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AI-Powered Real-Time Analytics for Liquidity Risk Assessment in Banking Sector

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Abstract - *In the banking sector, where regulatory compliance and financial stability rely on rapid, accurate risk assessment, liquidity risk still generates enormous concern. Emphasizing forecast accuracy, efficiency, and flexibility, this work explores artificial intelligence (AI) application to enhance real-time liquidity risk assessment. We develop a model to provide dynamic risk insights by combining transactional data, market conditions, and historical liquidity patterns using machine learning (ML) and deep learning (DL) techniques. Early identification of probable liquidity stress by the AI-driven technique not only offers a sophisticated solution for traditional static procedures but also matches evolving market trends. Comparative investigation utilizing conventional models reveals considerable gains in reaction times and prediction accuracy, therefore enabling better liquidity management decisions. This paper supports the growing domain of artificial intelligence in financial risk management by stressing the opportunities of AI-based solutions for proactive and responsive liquidity risk assessment in banks.*

Key Words: Risk Assessment, Artificial Intelligence, Real-Time Risk Management, Deep learning model, LSTM

1.INTRODUCTION

Since it immediately affects a bank's capacity to satisfy its short-term commitments and preserve operational stability, liquidity risk is a major threat to financial institutions. Inaccurate management of liquidity can cause major disturbances that would compromise the institution as well as the larger financial system. Often relying on historical data and stationary models, conventional approaches of liquidity risk assessment lack the agility required in the fast-paced financial markets of today. Usually reactive, these traditional methods identify liquidity issues only once risk levels have risen. As such, the requirement of proactive, real-time evaluation tools has never been more urgent [1].

Artificial intelligence (AI) advances—especially in machine learning (ML) and deep learning (DL)—offer fresh paths for revolutionizing risk management strategies. Using artificial intelligence will allow banks to quickly handle enormous amounts of transactional and market data, therefore allowing dynamic and accurate liquidity risk forecasts. Unlike more conventional approaches, artificial intelligence models may learn and adapt over time, seeing intricate trends and basing forecasts on changing market conditions. By means of these real-time information, financial institutions may implement preventative actions, therefore guaranteeing more financial resilience and regulatory compliance [2].

Adoption of cloud technology provides major benefits in data processing, real-time analytics, and scalability, therefore fundamentally changing how banks evaluate and control liquidity risk [3][4]. Cloud systems help banks to simplify data retrieval and adopt a complete approach to liquidity research, thereby effectively recognizing trends and developing threats by centralizing enormous volumes of data comprising transactional records, market information, and historical liquidity measurements. Moreover, cloud infrastructure offers the computing capability required to run sophisticated artificial intelligence and machine learning models on demand, therefore enabling large-scale, real-time data processing free from the high expenses connected with on-site systems. This capacity gives banks rapid insights and allows ongoing monitoring of liquidity indicators, therefore enabling proactive choices to prevent possible liquidity shortages. By means of strong disaster recovery solutions, cloud providers also guarantee data availability and business continuity. Improved cooperation among several areas as staff members may safely access data and risk management tools, therefore facilitating real-time decision-making. Reducing infrastructure costs and guaranteeing regulatory standard compliance for data security helps banks to be flexible, powerful, and secure enough for efficient liquidity risk management and enhanced financial stability. Figure 1 shows the adoption of cloud computing in assessing liquidity risk .

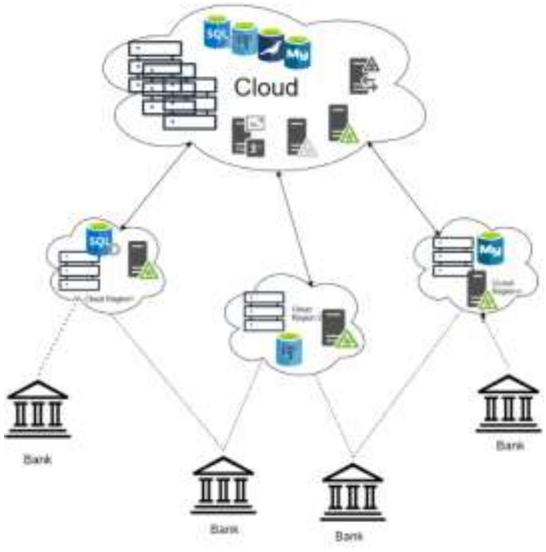

Figure 1: adoption of cloud computing in assessing liquidity risk.

