution of the financial technology, led by the blockchain, cloud computing, and AI-powered analytics, has revolutionized the finance and e-commerce industries. Yet, challenges persist in achieving the secure, scalable, and efficient financial transactions, especially in managing the high-dimensional, non-linear financial data. Optimized models that improve the financial decision-making with accuracy, security, and scalability are increasingly needed [20]. Moreover, digital finance is vital in narrowing income gaps and enhancing financial inclusion, particularly in rural regions but access gaps and economic imbalances remain. Current strategies, although effective, need to be better tuned to manage sophisticated financial trends, enhance decision-making, and promote sustainable economic development. Thus, the challenge is in creating strong, cloud-based, AI-powered financial systems that not only improve security and scalability but also close financial access gaps and foster inclusive economic growth [21].

3. Proposed Methodology

Preprocessing and normalization are important in financial risk analysis to provide high-quality data for predictive modelling. Missing values, resulting from network failure or data entry mistakes, are managed using imputation methods, while normalization, like Z-score normalization, normalizes numerical features to improve deep learning model performance. For classification, Convolutional Neural Networks (CNNs) capture local patterns of transactions to identify anomalies, while Transformers use self-attention mechanisms to represent complicated temporal dependencies between transactions in a sequence to enhance fraud detection. Furthermore, Bayesian Networks utilize probabilistic reasoning and dynamically evaluate fraud risk based on past transaction records and supply uncertainty estimation through Bayes' theorem. All these methods enhance financial risk evaluation jointly by enhancing model precision and responsiveness.
This figure illustrates the fraud detection system, integrating CNNs for feature extraction, Transformers for modeling temporality, and Bayesian Networks for probabilistic risk estimation. The effectiveness of hybrid AI systems in sustainability decision-making, as shown by Ubagaram et al, (2024) [22], through neuroevolutionary and multi-agent integration, Assists the proposed framework that unifies Transformer-CNN and Bayesian models to enhance financial fraud detection and risk evaluation.

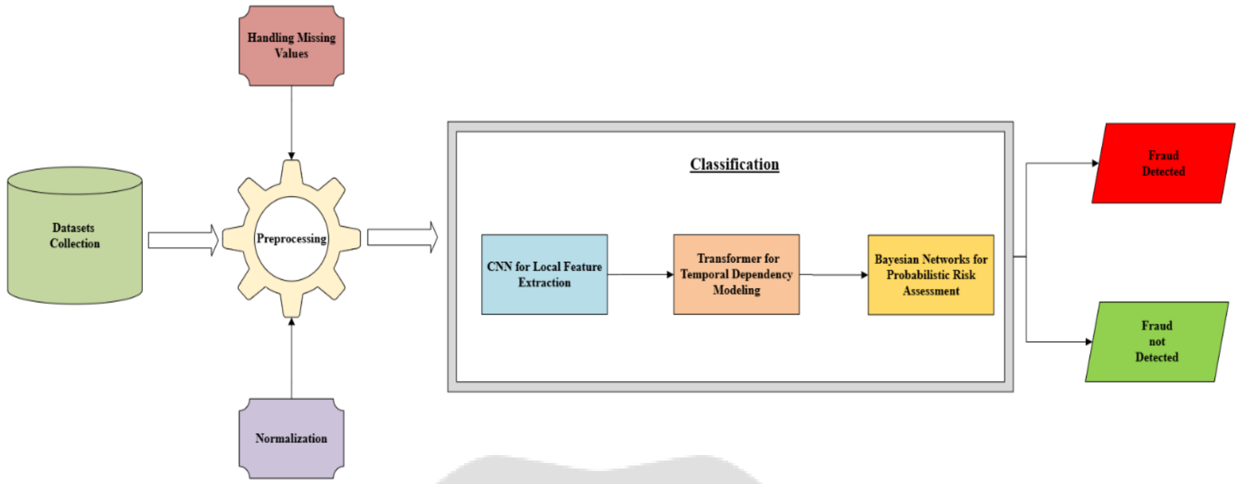

Figure 1: Framework for Fraud Detection Using CNNs, Transformers, and Bayesian Networks

