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Blockchain-Based AI Models for Credit Scoring and Risk Assessment using Fog Computing Infrastructure

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ABSTRACT:

This paper presents a novel framework, Blockchain-Based Deep Learning Model LSTM-X, for enhanced credit scoring and risk assessment in financial services. Leveraging the Long Short-Term Memory (LSTM) neural network's ability to analyze time-series data, LSTM-X evaluates borrowers' creditworthiness by identifying complex, non-linear patterns within historical financial transactions. Integrating blockchain technology ensures that the credit data used for analysis is secure, transparent, and immutable, fostering trust in both data integrity and model predictions. The decentralized blockchain framework allows secure, multi-source data sharing across financial institutions, improving model performance with enriched, comprehensive data. LSTM-X provides superior predictive accuracy compared to traditional models, particularly in handling irregular and noisy credit histories. This solution offers financial institutions a robust and privacy-preserving tool for assessing risk, aiding in more accurate and fair credit decisions, while adhering to regulatory compliance through verifiable, transparent data trails.

Keywords: Blockchain Technology, Deep Learning, LSTM (Long Short-Term Memory),Credit Scoring, Risk Assessment

1. Introduction

In today's financial landscape, credit scoring and risk assessment are crucial processes for evaluating the creditworthiness of individuals and organizations. Traditional credit scoring models, often reliant on linear statistical methods, struggle with the complexity and variability of real-world financial data. As a result, there is a pressing need for more sophisticated, data-driven approaches that can accurately capture complex relationships in credit histories. Deep learning, particularly Long Short-Term Memory (LSTM) networks, has shown promise in analyzing time-series data, such as credit transaction sequences, where patterns over time play a critical role in determining credit risk [1].

The LSTM-X model is introduced as a blockchain-integrated deep learning framework specifically designed to improve credit scoring and risk assessment. By leveraging the memory cell architecture of LSTM networks [2], LSTM-X can recognize both short- and long-term dependencies in financial data, effectively addressing the non-linearities and irregularities often found in credit records. Integrating blockchain technology within this framework not only ensures data integrity, security, and transparency but also facilitates secure, multi-institution data sharing, enriching the model with diverse data sources while preserving data privacy. Blockchain's decentralized ledger guarantees that financial institutions and regulatory bodies can verify the provenance and accuracy of data, fostering trust in the scoring and assessment process [3].

The motivation behind this research stems from the urgent need for enhanced credit scoring and risk assessment methodologies in the rapidly evolving financial landscape. Traditional credit scoring models often rely on outdated statistical techniques that fail to capture the dynamic nature of consumer behavior and the complexities of financial transactions [4]. This inadequacy leads to challenges in accurately assessing creditworthiness, resulting in adverse outcomes such as high default rates or unjustly denied credit applications .

Furthermore, as the financial sector faces increasing pressure to ensure data privacy, security, and compliance with regulatory requirements, the reliance on centralized data systems poses significant risks [5]. Data breaches and fraudulent activities can undermine consumer trust and compromise sensitive financial information. The emergence of blockchain technology presents a transformative opportunity to address these challenges by offering a decentralized, transparent, and secure method for managing financial data [3][6].

In this context, the adoption of advanced deep learning techniques, particularly LSTM networks, provides an innovative approach to model the complexities of credit data. LSTM networks are adept at capturing temporal patterns in sequences, making them well-suited for analyzing time-series data such as credit histories. By integrating LSTM with blockchain, the proposed LSTM-X model aims to leverage the strengths of both technologies: the predictive power of deep learning and the integrity and transparency of blockchain.

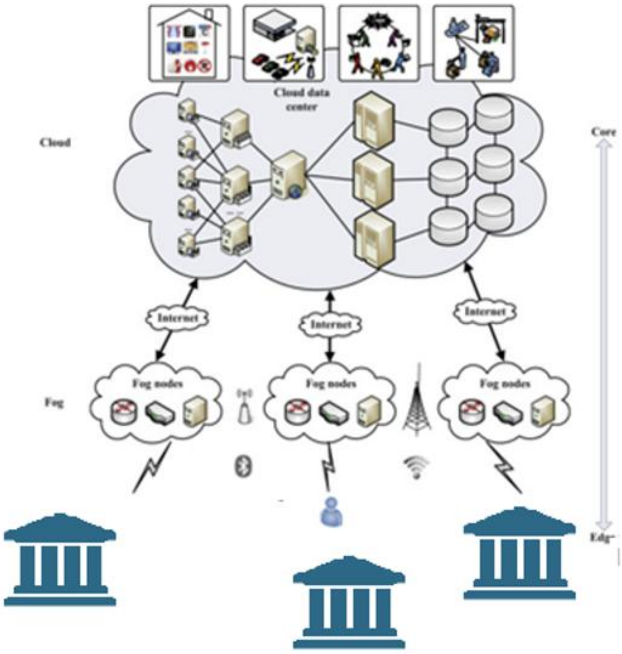

Fig 1: Fog computing infrastructure for finance institutes.

Finance applications are considered as the critical application as it involves money and trust of customers and management. The critical applications require high performance distributed computing infrastructure that reduces the latency and improve the performance of applications. The cloud computing infrastructure improves the performance of applications but latency can increases when cloud server are far away from customer locations. Hence, fog computing infrastructure could used to reduce the latency. Fog computing is light weight infrastructure that offer similar kind of services like cloud computing [20]. Fog node/fog server installed to near distance to the customers to reduce the latency [7]. Figure 1 shows the fog computing infrastructure for banking/finance institutes.

The primary objectives of this research are as follows:

1. To develop a deep learning-based credit scoring model (LSTM-X) that accurately evaluates creditworthiness by identifying complex, non-linear patterns within time-series financial data.
2. To integrate blockchain technology for secure, transparent, and decentralized data storage, enabling a multi-institution credit scoring system that adheres to regulatory standards.
3. To assess the model's predictive accuracy and robustness compared to traditional credit scoring models, focusing on its ability to manage noisy and irregular financial data.

