International Journal of Research Publication and Reviews, Vol 5, no 10, pp 4341-4351 October 2024

WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

AI-Driven Solution for Instant Liquidity Risk Assessment in Financial Institutions

Anita Kori[1], Dr. Chetan Bulla[2]

[1]Assistant Professor, Dept of AIML, BEC, Bagalkot

[2]Solution Architect, Citi Bank Bangalore

Mail: bulla.chetan@gmail.com

DOI : https://doi.org/10.55248/gengpi.5.1024.3024

ABSTRACT

In the banking industry, where quick, precise risk assessment determines regulatory compliance and financial stability, liquidity risk still causes great worry. Emphasizing forecast accuracy, efficiency, and flexibility, this work investigates artificial intelligence (AI) application to improve real-time liquidity risk assessment. Using machine learning (ML) and deep learning (DL) approaches, we construct a model to offer dynamic risk insights by aggregating transactional data, market circumstances, and historical liquidity trends. Early detection of likely liquidity stress by the AI-driven approach not only provides a smart alternative for conventional static operations but also fits changing market patterns. Comparative study using traditional models shows significant improvements in reaction times and forecast accuracy, hence improving liquidity management choices. Emphasizing the possibilities of AI-based solutions for proactive and responsive liquidity risk assessment in banks, this study supports the expanding area of artificial intelligence in financial risk management.

Keywords: **Liquidity Risk Assessment, Artificial Intelligence, Real-Time Risk Management, Deep learning model, LSTM**

1. Introduction

Liquidity risk is a great concern to financial institutions as it instantly influences a bank's capability to meet its short-term obligations and maintain operational stability. Inaccurate management of liquidity can lead to significant problems compromising the institution as well as the more general financial system. Often depending on historical data and immobile models, conventional methodologies of liquidity risk assessment lack the agility needed in the fast-paced financial markets of today. Usually reactive, these conventional approaches find liquidity problems just once risk levels have increased. Therefore, the need of proactive, real-time evaluation tools has never been more critical [1].

Especially in machine learning (ML) and deep learning (DL), artificial intelligence (AI) breakthroughs provide new avenues for transforming risk management practices. By using artificial intelligence, banks will be able to rapidly manage vast volumes of transactional and market data, therefore enabling accurate and dynamic liquidity risk projections. Unlike more traditional methods, artificial intelligence models might learn and adapt over time, observing complex trends and basing projections on evolving market conditions. Through proactive steps implemented by financial institutions using real-time data, better financial resilience and regulatory compliance are guaranteed [2].

Adoption of cloud technology offers great benefits in data processing, real-time analytics, and scalability, therefore radically changing how banks analyze and handle liquidity risk [3][4]. By centralizing massive amounts of data including transactional records, market information, and historical liquidity measurements, cloud systems help banks to simplify data retrieval and adopt a complete approach to liquidity research, so effectively recognizing trends and developing threats. Furthermore, cloud infrastructure provides the computational capacity needed to run complex artificial intelligence and machine learning models on demand, therefore allowing large-scale, real-time data processing free from the significant costs linked with on-site systems. This capacity enables banks to make quick decisions based on fast insights and to continuously monitor liquidity indicators, therefore enabling preventive actions to avoid likely liquidity shortages. Strong disaster recovery solutions allow cloud providers to additionally ensure data availability and business continuity. Enhanced cooperation in many spheres as staff members may safely access risk management tools and data, therefore enabling real-time decision-making. Reducing infrastructure costs and ensuring regulatory standard compliance for data security allows banks to be flexible, strong, and safe enough for effective liquidity risk management and improved financial stability. Figure 1 displays the acceptance of cloud computing in evaluation of liquidity risk.

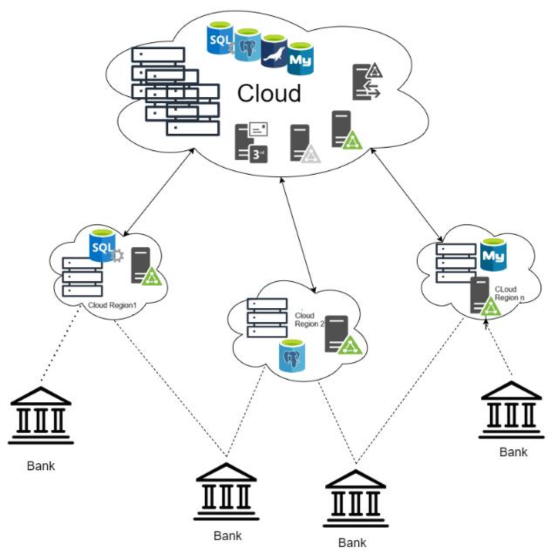


Figure 1: adoption of cloud computing in assessing liquidity risk.

This paper investigates the possibilities of artificial intelligence in enhancing real-time liquidity risk evaluation in the banking sector. Combining several artificial intelligence algorithms, we develop a prediction model utilizing historical liquidity patterns, transactional behavior, market volatility, and artificial intelligence algorithms themselves to dynamically evaluate liquidity risk. We also illustrate how, when we compare artificial intelligence-driven models with traditional static models, expected accuracy and reaction time change. This paper aims to contribute to the growing field of artificial intelligence applications in finance by demonstrating the advantage of AI-enabled systems for robust, proactive liquidity management in banks. The following arranges the remaining paper: Section 2 investigates state of the art liquidity risk assessment model; Section 3 suggests the liquidity risk assessment model and its working concepts; Section 4 offers experiment evaluation of suggested model; Section 5: concludes the study with observations and evaluation findings.