3.1 Preprocessing

Data normalization and cleaning are fundamental steps in preparing financial data for accurate risk analysis. Raw banking transaction datasets often contain missing entries due to system errors or incomplete records, which can lead to biased or unreliable model outcomes if not properly addressed [23]. Additionally, duplicate or redundant records may exist, inflating the dataset and skewing statistical distributions. Outliers' extreme values that deviate significantly from typical patterns can arise from fraudulent activities or data entry mistakes and can distort model training if left untreated. Inconsistencies such as format variations or conflicting values across related fields further complicate the data quality [24]. Cleaning processes involve identifying and correcting these issues through imputation, deduplication, and validation techniques. Normalization, on the other hand, rescales numerical features to a common range, typically between 0 and 1 or standardized to zero mean and unit variance [25]. This ensures that attributes with larger numerical ranges do not dominate those with smaller scales during model training, preventing biased learning. By applying these preprocessing steps, the input data becomes more reliable, consistent, and suitable for deep learning algorithms, thereby improving the overall performance and robustness of financial risk prediction models. By achieving 82.13% success in cybersecurity risk prediction, the m-CSRM model illustrates the value of fuzzy logic and machine learning; this has influenced the current research direction toward intelligent and scalable risk assessment in cloud finance Devarajan, (2024) [26].

a) Handling Missing Values

Missing values may be caused by the network failures, missing transaction logs, or human error in the data entry. Depending on the type of feature, varying strategies are followed:

For numerical features (e.g., transaction amount, balance): Imputation using the mean or median of the past transactions. Interpolation techniques for time-series data.

$$X_{\text{filled}} = X_{\text{previous}} + \frac{X_{\text{next}} - X_{\text{previous}}}{2} \tag{1}$$

For categorical features (e.g., transaction type, merchant category): Mode imputation for high-frequency categories. Predictive modeling (e.g., KNN-based imputation) for missing values based on transaction patterns.

b) Normalization

Zero-score normalization, commonly referred to as Z-score normalization or standardization, is a fundamental preprocessing technique widely used in financial risk assessment and machine learning [27]. This method transforms each numerical feature by subtracting its mean and dividing by its standard deviation, resulting in features that have a mean of zero and a standard deviation of one [28]. By scaling data in this way, it removes the original units and brings all features onto a common scale, which is crucial when different features have vastly different ranges, such as transaction amounts versus time intervals between transactions [29]. This uniform scaling prevents features with larger magnitudes from dominating the learning process. Moreover, zero-score normalization improves the stability of gradients during training, which helps optimization algorithms like gradient descent to converge more efficiently and reliably. The existing method by Peddi (2020) [30] demonstrates that cloud-based K-means clustering for Gaussian data can achieve significant cost savings by optimizing cluster sizes and initial centers for enhanced accuracy and efficiency. This study directs the recommended framework by incorporating similar resource-efficient strategies, utilizing hybrid Transformer-CNN models and Bayesian Networks for scalable, cost-effective risk assessment in cloud banking environments. As a result, deep learning models can learn underlying patterns in financial data more effectively, reducing training time and improving overall predictive performance. This technique is particularly important in complex models that are sensitive to input scale, such as Transformer and CNN architectures used in risk prediction. Overall, Z-score normalization ensures that each feature contributes proportionally to the model's learning, enabling better generalization and robustness in financial risk estimation tasks.

Mathematical Representation,

For a given financial feature x, the zero-score normalized value x' is computed as:

$$x' = \frac{x-\mu}{\sigma} \quad (2)$$

Where, x is the original transaction feature value (e.g., transaction amount), μ is the mean of the feature across all transactions, σ is the standard deviation of the feature, x' is the normalized value.