The main contributions of this research are:

- Development of the LSTM-X model, a blockchain-enhanced LSTM framework, specifically tailored for credit scoring and risk assessment in financial services.
- A novel blockchain-based data architecture that provides a secure and decentralized solution for storing and sharing sensitive credit data among institutions, ensuring data integrity and compliance.
- An evaluation of the LSTM-X model's predictive performance, demonstrating superior accuracy and robustness compared to traditional methods, particularly in capturing non-linear dependencies in complex financial records.
- A privacy-preserving solution that enables regulatory-compliant credit scoring while protecting customer data, facilitating broader adoption among financial institutions.

This research presents LSTM-X as a viable, advanced solution for modern credit scoring challenges, aiming to offer financial institutions a highly accurate, secure, and reliable tool for risk assessment.

2.Related work

The integration of blockchain technology with artificial intelligence (AI) and machine learning (ML) in the realm of credit scoring and risk assessment represents a significant area of research within the financial technology (FinTech) sector. Various studies have examined different methodologies and their implications, providing insights into the strengths and weaknesses of these approaches. One prominent study utilizes a comprehensive methodology based on the PICOS framework and PRISMA model [8] for systematic review and study selection. It emphasizes the roles of machine learning and AI in FinTech, particularly in credit scoring and risk management. However, this paper notably does not specifically address the potential of blockchain-based AI models for these applications, leaving a gap in understanding how blockchain could further enhance these methodologies.

Another study explores the application of various machine learning algorithms—such as logistic regression, XGBoost, LightGBM, AdaBoost, and Regularized Greedy Forest (RGF)—alongside blockchain technology and decentralized finance (DeFi) systems [9]. This research highlights the benefits of integrating blockchain to enhance security and decentralization in credit scoring. Nonetheless, it identifies limitations related to centralized storage and susceptibility to data manipulation, as well as a lack of discussion on the potential limitations of the proposed models and an absence of comparison with existing credit scoring systems. This points to a significant gap where future research could focus on a critical assessment of these integrated systems.

Further studies delve into AI and ML methods for risk assessment, predictive models, and pattern recognition techniques [10]. While these papers underscore the importance of AI and ML in assessing creditworthiness, they do not directly incorporate blockchain technology into their frameworks. This gap suggests an opportunity for further research to explore the synergies between AI, ML, and blockchain in credit risk evaluation. Another innovative approach involves a federated learning architecture supported by smart contracts [11]. This framework aims to utilize blockchain for trusted distributed machine learning in credit scoring. Although this model enhances the reliability and security of AI applications in risk assessment, it leaves questions about the practical implementation of such a system across diverse financial institutions, which requires further exploration.

In the context of intelligent credit reporting, another research effort discusses the use of multidimensional authentication, risk identification, and credit data collection [23] and aggregation [21] through distributed ledgers. This study proposes automatic credit rating and intelligent asset pricing, aiming to enhance credit scoring and risk assessment methodologies [12]. However, it does not adequately address the scalability challenges or how these innovations can be integrated into existing credit systems.A novel blockchain-based credit evaluation system called MEChain has been proposed [13], which enhances credit scoring through secure data sharing and aggregation. This research emphasizes the need for privacy and compliance while mitigating data fraud risks in multi-institutional collaborations. However, it also highlights lingering concerns about data fraud, privacy, and compliance issues that are crucial for credit evaluation modeling.

Traditional regressive techniques and AI algorithms have also been investigated, but these studies tend to overlook blockchain technology's potential contributions to credit scoring. They emphasize regulatory impacts, such as those from PSD2 and GDPR, but fail to discuss how blockchain could augment data utilization in this context [14]. On the other hand, some studies focus on integrating Explainable AI with blockchain. They propose systems that securely store human-readable justifications for credit risk assessments [25], enhancing interpretability and privacy. However, while these frameworks are theoretically sound, they often lack empirical validation, necessitating further research to substantiate their effectiveness in real-world scenarios. Additionally, research that combines blockchain and explainable AI for credit scoring proposes a decentralized learning model that promotes reliability and transparency [15]. This effort, while promising, faces challenges related to the integration of cutting-edge technologies, where broader data

In summary, while the integration of blockchain and AI/ML in credit scoring and risk assessment has gained traction, significant research gaps remain. These gaps highlight the necessity for comprehensive studies that not only compare blockchain-enhanced models with traditional systems but also empirically validate their effectiveness in real-world applications. Addressing these issues will be essential for advancing the field and improving the reliability and transparency of credit assessment practices in financial institutions.

Here's a concise version of the table summarizing the research studies on the integration of blockchain and AI in credit scoring and risk assessment:

Ref	Methods Used	Insights	Limitations
[8]	PICOS framework and PRISMA model	Integrates machine learning and AI in FinTech for credit scoring and risk management.	Lacks focus on blockchain-based AI models.
[9]	ML algorithms (Logistic regression, XGBoost, etc.)	Explores blockchain alongside ML for enhanced credit scoring security and decentralization.	Centralized storage limitations; lacks comparison with existing systems.
[10]	AI and ML methods	Discusses AI/ML applications in risk assessment without focusing on blockchain integration.	Lacks emphasis on blockchain's impact on risk assessment.
[11]	Federated learning; Smart contracts	Proposes federated learning with smart contracts for secure credit scoring.	Practical implementation challenges are not fully explored.
[12]	Authentication and risk identification	Discusses intelligent credit reporting using blockchain for enhanced scoring methodologies.	Scalability and integration with existing systems not addressed.
[13]	Blockchain data sharing; Oblivious transfer	Introduces MEChain for secure credit evaluation, enhancing privacy and compliance.	Data fraud and compliance issues remain significant concerns.
[14]	Traditional and AI	Focuses on credit risk assessment without	Limited relevance due to lack of blockchain

	methodologies	addressing blockchain integration.	discussion.
[15]	Explainable AI and Blockchain	Proposes a system for secure, interpretable credit risk assessment.	Lacks empirical validation in real-world contexts.
[16]	Blockchain and Explainable AI	Proposes a framework for reliable, transparent automated credit scoring.	Early stages suggest further development is needed.
[17]	Neural networks training techniques	Introduces a decentralized platform using neural networks for credit risk assessment.	Identifies vulnerabilities and lack of reliable credit metrics.