2. Related Work

One key tactic indicated is artificial intelligence algorithm real-time IoT data processing. By using predictive modeling tools, anomaly detection, and pattern recognition, these systems serve to enhance liquidity risk assessment [5]. From this follows improved operational resilience and decision-making. One obvious disadvantage, though, is the rising complexity and volume of financial data, which requires ever more sophisticated analytical methods to correctly spot risks[6]. Complementing bibliometric analysis with VOSviewer tool, the use of the Scopus database for literature search emphasizes artificial intelligence's ability to analyze vast amounts. This enhances real-time liquidity risk assessment [7] and helps to lower cognitive biases occasionally present in traditional risk assessment. Still, challenges include inherent cognitive biases and human constraints in decision-making procedures.

In real-time liquidity risk estimates, Random Forest (RF) and Multi-Layer Perceptron (MLP) used in a hybrid model increase accuracy and sensitivity [8]. Nevertheless, this approach suffers with data quality and the small number of liquidity risk factors, which might overlook reasonable impacts. Several machine learning techniques like K-Nearest Neighbors (KNN), Support Vector Machine (SVM), decision trees, and XGBoost show great potential in generating real-time liquidity risk assessment systems [9] especially for Indian banks. Though the MLP model performs worse than other methods, the small sample sizes of the studies constrain the generalizability of the conclusions.

Moreover, although they do not particularly address liquidity risk assessment, artificial intelligence-driven predictive analytics focus on credit risk and financial inclusion [10]. Among these limitations of these approaches include ethical and legal consequences, data privacy concerns, and probable biases in AI models.

Although accuracy problems still remain, the discussion of supervised machine learning models for liquidity stress prediction reveals the application of the RUSBoost algorithm to improve liquidity risk management by way of early market stress warnings [11].

Combining transactional records with compliance reports, the mixed-methods approach—which employs qualitative interviews and quantitative data analysis—combines Although research shows that artificial intelligence-enhanced real-time financial monitoring systems lower liquidity risk assessment, this approach introduces a degree of complexity that might be challenging to manage even [12]. Moreover underlining changes in assessing liquidity risk is the application of text analysis and web crawling to create an intelligent early warning model using recurrent neural networks [13]. This method not only improves real-time monitoring skills by way of a Dropout layer, so addressing overfitting difficulties, but also a layered cyclic neural network to raise model fitting capacity. Finally, the use of an adaptive neuro-fuzzy inference system (ANFIS) for risk rating based on Mahalanobis Distance [14] shows at last the mix of techniques to accurately analyze banking risks. Nevertheless, ANFIS offers complexity that could impede interpretability in practical uses even if it sufficiently records nonlinear connections[[15].All things considered, the table 1 demonstrates a broad range of approaches for liquidity risk assessment in banking, thereby stressing the transformational power of artificial intelligence and machine learning as well as the complexity and limitations linked with these methods. Every method provides unique insights but also has problems that have to be fixed if they are to be implemented in real-world financial environments.

Ref.	Method/Model	Insights	Limitations
[5]	AI algorithms for real-time IoT data analysis Integration of pattern recognition, anomaly detection, predictive modeling capabilities	AI algorithms can enhance real-time liquidity risk assessment in banks by analyzing IoT data for pattern recognition, anomaly detection, and predictive modeling, improving decision-making and operational resilience.	Increasing complexity and volume of banking data. Need for sophisticated analytical methods for risk detection
[6]	Scopus database utilized for literature search. Bibliometric analysis conducted using VOSviewer software.	AI enhances real-time liquidity risk assessment in banks by analyzing vast data sets, improving decision-making processes, and mitigating cognitive biases inherent in traditional risk evaluation methods.	Cognitive biases in risk evaluation Human limitations in decision-making processes
[7]	Random Forest (RF) model for analysis. Multi-Layer Perceptron (MLP) model for classification.	The study developed a hybrid RF-MLP model for real-time liquidity risk assessment, enhancing sensitivity and accuracy while addressing data integrity and practical liquidity risk determinants in banks.	Data integrity vulnerabilities in liquidity risk measures. Narrow composition of liquidity risk factors excluded practical determinants.
[8]	KNN, SVM, decision tree, RF, XGBoost Financial ratios used as predictors for liquidity risk prediction	The study highlights the potential of machine learning algorithms, particularly KNN and XGBoost, for developing real-time liquidity risk assessment systems in Indian banks.	Small sample limits generalizability of results. MLP performed poorly compared to other models.
[9]	AI-driven predictive analytics Machine learning algorithms, alternative data sources, real-time analytics	The paper focuses on AI-driven predictive analytics for credit risk and financial inclusion, not specifically on real-time liquidity risk assessment in banks.	Bias in AI models and data privacy concerns. Regulatory considerations and ethical implications of AI solutions.
[10]	Machine learning algorithms for data analysis Scenario simulations, predictive modeling, real-time data analysis	The paper discusses AI's role in enhancing predictive capabilities and operational efficiency, which can be applied to real-time liquidity risk assessment through advanced data analysis and decision-making.	High Complexity limited features in dataset is used to evaluate
[11]	Supervised machine learning models for liquidity stress prediction. RUSBoost algorithm in ensemble model for improved accuracy.	The study employs machine learning models to enhance liquidity risk management, offering early warnings of stress through market-based indicators, thus facilitating real-time assessments .	Less accuracy
[12]	Mixed-methods approach: qualitative interviews and quantitative data analysis Incorporates transactional records, compliance reports, and stakeholder surveys	Real-time financial monitoring systems utilizing AI enhance liquidity risk assessment in banks by improving predictive capabilities and response times, leading to more accurate risk evaluations and operational efficiency.	High complexity
[13]	Web crawler, text analysis, grounded analysis Recurrent neural network model for risk early warning	The paper constructs an intelligent early warning model using deep learning to assess liquidity risk in banks, enhancing real-time monitoring and prediction capabilities based on complex financials.	Overfitting issue addressed with Dropout layer in recurrent neural network. Stacked cyclic neural network used to improve model fitting .
[14]	Risk ranking index based on	The paper "The role of artificial intelligence in developing a banking risk index: an application	The use of an Adaptive Neuro-Fuzzy Inference System (ANFIS)