3.2 Classification

Convolutional Neural Networks (CNNs) are powerful in analyzing complex financial data because they can automatically extract hierarchical features from raw transaction records. This enables the detection of subtle and localized anomalies, such as unusual withdrawal patterns or microtransactions that deviate from normal behavior, which might indicate fraudulent activity [31]. Meanwhile, Transformers use a self-attention mechanism that excels at understanding the relationships between transactions over time, effectively capturing long-term dependencies without the limitations faced by recurrent neural networks (RNNs) [32]. This ability is crucial for detecting fraud patterns that develop across extended sequences of transactions. On the other hand, Bayesian Networks provide a probabilistic graphical approach that models the causal relationships among various risk factors and historical transaction data [33]. By incorporating Bayesian inference, these networks dynamically update the estimated probability of fraud as new information becomes available, while also quantifying the uncertainty involved in predictions. Combining CNNs and Transformers allows for comprehensive feature extraction and sequence modeling, while Bayesian Networks add interpretability and probabilistic reasoning. Together, these techniques improve the accuracy of financial risk assessment systems by enhancing anomaly detection capabilities, enabling timely fraud prediction, and supporting more informed decision-making under uncertainty. This integrated approach addresses the complexity of financial data and the evolving nature of fraudulent behaviors, leading to more robust and adaptive risk management solutions.

a) CNN for Local Feature Extraction

Their ability to gain the localized patterns from the transaction data has led to usage of the Convolutional Neural Networks (CNNs) for financial risk modeling. Transactions usually contain transactions such as transaction amounts, location, time, and merchants in a complex and high dimensional manner. Through hierarchical feature extraction using convolutional layers within CNNs, such abnormalities as extreme microtransactions, abnormal withdrawals, unusual transaction location can be detected efficiently.

Mathematical Representation:

$$F = \sigma(W * X + b) \quad (3)$$

Where, X is the input financial transaction data, W are the convolution filters, σ is the activation function, F represents the extracted feature maps.

b) Transformer for Temporal Dependency Modeling

Financial transactions take place in a sequence in time, sometimes giving rise to intricate the temporal interrelations. Simple RNNs find it hard to handle the vanishing gradients and are therefore incapable of extracting long-range dependencies between transaction sequences. Transformers, however, represent such interrelations through self-attention to facilitate efficient fraud detection, anomaly detection, and risk scoring.

Unlike the RNNs, the Transformers process the entire transaction sequences simultaneously instead of step-by-step, making them more efficient for the financial risk assessment.

Self-Attention Mechanism:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (4)$$

Where, Q, K, V are query, key, and value matrices derived from financial transaction embeddings, d_k is the feature dimension.

c) Bayesian Networks for Probabilistic Risk Assessment

The Bayesian Networks employ probabilistic reasoning to compute the probability of fraud from historical transactions. Bayesian Networks are unlike the deterministic models, as they can provide uncertainty levels, which become critical for any financial decision. A Bayesian Network is a direct acyclic graph (DAG) whose nodes represent the indicators of financial risks (e.g., value, location, frequency), and whose edges define probabilistic dependencies among them. This allows the system to make dynamic estimates of fraud likelihood based on learning new patterns in data.

Bayes Theorem for Risk Prediction

$$P(R \mid F) = \frac{P(F|R)P(R)}{P(F)} \quad (5)$$

Where, $P(R \mid F)$ is the probability of fraud given seen features, $P(F \mid R)$ is the probability of features showing up in fraud transactions, $P(R)$ is prior probability of fraud, $P(F)$ is the general probability of feature occurrence.