The possibility of artificial intelligence in improving real-time liquidity risk evaluation in the banking industry is investigated in this work. We create a prediction model combining many artificial intelligence algorithms to dynamically assess liquidity risk by considering historical liquidity trends, transactional behavior, market volatility, and artificial intelligence algorithms themselves. We also show how predicted accuracy and reaction time increase when we contrast artificial intelligence-driven models with conventional static models. This study attempts to add to the expanding field of artificial intelligence applications in finance by proving the benefit of AI-enabled solutions for strong, proactive liquidity management in banks. The rest of paper is organized as follows: section 2 explores state of the art liquidity risk assessment model, section 3 proposes the liquidity risk assessment model and its working principles, section 4 presents experiment evaluation of proposed model and section 5 : conclude the article with observations and evaluation results.

2. RELATED WORK

One important strategy underlined is the real-time IoT data processing using artificial intelligence algorithms. Leveraging pattern identification, anomaly detection, and predictive modeling features, these algorithms help improve liquidity risk assessment [5]. Enhanced operational resilience and decision-making follow from this. A clear drawback, though, is the growing complexity and volume of financial data, which calls for increasingly advanced analytical techniques to properly identify risks[6]. Complementing bibliometric analysis using VOSviewer software, the utilization of the Scopus database for literature search highlights AI's capacity to evaluate enormous volumes. This helps to reduce cognitive biases sometimes found in conventional risk assessment and improves real-time liquidity risk assessment [7]. Still, difficulties include human limits in decision-making processes and natural cognitive biases .

Random Forest (RF) and Multi-Layer Perceptron (MLP) used in a hybrid model improves accuracy and sensitivity in real-time liquidity risk calculations [8]. This strategy, however, has problems with data quality and the limited composition of liquidity risk variables, which might ignore sensible influences. Especially for Indian banks, several machine learning methods such K-Nearest Neighbors (KNN), Support Vector Machine (SVM), decision trees, and XGBoost show significant promise in creating real-time liquidity risk assessment systems [9]. The small sample sizes of the experiments restrict the generalizability of the findings, though, and the MLP model performs worse than other techniques.

Moreover, although they do not especially handle liquidity risk assessment, AI-driven predictive analytics concentrate on credit risk and financial inclusion [10]. Among the restrictions of these methods are possible biases in AI models, data privacy issues, and ethical and legal ramifications. Although accuracy issues still exist, the discussion of supervised machine learning models for liquidity stress prediction shows the application of the RUSBoost algorithm to improve liquidity risk management by means of early market stress alerts [11].Combining transactional records with compliance reports, the mixed-methods approach—which uses qualitative interviews and quantitative data analysis—combines This method adds a degree of complexity that might be difficult to control even while it reveals that artificial intelligence-enhanced real-time financial monitoring systems reduce liquidity risk assessment [12]. Furthermore stressing developments in evaluating liquidity risk is the use of web crawlers and text analysis to build an intelligent early warning model with recurrent neural networks [13]. Along with a layered cyclic neural network to boost model fitting ability, this approach increases real-time monitoring capabilities by means of a Dropout layer, hence addressing overfitting problems. At last, the combination of approaches to properly evaluate banking risks is demonstrated by the implementation of an adaptive neuro-fuzzy inference system (ANFIS) for risk ranking based on Mahalanobis Distance [14]. ANFIS does, however, provide complexity that could hinder interpretability in useful applications even as it adequately captures nonlinear connections [15].

All things considered, the table 1 shows a wide range of techniques for liquidity risk assessment in banking, thereby underlining the transforming power of artificial intelligence and machine learning as well as the complexity and constraints related with these methods. Every approach offers special insights but also presents issues that must be resolved if they are to be applied in practical banking situations.