	Mahalanobis Distance (MD) Adaptive Neuro-Fuzzy Inference System (ANFIS) for determining relative importance of risk ratios	of Adaptive Neural Network-Based Fuzzy Inference System (ANFIS)" utilizes a combination of methodologies to assess banking risks effectively.	introduces complexity in the model. While ANFIS can capture nonlinear relationships, it may also lead to challenges in interpretability [16].
[15]	The paper "The role of artificial intelligence in developing a banking risk index: an application of Adaptive Neural Network-Based Fuzzy Inference System (ANFIS)" utilizes a combination of methodologies to assess banking risks effectively.	Hybrid methods have more advantages in terms of accuracy	High complexity

Table1 : state of the art risk assessment model using AI Techniques

3.Proposed Model

LSTM-X is the suggested model for evaluating liquidity risk in banks as it combines external variables (X) with Long Short-Term Memory (LSTM) networks to improve assessment of liquidity risk. This hybrid model provides a more complete assessment framework as it is especially meant to examine temporal data while including other important elements that could affect liquidity risk [17].

Symbol	**Description**
σ	sigmoid activation function.
Wf, Wi, WC, Wo, Wf, Wi, WC, Wo, Wf , Wi ,WC ,Wo	weight matrices for the forget, input, cell state, and output gates, respectively.
bf,bi,bC,bob_f, b_i, b_C, b_obf ,bi ,bC ,bo	are the bias terms for each gate.
ht_h	hidden state at time t.
x_t	input feature vector at time t.
Ct	cell state at time t.

Table 2: list of mathematical symbols

Starting with an input layer comprising time-series data on liquidity, including cash flow, assets, and liabilities, together with external factors such market conditions and interest rates, the LSTM-X model's architecture proceeds. The LSTM layer—where LSTM cells handle sequential data—is fundamental to the model. Through efficient capture of long-term relationships and temporal patterns in liquidity risk, this processing enables the model After the LSTM layer comes a thick layer designed to incorporate the learnt characteristics from processing LSTM output. At last, the output layer offers the prediction of liquidity risk, which might be presented as a binary classification—that is, liquid against illiquid—or as a regression output value estimating the risk level. Figure 2 displays the LSTM-X model designed for evaluation of liquidity risk.

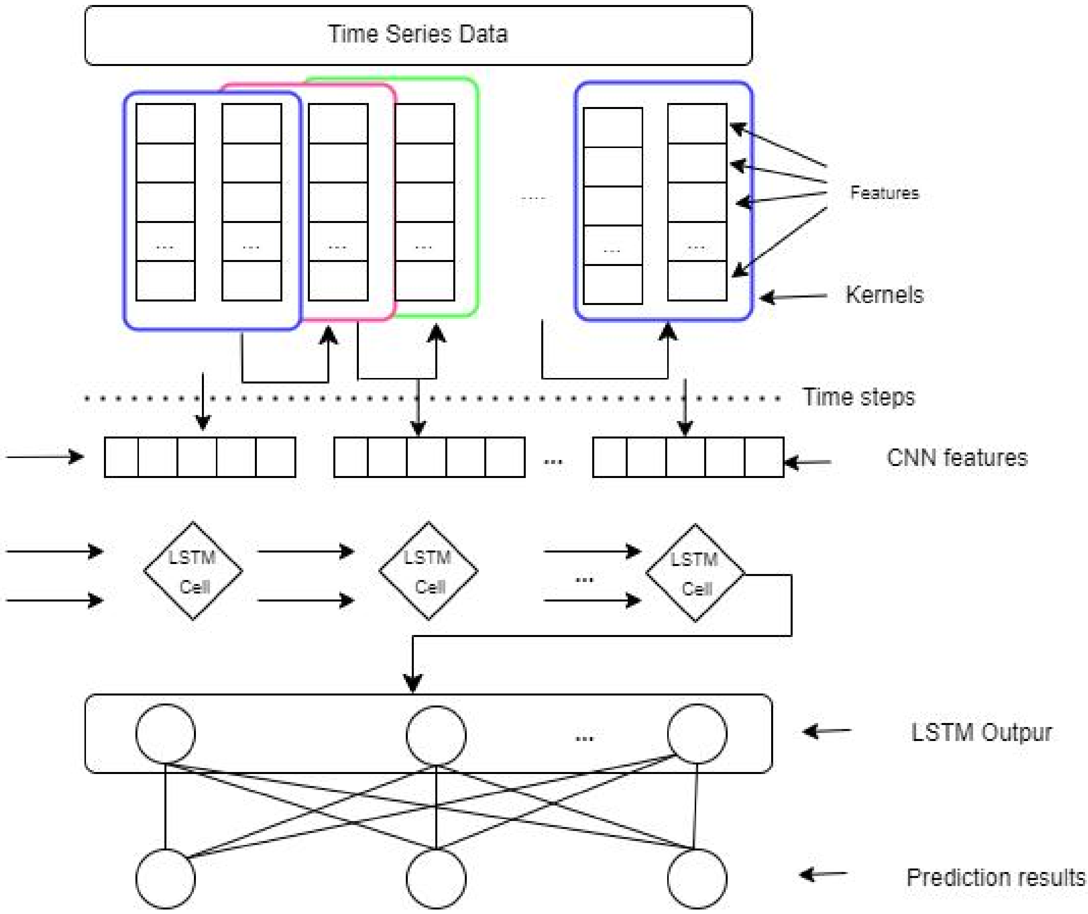


Figure 2 : CLSTM model for training risk prediction model

Mathematically, the LSTM unit operates using several key equations. The forget gate, defined as