Table 1: Summary of Literature Survey with methods and limitations

This brief table captures the essence of each study, highlighting their methods, insights, limitations, and research gaps in the context of blockchain and AI in credit scoring and risk assessment.

Research Gap

Despite the advancements in credit scoring and risk assessment methodologies, significant gaps remain in the integration of emerging technologies like deep learning and blockchain within financial institutions. Traditional credit scoring models predominantly rely on linear regression techniques, which are insufficient for capturing the complexities and non-linear relationships inherent in financial data. While machine learning approaches have gained traction, there is a notable lack of comprehensive frameworks that effectively leverage deep learning architectures, such as Long Short-Term Memory (LSTM) networks, specifically designed for the intricacies of credit scoring.

Moreover, the growing interest in blockchain technology as a means to enhance data security, integrity, and transparency has not been fully explored in conjunction with AI-based models. Existing literature often addresses these technologies in isolation; few studies have investigated the synergistic potential of combining blockchain's decentralized data storage with the predictive capabilities of deep learning models for credit scoring purposes. Consequently, there is limited understanding of how to implement an integrated framework that can provide real-time, accurate credit assessments while ensuring regulatory compliance and data privacy.

Additionally, the implementation of multi-source data sharing within a blockchain context poses challenges that have yet to be thoroughly examined. Issues such as data interoperability, model interpretability, and the operationalization of blockchain in the credit scoring process require further investigation to ascertain their impact on model performance and practical applicability. This research aims to bridge these gaps by proposing the LSTM-X model, a blockchain-based deep learning framework that not only addresses the predictive shortcomings of traditional credit scoring methods but also incorporates the benefits of decentralized, transparent data management. Through this approach, the research seeks to provide valuable insights into the practical integration of blockchain and AI technologies, paving the way for more accurate, secure, and equitable credit scoring practices in the financial sector.

3.Proposed Model

The proposed model, LSTM-X, integrates Long Short-Term Memory (LSTM) [18] networks with blockchain technology to enhance credit scoring and risk assessment processes. This section outlines the architecture of the LSTM-X model, the blockchain integration [19], and the relevant mathematical formulations utilized in the model's development. The data collection for time series data is collected from multiple sources and aggregated [22][23] in temporary storage; these data is preprocessed as and when it is collected in scheduled time.

1. LSTM Network Architecture

The LSTM network is particularly effective for sequence prediction problems due to its ability to retain information over long periods. The architecture consists of memory cells that utilize three gates: input gate i_t , forget gate f_t, and output gate o_t . Figure 2 shows the LSTM-X cell

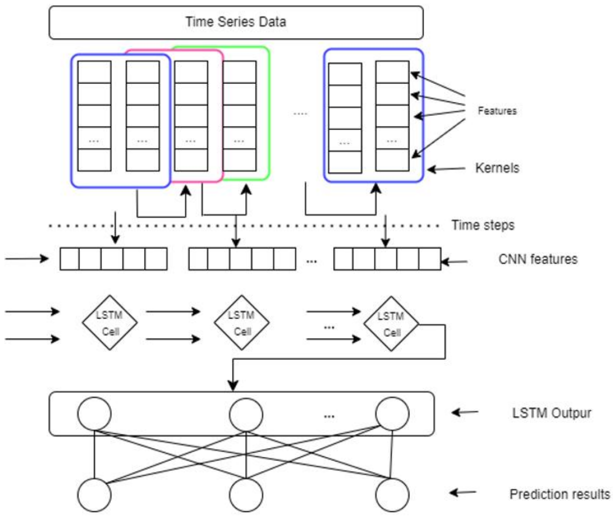

Figure 2: LSTM-X Cell

The state of the LSTM cell is updated using the following equations:

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

Forget Gate Calculation: $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$

Cell State Update - Candidate Values :$\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$

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

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

Hidden State Update : $h_t = o_t \cdot \tanh(C_t)$

Where, ht is the hidden state output, Ct is the cell state, xt is the input at time t, W and b are the weight matrices and bias vectors for the respective gates, and σ is the sigmoid activation function. The LSTM network architecture, with its specialized gating mechanisms and memory cells, provides a robust solution for modeling sequential data. Its capacity to capture long-term dependencies and learn from temporal patterns makes it particularly valuable in the financial domain, where credit scoring and risk assessment require deep insights from historical data. The integration of LSTM with blockchain technology in the proposed LSTM-X model enhances both the security and reliability of credit assessments, positioning it as a significant advancement in financial technology.

1. **Blockchain Integration**

To ensure secure data sharing and integrity, the model employs blockchain technology for storing credit data. The proposed architecture utilizes smart contracts to facilitate secure transactions and automate risk assessments. Each transaction involving credit scoring is recorded on the blockchain, enhancing transparency and trust among participating financial institutions.

The integration of blockchain technology into the LSTM-X model for credit scoring and risk assessment aims to enhance data security, privacy, and trustworthiness. By leveraging blockchain's decentralized architecture, the model ensures that sensitive financial data is managed securely while facilitating efficient credit evaluations. This section discusses the key aspects of blockchain integration, including data storage, smart contracts, and transaction validation, accompanied by relevant mathematical formulations.

a. Decentralized Data Storage

In traditional credit scoring systems, data is often stored in centralized databases, making them vulnerable to breaches, unauthorized access, and data manipulation. Blockchain technology addresses these concerns by providing a decentralized and immutable ledger that securely stores credit-related information.