Table -1: State of the art Liquidity risk assessment model using AI

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.	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 VOS viewer software.	AI enhances real-time liquidity risk assessment in banks by analyzing vast data sets.	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.	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 .	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	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	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	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	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,	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 Mahalanobis Distance (MD)	Adaptive Neural Network-Based Fuzzy	The use of an Adaptive Neuro-Fuzzy Inference

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	Adaptive Neuro-Fuzzy Inference System (ANFIS) for determining relative importance of risk ratios	Inference System (ANFIS)" utilizes a combinations.	System (ANFIS) introduces complexity in the model. While ANFIS can capture nonlinear relationships, it may also lead to challenges in interpretability [16].
[15]	an application of Adaptive Neural Network-Based Fuzzy Inference System	Hybrid methods have more advantages in terms of accuracy	High complexity

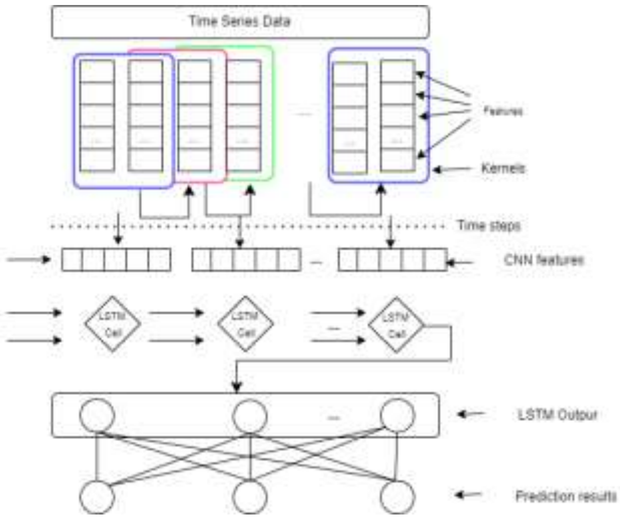

Figure 2 : CLSTM model for training risk prediction model

3. PROPOSED MODEL

The proposed model for assessing liquidity risk in banks is referred to as LSTM-X, which integrates Long Short-Term Memory (LSTM) networks with external features (X) to enhance liquidity risk evaluation. This hybrid model is specifically designed to analyze temporal data while incorporating additional relevant factors that may influence liquidity risk, offering a more comprehensive assessment framework [17].

The architecture of the LSTM-X model begins with an input layer that receives time-series data related to liquidity, such as cash flow, assets, and liabilities, alongside external features like market conditions and interest rates. At the core of the model lies the LSTM layer, where LSTM cells process the sequential data. This processing allows the model to capture long-term dependencies and temporal patterns in liquidity risk effectively. Following the LSTM layer, a dense layer is included, which processes the output from the LSTM to combine the learned features. Finally, the output layer provides the liquidity risk prediction, which could be framed as a binary classification (e.g., liquid vs. illiquid) or as a regression output quantifying the risk level. Figure 2 shows the LSTM-X model for liquidity risk assessment

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

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

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

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

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

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

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

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

The performance of the LSTM-X model is evaluated using various metrics such as accuracy, precision, recall, and F1-score. For regression-based risk predictions, metrics like Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are commonly used:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|$$

4. EXPERIMENTAL 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.

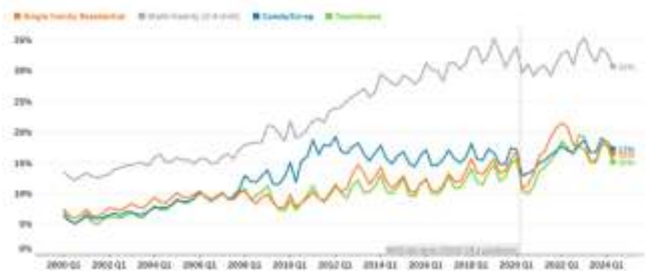

Fig. 4. Redfin investor data

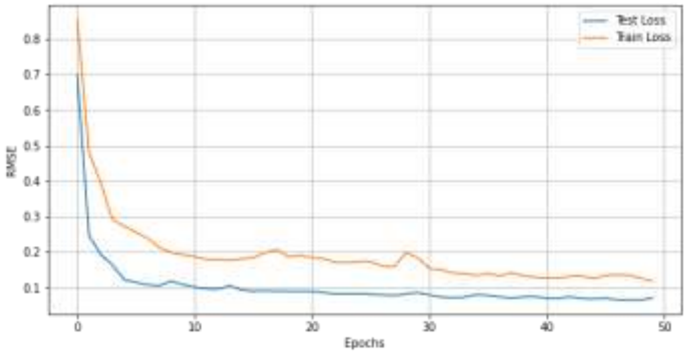

Fig 5: RMSE for epochs

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.

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.