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

determines which information should be discarded from the cell state. Meanwhile, the input gate, expressed as

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

identifies which values will be updated. The cell state is updated through the equation

$$\widetilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right)$$

leading to the new cell state

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t$$

The output gate determines what should be output from the LSTM using the equation

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

with the hidden state being computed as

$$h_t = o_t \cdot \tanh\left(C_t\right)$$

Incorporating external features into the model is achieved by concatenating these features with the output of the LSTM layer before passing them to the dense layer. This process can be represented mathematically

$$h_t^{'} = [h_t, X_t]$$

combines the LSTM output and the external features.

The prediction output of the model is derived from the dense layer using a suitable activation function, such as the sigmoid function for binary classification or a linear activation for regression tasks. This can be expressed as

$$Y = \text{Activation}(W_d \cdot h_t^{'} + b_d)$$

where Wd and bd are the weight matrix and bias for the dense layer, respectively.

The model's training process involves minimizing a loss function appropriate to the prediction task. For binary classification, the binary cross-entropy loss function is used, formulated as

$$L(Y,\widehat{Y}) = -\frac{1}{N}\sum_{i=1}^{N}\left[Y_i \log\left(\widehat{Y}_i\right) + (1 - Y_i)\log\left(1 - \widehat{Y}_i\right)\right]$$

where Y is the true label and Y^ is the predicted label.

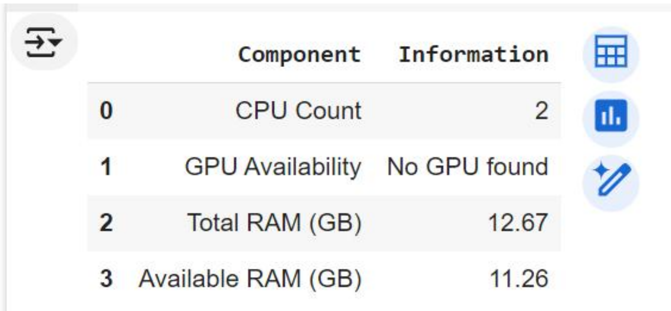
During training, the LSTM-X model employs backpropagation through time (BPTT) to update the weights and biases in both the LSTM and dense layers. This optimization is typically performed using algorithms such as Adam or RMSprop [18].

4. Experiment Evaluation

This section demonstrate the significance of proposed model by conducting simulation experiments. The Python programming language in Google Colab framework is used to implement the simulation model for proposed risk assessment model. The standard dataset from UCI Machine Learning Repository called Redfin dataset is used [20]. The proposed model simulated with different configurations and recorded its results and same result is compared state-of-the-art existing risk assessment model. The following sub section discusses about simulation setup, proposed model results, evaluation of result with existing model and represents advantages and limitations of proposed model.

Simulation Setup

The Google Colab framework with Python programming is used to implement the simulation model. Colab is cloud-based platform to create and run Python code in a Jupiter notebook environment, Its IaaS freeware service to collaboratively work and experiment different AI model. The availability of GPUs and TPUs in Colab makes it an attractive option for training massive ML models. Furthermore, Python is having rich set predefined libraries that makes programmer to write flexible code. Figure 3 below shows colab configurations used to experimentation.



	Component	Information
0	CPU Count	2
1	GPU Availability	No GPU found
2	Total RAM (GB)	12.67
3	Available RAM (GB)	11.26

Fig 3. Golab configurations

Dataset

Redfin provides property data, including recent home sales, listings, and market trends, for cities across the U.S. This dataset is useful for evaluating property investment opportunities based on recent market activities. There are 50+ features of dataset and the key features of this dataset are : Property Details, Location Information, Price and Sales Information, Transaction and Market Data, Property Condition and Features, Market Indicators and Additional Features [19]. Figure 4 shows the investor data for different previous quarters. The data is taken from the Redfin[19] website.

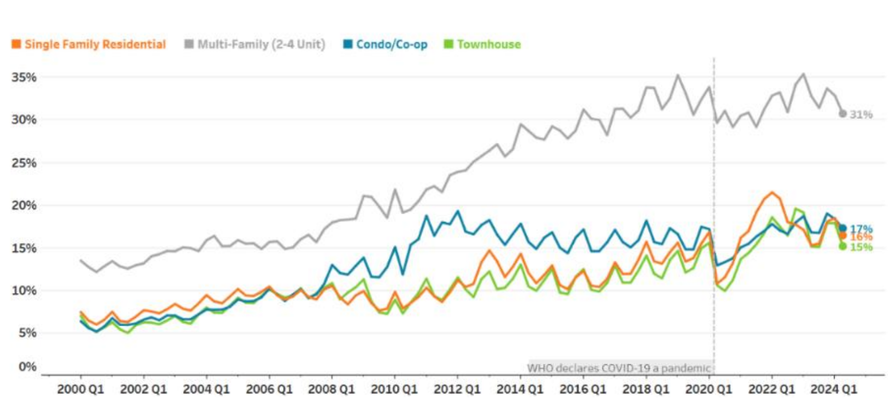


Fig. 4. Redfin investor data

Performance parameters:

The various performance parameters are considered to evaluate the performance of proposed model. The proposed model uses machine learning and deep learning model ; hence the common and most popular performance parameters are considered : these are Recall, precision, F1-Score, RMSE and computation efficiency parameters CPU and memory consumptions [18][23][27]: These are defined as follows:

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

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}]$$

$$\text{AUC} = \int_0^1 \text{TPR } d(\text{FPR})$$

$$\text{FPR} = \frac{FP}{FP + TN}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Most often used metrics to assess AI based solutions are accuracy, precision, recall F1, RMSE; their definitions are not provided since they are well-known measures. Evaluating the performance of classification and compiling the model's capacity to differentiate between the positive and negative classes across several threshold values, the AUC helps Log loss gauges a classification model's performance in which the prediction is a probability value ranging from 0 to 1.

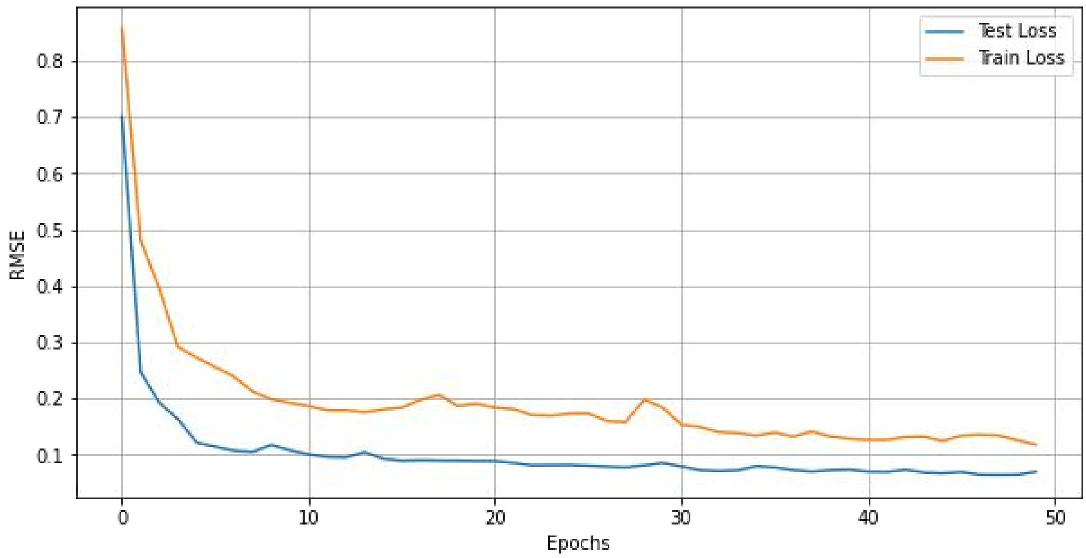


Fig 5: RMSE for epochs

Figure 5 shows the difference between the test and train loss for different epochs. The difference in loss between the test and train datasets is very small, and as the number of epochs increases, the loss continues to decrease. The accuracy of the proposed model for detecting suspicious activity is shown to be towards the higher end of the graph. Figure 6 shows a comparison of the root mean square error (RMSE) for different models used in suspicious activity detection, such as HMM [21], DBN[30], LSTM [6] and ARIMA [27]. The proposed model has a lower Root Mean Square Error (RMSE) when compared to other models for detecting suspicious behavior.

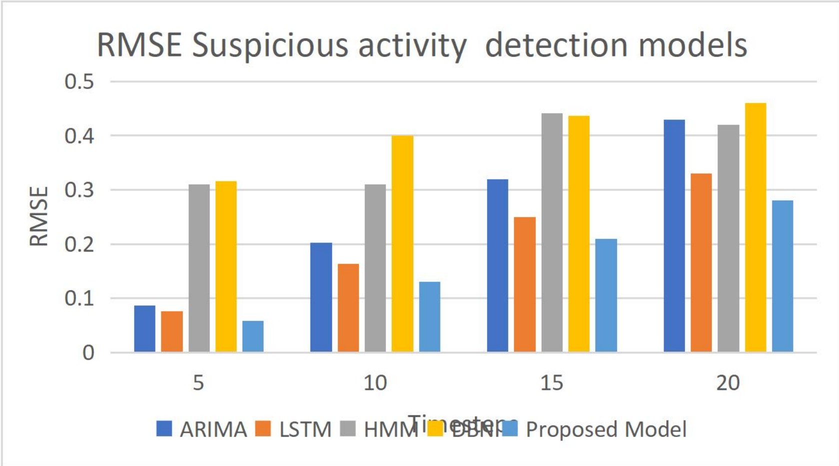


Fig 6: Comparison of RMSE values for various models and proposed models.

The accuracy of the proposed model has increased compared to existing models. However, tuning the hyperparameters requires more memory and CPU cycles. So, the proposed method can be applied in critical application like finance where accuracy is extremely important. Figure 7 presents a comparison of various performance metrics, such as CPU and memory usage, detection time, and accuracy of suspicious behavior.