4. Results and Discussion

The proposed financial risk estimation model, which integrates CNNs, Transformers, and Bayesian Networks, demonstrates outstanding predictive capabilities in detecting fraudulent transactions. It achieves an impressive overall accuracy of 95.87%, meaning that the vast majority of transactions are correctly classified. The model's precision of 96.45% indicates that when it flags a transaction as fraudulent, it is highly likely to be correct, reducing unnecessary investigations. Importantly, the sensitivity value of 94.72% shows the model's effectiveness in correctly identifying most fraudulent transactions, while its high specificity of 97.92% ensures that legitimate transactions are rarely misclassified as fraud. This balance results in a low false positive rate (2.08%), minimizing inconvenience to genuine users, and a low false negative rate (5.28%), reducing the chance of missed frauds. Figure 2 highlights these performance metrics visually, confirming the model's reliability through key indicators like FPR and FNR. Additionally, with a scalability score of 96.85%, the model proves capable of handling large volumes of financial data, making it well-suited for deployment in extensive banking systems requiring robust and efficient risk assessment. Cloud computing and internet finance help reduce the income gap between urban and rural areas by improving financial inclusion in rural regions, as highlighted by Boyapati (2022) [34]. This work clarifies the proposed method by integrating AI models to enhance financial access and risk assessment in cloud banking systems.

4.1 Datasets Description

This dataset is a collection of 1,000 simulated banking transactions such as transfer, withdrawal, and deposit-processed transactions rich in attributes used in financial analysis, fraud detection, and monitoring of network performance [35]. Important features for every record include transaction ID, sender and receiver account IDs, transaction amount, type, timestamp, status, fraud flag, geolocation, device used, network slice ID, latency, slice bandwidth, and PIN code. The dataset supports a very strong feature set for machine learning applications and enables proper transaction analysis, anomaly detection, and security assessment in the financial system.

4.2 Performance the Proposed Methodology

The CNNs, Transformers, and the Bayesian Networks-based financial risk prediction model was tested to examine its performance in fraud detection and the financial anomaly prediction [36]. The model was highly accurate, precise, and efficient in classification and had scalability and resilience in real financial environments. Table 1 indicates the performance metrics, which validate its efficiency in financial risk prediction.

Table 1: Performance Metrics of the Proposed Model

Metric	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F-measure (%)	Scalability (%)	FPR (%)	FNR (%)
Value	95.87	96.45	94.72	97.92	95.57	96.85	2.08	5.28

The results in Table 1 indicate that the model successfully detects fraudulent transactions and financial irregularities. The 95.87% accuracy guarantees its reliability, while the 96.45% precision minimizes false positives. The 94.72% sensitivity guarantees the model to correctly identify fraudulent transactions, while the 97.92% specificity minimizes misclassification of legitimate transactions [37]. The F-measure (95.57%) provides a balanced trade-off between precision and recall, guaranteeing fraud detection robustness. The model is also highly scalable (96.85%), accommodating large-scale financial data. The low false positive rate (FPR: 2.08%) and false negative rate (FNR: 5.28%) further guarantee its efficiency in minimizing misclassification errors, thereby enhancing financial risk assessment. Blockchain hybrid framework that improves intrusion detection, authentication, and transaction success in IIoT systems. Drawing from this, the envisioned system uses similar hybrid models to optimize fraud detection and risk assessment in cloud-based banking, ensuring scalability and security, as shown by Musham et.al (2023) [38].