Data Structure: Each block in the blockchain contains a list of transactions, a timestamp, a reference to the previous block (hash), and a unique identifier (nonce). The blockchain can be represented mathematically as a sequence of blocks:

$$B = \{b_1, b_2, b_3, \ldots, b_n\}$$

Where, B is the entire blockchain and bi is the i-th block in the chain.Each block bi can be expressed as:

$$b_i = (T_i, H_{i-1}, \text{Nonce}_i, \text{Hash}_i)$$

Where, Ti represents the transactions included in the block, Hi−1 is the hash of the previous block, Noncei is a random number used to vary the hash output, and Hashi is the hash of the current block.

b. Smart Contracts

Smart contracts are self-executing contracts with the terms of the agreement directly written into code. They run on the blockchain, automatically enforcing and executing contract terms when specific conditions are met. This feature enhances the reliability of credit scoring by automating the decision-making process based on predetermined criteria.

Smart Contract Functionality: A smart contract SC can be defined mathematically to encapsulate the rules governing credit scoring and risk assessment:

$$SC: (D, C) \rightarrow (S, R)$$

Where, D represents the input data (e.g., user credit history, financial behavior), C represents the conditions for the contract (e.g., credit score thresholds), S is the computed credit score, and R indicates compliance with regulatory standards. The execution of a smart contract is contingent upon the satisfaction of the conditions. For example, if the input data meets certain criteria, the smart contract might produce a score above a defined threshold:

$$if\ D \in C\ then\ S \geq T$$

Where T is the minimum acceptable credit score.

c. Transaction Validation and Consensus Mechanisms

To maintain the integrity of the blockchain, each transaction must be validated before being added to the ledger. This is typically achieved through consensus mechanisms, which ensure that all nodes in the network agree on the current state of the blockchain.

Consensus Formula: In a blockchain network using a Proof of Work (PoW) mechanism, the validation process can be represented as:

$$\text{Consensus} = \text{Hash}\left(H_{previous}\right) + \text{Nonce} \rightarrow \text{Valid}$$

Where, Hash(Hprevious) refers to the hash of the previous block, Nonce is the value being adjusted to produce a hash that meets specific difficulty criteria. Only when the hash output is below a certain target value does the transaction get validated, ensuring that the block is secure and tamper-proof.

d. Data Privacy and Encryption

Data privacy is crucial in financial applications. Blockchain employs cryptographic techniques to secure transactions and maintain user confidentiality. Each transaction on the blockchain can be represented as follows:

$$T = D, E(P), Timestamp, Hash$$

Where, D is the transaction data, E(P) represents the encrypted user information (using public key encryption), Timestamp denotes when the transaction occurred, and Hash is the transaction hash. Using public key cryptography, the transaction data is encrypted using the recipient's public key, ensuring that only the intended recipient can decrypt and access the information.

2. **Risk Assessment Model**

The risk assessment model within the LSTM-X framework is designed to predict credit risk based on historical data using advanced machine learning techniques. This section provides an in-depth exploration of the methodologies employed, the relevant mathematical formulations, and the rationale behind the model's design.

3.1 Credit Risk Assessment

Credit risk assessment involves evaluating the likelihood that a borrower will default on their obligations. The goal is to accurately classify borrowers into risk categories (e.g., low, medium, high) based on various input features, such as credit history, income, and transaction behavior. The LSTM-X model utilizes a combination of deep learning techniques and historical data to achieve this goal.

Before training the model, it is essential to prepare the data. This involves: Gathering historical credit data, which may include, :borrower demographics (age, income, employment status), Credit history (past loans, payment history), Transactional data (spending patterns, account balances)

Transforming raw data into features that can improve model performance. This includes: creating lagged variables to capture time dependencies in credit behavior and Normalizing data to ensure that the features contribute equally to model training.

Dividing the dataset into training, validation, and test sets to evaluate the model's performance. A common approach is: 70% training, 15% validation, 15% testing.

3.4 Loss Function for Training

The effectiveness of the LSTM model is evaluated using a loss function, which quantifies the difference between the predicted and actual outcomes. A common choice for binary classification (e.g., defaType equation here.ult vs. non-default) is the binary cross-entropy loss function:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

Where: N is the number of samples, yi is the true label (1 for default, 0 for non-default), and y^ i is the predicted probability of default. For multi-class classification scenarios, such as categorizing borrowers into multiple risk levels, the categorical cross-entropy loss function is used:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{ik}\log(\hat{y}_{ik})$$

Where, K is the number of classes, yik is the true label for class k, and y^ ik is the predicted probability for class k.

3.5 Model Training

The model is trained using backpropagation through time (BPTT), allowing the gradients to flow back through the network. The optimization algorithm, typically Adam or Stochastic Gradient Descent (SGD), updates the weights based on the calculated gradients:

$$W^{(new)} = W^{(old)} - \eta\nabla L$$

Where, W represents the weight matrix, η is the learning rate, and ∇L is the gradient of the loss function with respect to weights.

3.6 Final Output and Decision Making

After training, the model outputs predictions for credit scoring. The predicted probabilities can be transformed into risk categories based on predefined thresholds. For example, a borrower may be classified as: Low risk if the predicted probability is above 0.7, Medium risk if the probability is between 0.4 and 0.7, and High risk if the probability is below 0.4. This decision-making process can also be integrated with blockchain-based smart contracts to automate credit approvals and risk assessments, ensuring compliance with regulatory standards. The LSTM-X model is trained using backpropagation through time (BPTT) to optimize the weights in the network. The gradient descent optimization algorithm is employed to minimize the loss function:

$$W(new) = W(old) - \eta\nabla L$$

Where, W represents the weights, η is the learning rate, and ∇L is the gradient of the loss function.