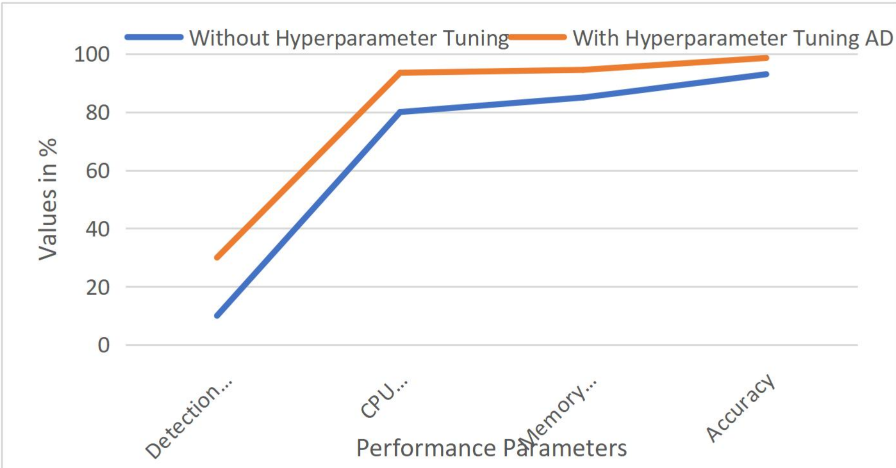


Fig 7 : Comparison of Normal AD and Hyperparameter Tuner AD

Figure 8 shows a comparison of the suggested method and other methods for finding suspicious behavior based on memory, accuracy, and F1-score. LSTMs [6], RNNs [28], and auto-encoders [26] are what the latest models are based on. Using the proposed model instead of the first three methods gives better precision, memory, and F1-score.

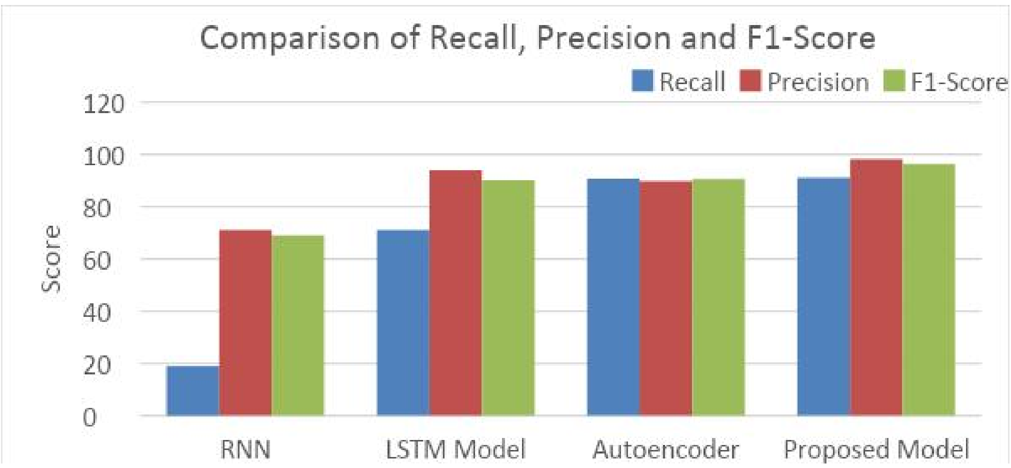


Fig 8: Accuracy parameters of the existing and proposed system

Table 3 shows the set of hyperparameters that resulted in an accuracy rate of 99.89% using a threshold value of 0..65.The results of the experiments indicate that hyperparameter optimization outperformed models in terms of accuracy.

Sliding-window-size	LSTM -units	dropout-rate	regula rize	regularizer-rate	optimizer	epochs	activation function	learning-rate	accuracy	Loss
20	50	0.3	L2	0.02	RMSProp	100	ReLu	0.45	99.89	0.01

Table 3: Hyperparameter values for highest accuracy

Table 4 shows comparison of proposed model and existing models with respect to accuracy, recall, precision, F1-Score, scalability, detection time, CPU and Memory Consumption. The data is collected from various research articles as part of literature survey. The proposed model recorded highest accuracy and support scalability as it is using combination of Deep Learning Model and Bio-inspired algorithms in fog computing infrastructure.

References	Accuracy	Precision	F1-Score	Detection Time	CPU consumption	Memory Consumption	Scalability support
LSTM Autoencoder[26]	97%	92%	96.6%	More	More	More	Yes
LSTM [22]	92%	90	94	Less	Less	Less	NA
Auto-encoder [32]	95%	90%	95%	More	Moderate	Moderate	Yes
RNN [28]	89%	90%	90%	Moderate	Moderate	Moderate	No
HMM[21]	70	73.2%	72%	Moderate	Moderate	Moderate	No
DBN [32]	80.5714%	94.5440%,	95.3%	More	Moderate	Moderate	No
Proposed Model	99.8%	98.2%	98%	More	More	More	Yes

Table 4: Hyperparameter values for highest accuracy

Discussion

By utilizing the capabilities of Long Short-Term Memory (LSTM) networks together with pertinent external variables, the LSTM-X model suggested in this research study offers a major improvement in the evaluation of liquidity risk in the banking industry. This connection helps the model to account for real-time changes affected by outside economic variables and catch intricate trends in past liquidity data. The results highlight the urgent requirement of banks using modern analytical methods to negotiate the complexity of liquidity risk, especially in a financial climate growing in volatility [24].

The LSTM-X model's capacity to properly manage sequential data is one of its main assets. Standard models can find it difficult to include the time-dependent character of financial data, which results in possible misestimations of liquidity risk. Our approach gains from the capacity to retain information over long times by using LSTM networks, which is essential for comprehending how historical liquidity situations impact present and future risks. More precise projection of liquidity needs made possible by this skill helps banks to make wise judgments about contingency planning, asset allocation, and cash management. Furthermore, adding outside elements to the LSTM architecture marks a major change in liquidity risk modeling. A bank's liquidity profile can be quite changed by outside elements such regulatory changes, economic data, and market interest rates. By combining these components, the LSTM-X model helps to provide a more complete picture of liquidity risk, hence transcending conventional measures that sometimes ignore the larger economic background. By means of this all-encompassing strategy, banks can foresee possible liquidity shortages and react aggressively to evolving market conditions [26].