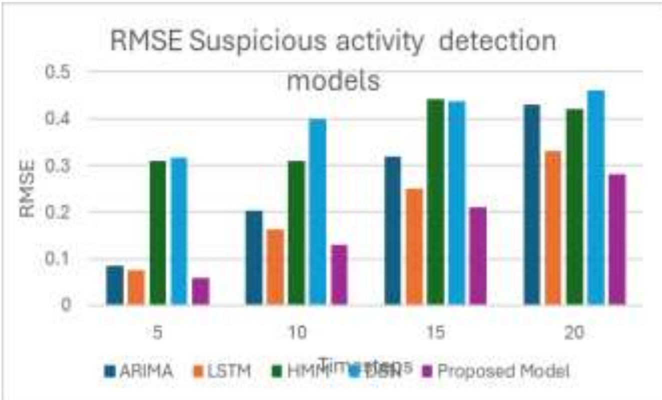

Fig 6: Comparison of RMSE values for various models and proposed models.

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.

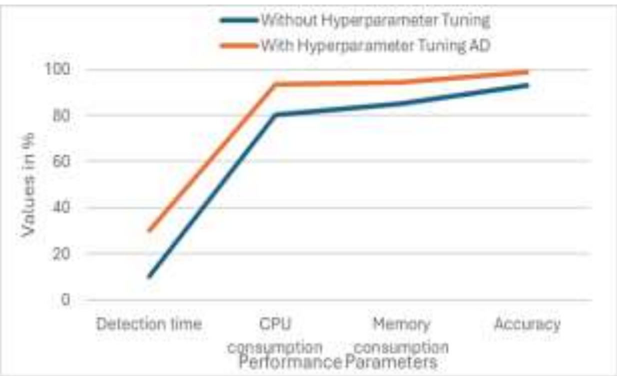

Fig 7 : Comparison of Normal AD and Hyperparameter Tuner AD

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.

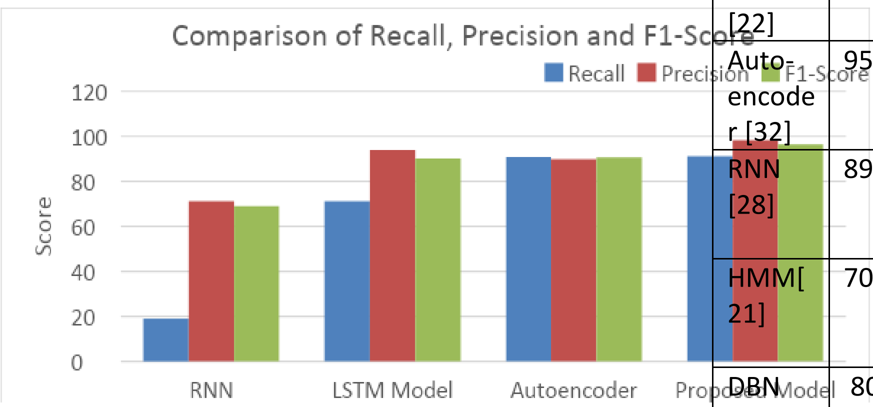

Fig 8: Accuracy parameters of the existing and proposed system

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.

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.

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

Table 3: Hyperparameter values for highest accuracy

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

In this research article, we proposed the LSTM-X model as a novel approach for real-time liquidity risk assessment in the banking sector. By integrating Long Short-Term Memory (LSTM) networks with external features, the model captures both the temporal dynamics of liquidity data and the impact of relevant external factors, offering a more comprehensive framework for risk evaluation. The mathematical formulation of the model, including the various components such as the forget gate, input gate, cell state updates, and output gate, demonstrates its capability to process complex sequential data while retaining essential information over time .The LSTM-X model's design addresses the limitations of traditional liquidity risk assessment methods, which often overlook critical external influences and temporal patterns. By leveraging advanced machine learning techniques, this model enhances predictive accuracy and operational efficiency, thereby facilitating better decision-making for financial institutions. The LSTM-X model represents a significant advancement in the use of artificial intelligence for liquidity risk assessment, paving the way for more resilient banking practices. Future research can build on this framework by exploring the integration of additional data sources, refining the model further, and validating its effectiveness in various banking contexts. The ultimate goal is to enhance the financial stability of institutions and contribute to a more robust banking system that can withstand potential liquidity challenges.

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