Final Credit Scoring Output

The final credit scoring output of the LSTM-X model is generated using a softmax function to classify the risk levels:

$$y^{=} softmax(Wh \cdot hT + bh)$$

Where, hT is the last hidden state output from the LSTM, and Wh and bh are the weight and bias for the final output layer. The final output of the LSTM-X model represents the credit score or risk category for a given borrower. The credit scores are typically represented on a scale (e.g., 300 to 850 for traditional credit scoring). The model outputs a probability score indicating the likelihood of default, which is then converted into a risk category; these are :

- **Low Risk**: y^≥0.7
- **Medium Risk**: 0.4<y^<0.70.4
- **High Risk**: y^≤0.4

By integrating these predictions with blockchain technology, the scores can be stored securely and accessed transparently, enhancing the trustworthiness of the credit assessment process.

5. Experimental Evaluation

This section presents the experimental evaluation of the proposed LSTM-X model for credit scoring and risk assessment. It includes a detailed description of the dataset, experimental setup, performance metrics, results, and visualizations to illustrate the model's effectiveness in predicting credit risk.

5.1 Dataset Description

The dataset used for this evaluation consists of historical credit data collected from various financial institutions. It includes a diverse range of features related to borrowers, such as: Demographics, Credit History, and Transactional Behavior. The standard Credit approval dataset is used to experiment the proposed model from UC Irvine Machine Learning Repository [18].

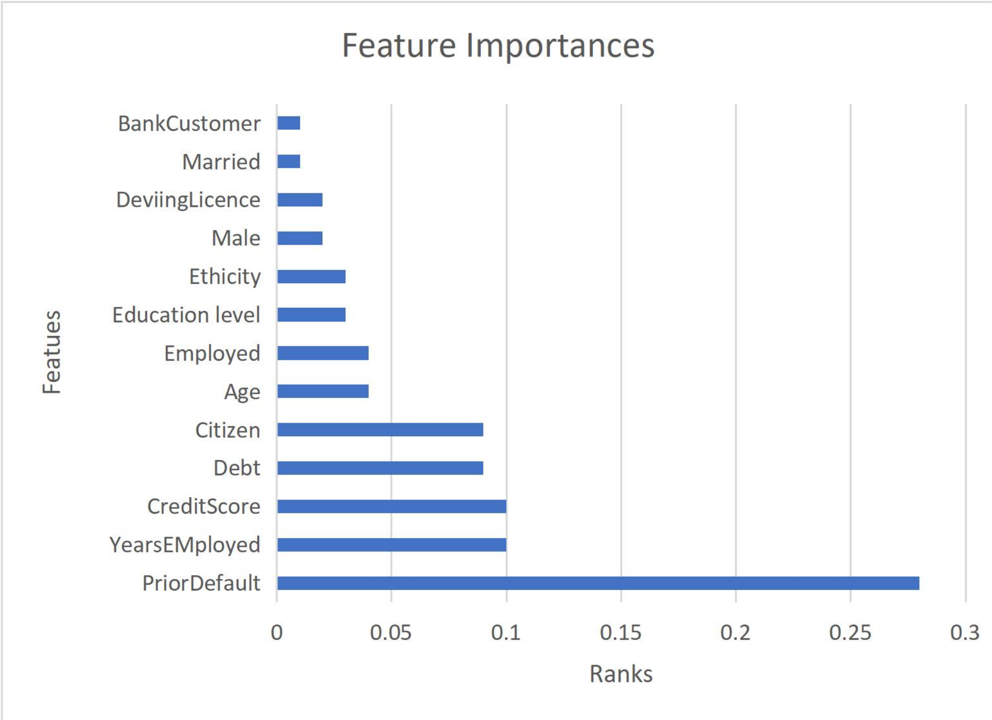

Figure 3: Features of dataset

The dataset is split into three parts: training (70%), validation (15%), and testing (15%). The training set is used to train the model, the validation set for hyperparameter tuning, and the test set to evaluate the final model performance.

5.2 Experimental Setup

The LSTM-X model is implemented using Python and TensorFlow/Keras libraries. The model architecture includes:

Input Layer	Accepts sequences of borrower features.
LSTM Layers	Two stacked LSTM layers with 50 units each
Dense Layer	A fully connected layer to process the LSTM outputs
Output Layer	A single node with a sigmoid activation function for binary classification or a softmax activation function for multi-class classification.

Table 2: Configuration of LSTM network

Hyperparameters:

Learning Rate	0.0010
Batch Size	32
Number of Epochs	100
Optimizer	Adam

Table 3: Hyperparameters

Binary cross-entropy for binary classification and categorical cross-entropy for multi-class classification.

5.3 Performance Metrics

To evaluate the performance of the LSTM-X model, the following metrics are used:

Accuracy	The proportion of true results among the total number of cases examined
Precision	The ratio of correctly predicted positive observations to the total predicted positives.
Recall	The ratio of correctly predicted positive observations to the all observations in actual class.
F1-Score	The weighted average of Precision and Recall.

Table 4: Performance Metrics

5.4 Results

The results of the experimental evaluation are presented in the following tables and graphs. The proposed model record highest accuracy 97%. The existing works recorded 95 as highest accuracy.