Although the LSTM-X model shows potential, some issues call for conversation. First, the performance of the model depends much on the quality and granularity of the input data. Inaccurate or insufficient data could produce less than ideal predictions, therefore compromising the efficacy of the model. Consequently, banks have to give data quality top priority and make investments in strong data management techniques to guarantee dependability of the predictions of the model.

Complexity of the model is another factor. Although LSTM networks are strong instruments for capturing nonlinear correlations in data, their implementation depends on considerable computing resources and knowledge, therefore they demand. Smaller organizations with less technological capability might find this complexity difficult. Future studies might look at methods to simplify the concept or provide user-friendly interfaces allowing its acceptance in many financial environments [25]. Moreover, model interpretability is really important. Although the LSTM-X model may produce accurate forecasts, understanding the fundamental causes of these forecasts remains difficult. Transparency in risk assessment approaches is demanded by regulators and stakeholders most of the time, so more study on methods that improve LSTM model [27] interpretability is essential. By means of feature significance analysis or the incorporation of explainable artificial intelligence techniques, approaches like these might assist close this gap and provide stakeholders with understanding of how outside variables affect evaluations of liquidity risk. At last, the LSTM-X model should be constantly validated and improved as the financial scene changes. Future research might evaluate its relevance in other banking contexts and stress-test its resilience under several economic conditions. Furthermore, including comments from banking professionals could offer insightful analysis of model performance and usability, thereby promoting cooperation between academics and business .

Conclusion

This study introduced the LSTM-X model for real-time banking liquidity risk assessment. The model incorporates liquidity data temporal dynamics and pertinent external elements by merging Long Short-Term Memory (LSTM) networks with external characteristics, providing a more complete risk evaluation framework. The mathematical model, containing the forget gate, input gate, cell status updates, and output gate, can handle complicated sequential data while keeping vital information. LSTM-X solves the shortcomings of standard liquidity risk assessment methodologies, which typically ignore important external factors and temporal patterns. By using powerful machine learning, this model improves predicted accuracy and operational efficiency, helping financial organizations make better decisions. Artificial intelligence for liquidity risk assessment has advanced with the LSTM-X model, making banking more robust. Future study can add data sources, refine the model, and test its efficacy in different banking scenarios. We want to improve institutions' financial stability and build a stronger banking system that can withstand liquidity issues.

References

[1] Wali, G., & Bulla, C. (2024). A Data Driven Risk Assessment in Fractional investment in Commercial Real Estate using Deep Learning Model and Fog Computing Infrastructure. *Library Progress International*, *44*(3), 4128-4141.

[2] Wali, G., & Bulla, C. (2024, July). Suspicious activity detection model in bank transactions using deep learning with fog computing infrastructure. In *International Conference on Computational Innovations and Emerging Trends (ICCIET-2024)* (pp. 292-302). Atlantis Press.

[3] Girish Wali1, Dr. Chetan Bulla (2024) Anomaly Detection in Fog Computing: State-of-the-Art Techniques, applications, Challenges, and Future Directions. Library Progress International, 44(3), 13967-13993

[4] Bulla, C. M., Bhojannavar, S. S., & Danawade, V. M. (2013). Cloud computing: Research activities and challenges. *International Journal of Emerging Trends & Technology in Computer Science*, *2*(5), 206-214.

[5] Wali, G. (2024). AI-Based LSTM-X Model for Risk Assessment in Fractional Commercial Real Estate Investments. *Library Progress International*, *44*(3), 10706-10722.

[6] P., G., Thirumagal., Surendar, Vaddepalli., Tapas, Das., Seshanwita, Das., Srinu, Madem., P., S., Immaculate. "1. AI-Enhanced IoT Data Analytics for Risk Management in Banking Operations." undefined (2024). doi: 10.1109/icrtcst61793.2024.10578533

[7] Ankita, Srivastava., Bhartrihari, Pandiya., Navtika, Singh, Nautiyal. "2. Application of Artificial Intelligence in Risk Assessment and Mitigation in Banks." undefined (2024). doi: 10.1002/9781394175574.ch2

[8] Rweyemamu, Ignatius, Barongo., Jimmy, Tibangayuka, Mbelwa. "3. Using machine learning for detecting liquidity risk in banks." Machine learning with applications, undefined (2023). doi: 10.1016/j.mlwa.2023.100511

[9] "Applying Machine Learning Algorithms to Predict Liquidity Risks." Journal of system and management sciences, undefined (2024). doi: 10.33168/jsms.2024.0307

[10] Edith, Ebele, Agu., Angela, Omozele, Abhulimen., Anwuli, Nkemchor, Obiki-Osafiele., Olajide, Soji, Osundare., Ibrahim, Adedeji, Adeniran., Christianah, Pelumi, Efunniyi. (2024).