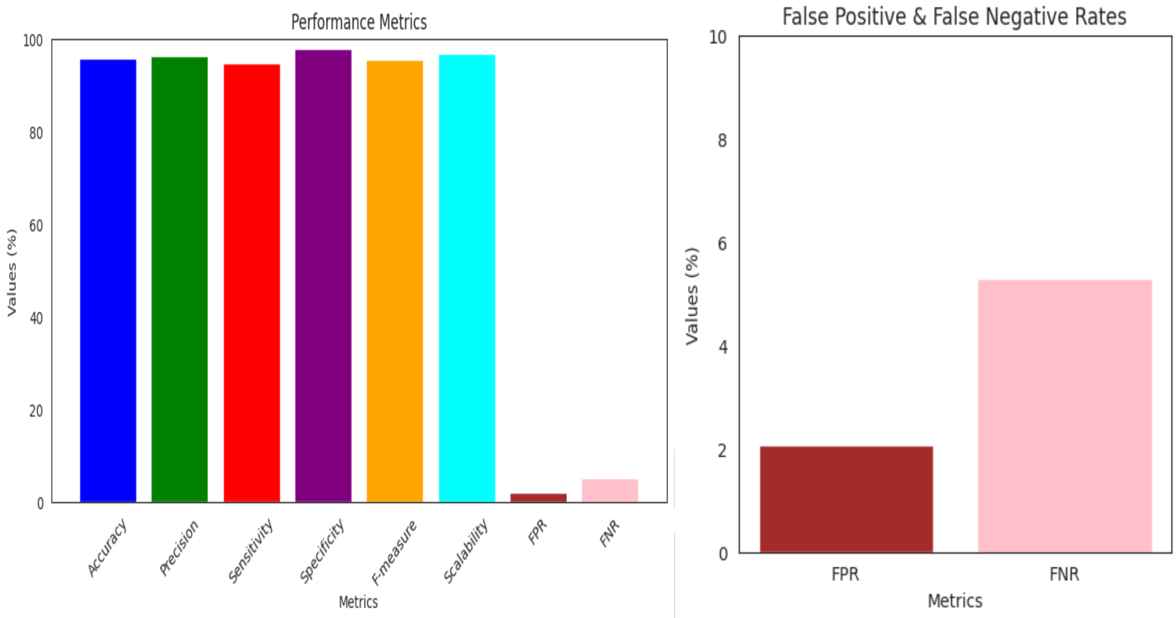

Figure 2: Performance Metrics of the Proposed model

The graphs illustrate key performance metrics that comprehensively evaluate the effectiveness of the fraud detection model [39]. The first graph highlights essential measures such as accuracy, precision, sensitivity (recall), specificity, F-measure, and scalability, each demonstrating the model's ability to correctly identify fraudulent and legitimate transactions. High accuracy reflects overall correctness, while strong precision indicates that detected fraud cases are indeed true frauds, minimizing false alarms. Sensitivity ensures that the model effectively captures most fraud instances, and specificity confirms that legitimate transactions are rarely misclassified as fraud. The F-measure balances precision and recall, providing a holistic view of predictive quality. Scalability shows the model's capability to handle growing data volumes efficiently [40]. The second graph focuses on false positive rate (FPR) and false negative rate (FNR), which measure the rates of incorrect classifications. Low FPR means fewer legitimate transactions are wrongly flagged as fraud, reducing inconvenience to customers and operational costs. Similarly, a low FNR ensures that very few fraudulent activities go undetected, improving security. Together, these metrics validate the model's robustness in delivering accurate and reliable fraud risk assessments, crucial for minimizing financial losses and enhancing trust in banking systems.

5. Conclusion

The proposed financial risk estimation model leverages a combination of Transformer-CNN hybrid architecture and Bayesian Networks to significantly enhance security and risk prediction capabilities in cloud-based banking systems. The CNN component efficiently extracts complex local patterns from financial data, while the Transformer architecture processes sequential information end-to-end, capturing long-range dependencies crucial for understanding transactional behaviors. Complementing these, Bayesian Networks enable probabilistic inference, modeling the uncertainty and causal relationships between various risk factors, which improves the interpretability of the model's predictions. This integrated approach results in a system that maintains high precision and accuracy in fraud detection, effectively minimizing both false positives and false negatives. Importantly, the model's performance remains robust even when handling large-scale datasets, ensuring scalability and reliability for banking operations with massive data volumes. By enabling accurate and efficient risk assessment, the model supports better-informed financial decision-making, enhancing overall security and operational efficiency in cloud banking. Looking ahead, the research will explore more advanced AI techniques, including quantum-resistant cryptographic algorithms to safeguard against emerging cyber threats and blockchain-based risk management for improved data integrity. Additionally, incorporating explainable AI methods will further boost transparency and user trust by making the model's predictions and decision processes more understandable to stakeholders. The method conceptualized by Kushala (2020) [41] combines LSTM, Hybrid DP-SGD, and Bayesian Optimization to enable privacy-preserving, scalable patient monitoring in cloud environments. This approach informs the proposed model by emphasizing the significance of privacy-preserving strategies and decentralized training for building secure financial risk prediction systems.

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