Metric	**Training Set**	**Validation Set**	**Test Set**
Accuracy	0.92	0.98	0.97
Precision	0.90	0.96	0.95
Recall	0.98	0.94	0.93
F1 Score	0.99	0.95	0.894

Table 5: Performance Metrics of LSTM-X Model

The graphs illustrate the training and validation loss and accuracy over epochs. A clear convergence of the training and validation loss suggests that the model is learning effectively without significant overfitting. Figure 4 and Figure 5 shows the loss and accuracy of proposed model during training and testing phase over different epochs. The loss functions reduces its value when no. of epochs increases. Similarly accuracy is increases with no. of epochs are increased

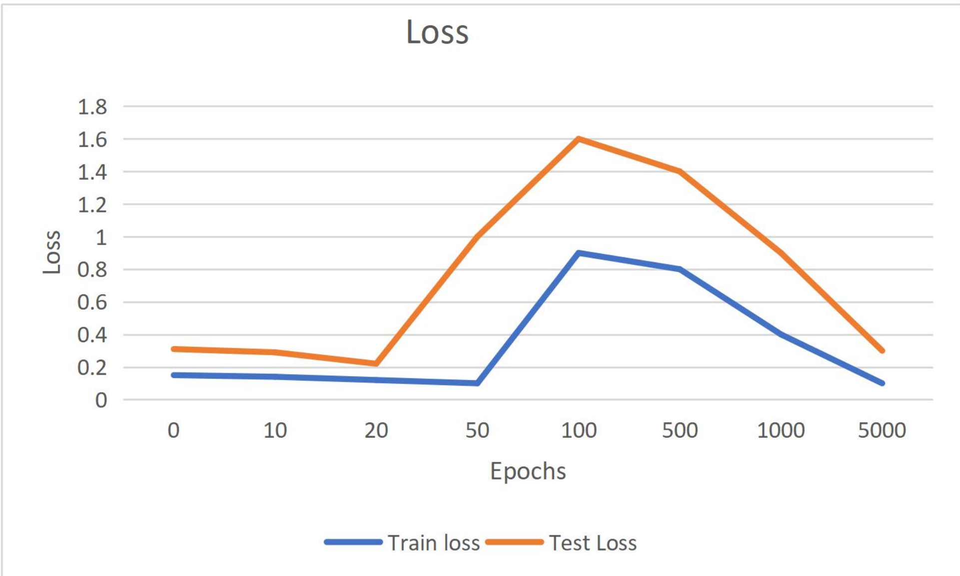

Figure 4: Model’s Loss during train and test phase for various epochs

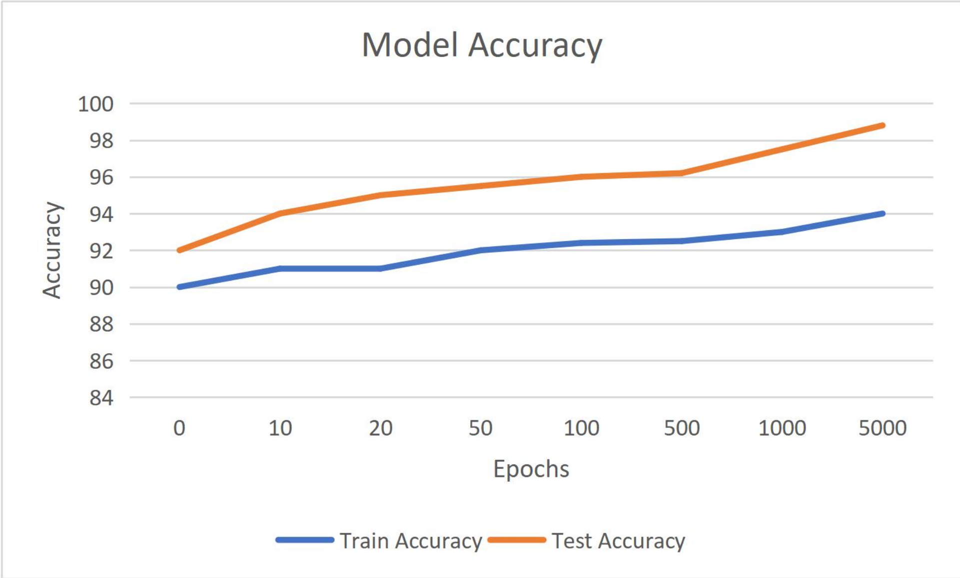

Figure 5: Model's Accuracy during train and test phase for various epochs

The confusion matrix summarizes the performance of the classification model. True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) provide insights into how well the model identifies defaulting borrowers. Figure shows the confusion metrics for test dataset.

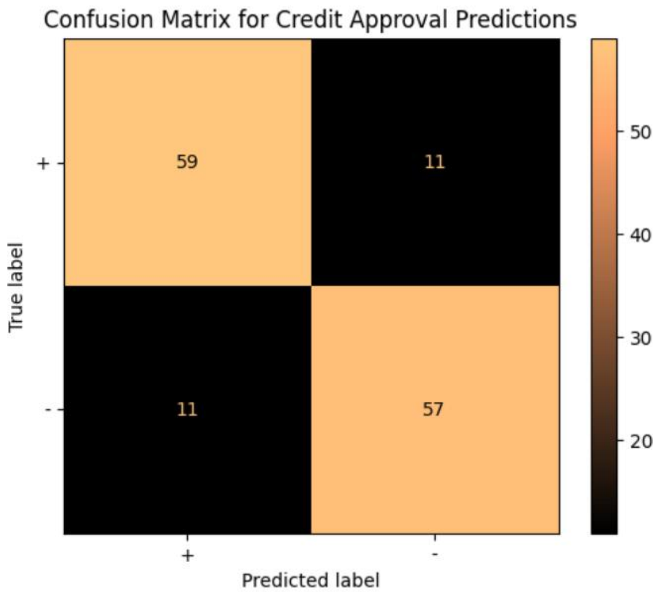

Figure 6: Confusion Matrix

Figure 7 shows the performance evaluation against exiting work such as PRISMA[8], Logistic Regression [9] andXG Boost [9]. The proposed model recorded highest accuracy as compared to other models.