[11] Utilizing AI-driven predictive analytics to reduce credit risk and enhance financial inclusion. International Journal of Frontline Research in Multidisciplinary Studies, doi: 10.56355/ijfrms.2024.3.2.0026

[12] Qi, Shen. "AI-driven financial risk management systems: Enhancing predictive capabilities and operational efficiency." Applied and Computational Engineering, undefined (2024). doi: 10.54254/2755-2721/69/20241494

[13] Coskun, Tarkocin., Murat, Donduran. "7. Constructing Early Warning Indicators for Banks Using Machine Learning Models." The North American Journal of Economics and Finance, undefined (2023). doi: 10.1016/j.najef.2023.102018

[14] Bibitayo, Ebunlomo, Abikoye., Temitope, Akinwunmi., Adesola, Oluwatosin, Adelaja., Stanley, Chidozie, Umeorah., Yewande, Mariam, Ogunsuji. "8. Real-time financial monitoring systems: Enhancing risk management through continuous oversight." GSC Advanced Research and Reviews, undefined (2024). doi: 10.30574/gscarr.2024.20.1.0287

[15] Weijian, Yan., Yinghua, Song. "9. Intelligent Evaluation and Early Warning of Liquidity Risk of Commercial Banks Based on RNN." Computational Intelligence and Neuroscience, undefined (2022). doi: 10.1155/2022/7325798

[16] 8Ibrahim, Ahmed., Riyadh, A., K., Mehdi., Elfadil, Abdelrahman, Mohamed. "10. The role of artificial intelligence in developing a banking risk index: an application of Adaptive Neural Network-Based Fuzzy Inference System (ANFIS)." Artificial Intelligence Review, undefined (2023). doi: 10.1007/s10462-023-10473-9

[17] Kumar, A., Sharma, N., Marriwala, N. K., Rao, D. N., Behera, S. K., Wali, G., & Jandwani, B. (2024). Mapping the trajectory of blockchain technology and non-fungible tokens: a comprehensive bibliometric analysis. *International Journal of Information Technology*, 1-8.

[18] Wali, G. (2024). AI-Based LSTM-X Model for Risk Assessment in Fractional Commercial Real Estate Investments. *Library Progress International*, *44*(3), 10706-10722.

[19] Wali, G., & Bulla, C. (2024). Anomaly Detection in Fog Computing: State-of-the-Art Techniques, applications, Challenges, and Future Directions. *Library Progress International*, *44*(3), 13967-13993

[20] https://www.kaggle.com/datasets/thuynyle/redfin-housing-market-data [Redfin Dataset]

[21] Bulla, C. M., & Birje, M. N. (2022). Efficient Resource Management Using Improved Bio-Inspired Algorithms for the Fog Computing Environment. *International Journal of Cloud Applications and Computing (IJCAC)*, *12*(1), 1-18.

[22] Samir, A., Pahl, C.: Detecting and Predicting Anomalies for Edge Cluster Environments using Hidden Markov Models (HMM). In: 2019 Fourth IC-FMEC. pp. 21–28. IEEE, Rome, Italy (2019)

[23] Dr. Chetan Bulla Girish Wali, Anita Kori,"Market Risk Assessment Using Deep Learning Model and Fog Computing Infrastructure",International Journal of Recent Advances in Multidisciplinary Research,2024

[24] Dayana, D. S., Shanthi, T. S., Wali, G., Pramila, P. V., Sumitha, T., & Sudhakar, M. (2024). Enhancing Usability and Control in Artificial Intelligence of Things Environments (AIoT) Through Semantic Web Control Models. In *Semantic Web Technologies and Applications in Artificial Intelligence of Things* (pp. 186-206). IGI Global.

[25] Meenakshi, R. K., RS, G. W., Bulla, C., Tanwar, J., Rao, M., & Surjeet, B. (2024). AI integrated approach for enhancing linguistic natural language processing (NLP) models for multilingual sentiment analysis. *Philological Investigations*, *23*(1), 233-247.

[26] Bulla, C., & Birje, M. N. (2022). Improved data-driven root cause analysis in fog computing environment. *Journal of Reliable Intelligent Environments*, *8*(4), 359-377.

[27] Wu, J., Yao, L., Liu, B., Ding, Z., Zhang, L.: Combining OC-SVMs With LSTM for Detecting Anomalies in Telemetry Data With Irregular Intervals. IEEE Access. 8, 106648–106659 (2020).

[28] Bulla, C., Birje, M.N. Improved data-driven root cause analysis in fog computing environment. J Reliable Intell Environ 8, 359–377 (2022).

[29] Demir, U., Ergen, S.C. ARIMA-based time variation model for beneath the chassis UWB channel. J Wireless Com Network 2016, 178 (2016). https://doi.org/10.1186/s13638-016-0676-3

[30] Ullah and Q. H. Mahmoud, "Design and Development of RNN Anomaly Detection Model for IoT Networks," in IEEE Access, vol. 10, pp. 62722-62750, 2022, doi: 10.1109/ACCESS.2022.3176317. keywords: {Internet of Things;Security;Deep learning;Intrusion detection;Computational modeling;Recurrent neural networks;Telecommunication traffic;Internet of Things;anomaly detection;recurrent neural network;convolutional neural network;LSTM;BiLSTM;GRU},

[31] Maya, S., Ueno, K., Nishikawa, T.: dLSTM: a new approach for anomaly detection using deep learning with delayed prediction. Int.Jou.of Dat.Sciee Ana. 8, 137–164 (2019).

[32] Pooja Sehgal Tabeck Dr.Surjeet Jitender Tanwar, Dr.Hiteshwari Sabrol,Girish Wali,Dr.Chetan Bulla, D.Meenakshi, "Integrating Block chain and Deep Learning for Enhanced Supply Chain Management in Healthcare: A Novel Approach for Alzheimer's and Parkinson's Disease Prevention and Control", International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING, VOL.12, ISS.22, 524-539, IJASEA.2024