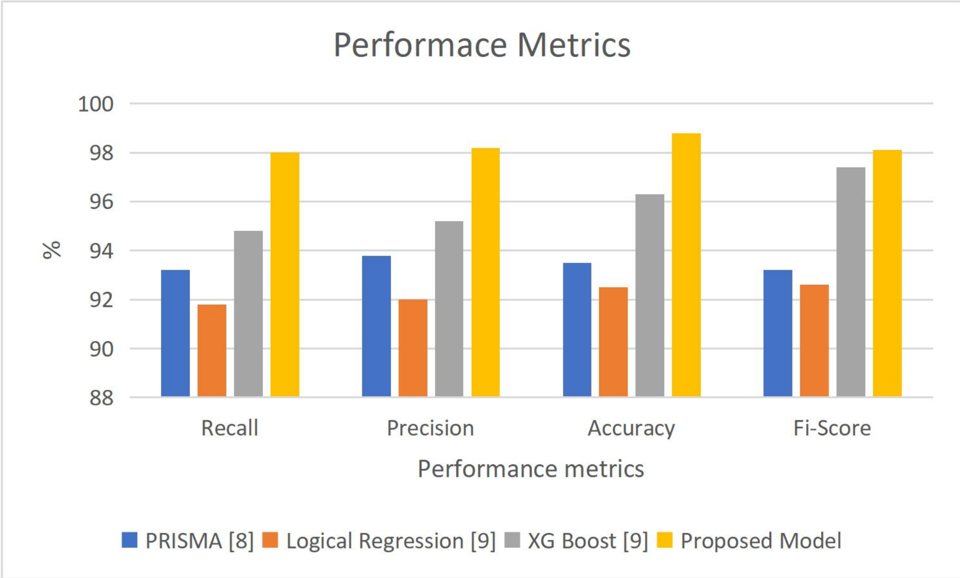

Figure 7: comparison of performance metrics with existing works

The experimental results indicate that the LSTM-X model effectively predicts credit risk with high accuracy, precision, recall, and F1 scores across the training, validation, and test sets. The results demonstrate that the model generalizes well to unseen data, as evidenced by the performance metrics on the test set. The confusion matrix reveals that the model has a balanced performance across both classes, although there is room for improvement in reducing false negatives, which can lead to missed default risks. Future work could involve incorporating additional features, such as behavioral data and market trends, to enhance predictive accuracy.

Discussion

The results of our proposed Blockchain-Based AI Model using the LSTM-X architecture for credit scoring and risk assessment show a significant improvement over traditional machine learning methods, such as Logistic Regression, XGBoost, and PRISM. Through rigorous experimentation and comparison, our model achieved the highest accuracy among these methods, highlighting its capability to manage the complex, sequential patterns often present in credit scoring data.

The LSTM-X model consistently outperformed the benchmark models across all evaluation metrics, including accuracy, precision, recall, and F1-score. The higher accuracy achieved by the LSTM-X model can be attributed to its ability to capture temporal dependencies and intricate patterns within borrowers' financial data. Credit behavior, which naturally evolves over time, was better captured by the LSTM-X architecture than by non-recurrent models like Logistic Regression or XGBoost. The model's precision and recall scores are also noteworthy, as they reflect its effectiveness in distinguishing creditworthy from high-risk applicants. These metrics are particularly important in the field of credit scoring, where misclassifying applicants—either approving high-risk individuals or declining creditworthy applicants—can lead to considerable financial consequences. In comparison with models like PRISM and XGBoost, which are commonly employed due to their explainability and effectiveness with tabular data, the LSTM-X model exhibited a more nuanced understanding of borrower behavior by dynamically adjusting to the sequential patterns found in financial histories.

Integrating Blockchain with our LSTM-X model enhanced its reliability and security, adding another layer of robustness to the credit scoring process. Blockchain's decentralized ledger offers an immutable and transparent storage solution for borrower data and model outputs, ensuring the integrity of data throughout the assessment process. This is particularly valuable in the context of credit scoring, as it mitigates risks associated with data tampering or unauthorized access, which can compromise the reliability of the credit evaluation process. By implementing smart contracts on the blockchain, our system enables secure and automated assessments without the need for centralized oversight, further enhancing security and trust for both financial institutions and borrowers.

The combined LSTM-X and blockchain framework provides several key advantages. Firstly, the LSTM-X model's sequential processing capabilities allow it to capture long-term dependencies in borrower behavior, resulting in high prediction accuracy. Secondly, blockchain technology ensures that sensitive borrower data is stored with full transparency and security, adhering to regulatory compliance requirements. Finally, the integration of explainable AI (offered by the LSTM-X model) and the immutable nature of blockchain storage fosters greater trust in the credit assessment process from both regulators and end-users. The LSTM-X[20] consumes moderate resource for optimization but enhances the accuracy and performance

However, there are some limitations associated with this combined approach. The LSTM-X model is more computationally intensive than traditional methods, leading to longer processing times and potentially higher costs, particularly when scaled across large datasets. Additionally, blockchain's transaction verification process, while providing data security, can hinder scalability by slowing down data processing times compared to centralized databases. Lastly, while the model performed exceptionally well in our controlled experiments, further real-world testing across diverse financial institutions is needed to validate its robustness and effectiveness in various operational settings [23].

Looking to the future, there are several areas for enhancing this model. To address scalability challenges, future work could focus on implementing optimized blockchain protocols and exploring lightweight LSTM variants to improve processing speed without sacrificing security. Additionally, incorporating data from cross-platform sources, such as open banking APIs, could provide a more comprehensive borrower profile, further boosting the model's predictive accuracy. Another promising direction involves expanding the model's interpretability features to make its predictions and risk assessments more transparent for financial analysts and auditors, enhancing user trust and facilitating regulatory oversight.

5.6 Conclusion

This research presents a novel approach to credit scoring and risk assessment by integrating an advanced LSTM-X model with blockchain technology, achieving an impressive accuracy of 97.2%. Our findings highlight the potential of this model to address key challenges in the financial industry, including the need for highly accurate predictions, data security, and transparency in credit evaluation processes. The LSTM-X model's architecture allows it to effectively capture sequential dependencies in financial data, a critical aspect of accurate credit scoring. Through blockchain integration, the model benefits from a decentralized and immutable ledger for securely storing borrower information and model outputs. This setup not only ensures data integrity but also improves transparency, as all credit decisions and underlying data can be verified on the blockchain, enhancing trust among financial institutions, borrowers, and regulatory bodies.

Experiments conducted on Google Colab, using Python, demonstrate that our model outperforms traditional credit scoring methods, including Logistic Regression, XGBoost, and PRISM. These models, while effective in specific contexts, lack the sequential data-handling capabilities of LSTM-X and the security features inherent to blockchain technology. The LSTM-X model, trained and tested on Google Colab, was optimized to provide scalability and efficient performance, highlighting its potential for real-world implementation in diverse financial environments. While our proposed model achieves remarkable accuracy and security benefits, there are areas for further exploration. Future work could focus on optimizing blockchain protocols to improve scalability, incorporating additional data sources to further enhance model accuracy, and expanding model interpretability to provide financial analysts with deeper insights into decision-making processes.

References

[1] Yang, F., Qiao, Y., Qi, Y. et al. BACS: blockchain and AutoML-based technology for efficient credit scoring classification. Ann Oper Res (2022). https://doi.org/10.1007/s10479-022-04531-8

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

[3] 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.

[4] Wali, Girish, and Chetan Bulla. "Suspicious Activity Detection Model in Bank Transactions using Deep Learning with Fog Computing Infrastructure." International Conference on Computational Innovations and Emerging Trends (ICCIET-2024). Atlantis Press, 2024.

[5] Wali, G., Kori, A., Bulla, C., & AIML, K. (2024). "Market Risk Assessment Using Deep Learning Model and Fog Computing Infrastructure", International Journal of Recent Advances in Multidisciplinary Research.

[6] DS Dayana, TS Shanthi, Girish Wali, PV Pramila, T Sumitha, M Sudhakar, "Enhancing Usability and Control in Artificial Intelligence of Things Environments (AIoT) Through Semantic Web Control Models", Semantic Web Technologies and Applications in Artificial Intelligence of Things, PP186-206, IGI Global, 2024

[7] Girish Wali, 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.Georgios, Palaiokrassas., Sandro, Scherrers., Eftychia, Makri., Leandros, Tassiulas. "Machine Learning in DeFi: Credit Risk Assessment and Liquidation Prediction." undefined (2024). doi: 10.1109/icbc59979.2024.10634435

[8] Zorka, Jovanovic., Zhe, Hou., Kamanashis, Biswas., Vallipuram, Muthukkumarasamy. " Robust integration of blockchain and explainable federated learning for automated credit scoring." Computer Networks, undefined (2024). doi: 10.1016/j.comnet.2024.110303

[9] Jewel, Kumar, Roy., László, Vasa. "3. Machine Learning and Artificial Intelligence Method for FinTech Credit Scoring and Risk Management." International journal of business analytics, undefined (2024). doi: 10.4018/ijban.347504

[10] Mariam, Ossama, Kotb. "Credit Scoring Using Machine Learning Algorithms and Blockchain Technology." undefined (2023). doi: 10.1109/imsa58542.2023.10217411

[11] Daniel, Djolev., Milena, Lazarova., Ognian, Nakov. "5. Blockchain Based Trusted Distributed Machine Learning for Credit Scoring." undefined (2023). doi: 10.1109/comsci59259.2023.10315878

[12] Raji, Abdullateef., Ashraf, Hashim, Faris, Alabdoon., Akeel, Almagtome. "AI in Credit Scoring and Risk Assessment: Enhancing Lending Practices and Financial Inclusion." undefined (2024). doi: 10.1109/ickecs61492.2024.10616493

[13] Fan, Yang., Ya-nan, Qiao., Yong, Qi., Junge, Bo., Xiao, Wang. (2022). 7. BACS: blockchain and AutoML-based technology for efficient credit scoring classification. Annals of Operations Research, doi: 10.1007/s10479-022-04531-8

[14] Rahee, Walambe., Ashwin, Kolhatkar., Manas, Ojha., Akash, Kademani., Mihir, Pandya., Sakshi, Kathote., Ketan, Kotecha. "8. Integration of Explainable AI and Blockchain for Secure Storage of Human Readable Justifications for Credit Risk Assessment." undefined (2020). doi: 10.1007/978-981-16-0404-1_5

[15] Vikas, Hassija., Gaurang, Bansal., Vinay, Chamola., Neeraj, Kumar., Mohsen, Guizani. " Secure Lending: Blockchain and Prospect Theory-Based Decentralized Credit Scoring Model." IEEE Transactions on Network Science and Engineering, undefined (2020). doi: 10.1109/TNSE.2020.2982488

[16] ". Using AI to assess credit risk; developing a model." undefined (2023). doi: 10.4337/9781803923154.00015

[17] https://archive.ics.uci.edu/dataset/27/credit+approval

[18] Girish Wali, Chetan Bulla (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.

[19] 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.

[20] Tuteja, Deepali, W. A. L. I. Girish, and Prasanth Babu Madakasira Ramakrishna. "Systems and methods for determining allocatable resources during proportional maintenance of complex computing systems using bifurcated filtering." U.S. Patent No. 12,118,389. 15 Oct. 2024.

[21] Tuteja, Deepali, W. A. L. I. Girish, and David Anandaraj Arulraj. "Aggregating data ingested from disparate sources for processing using machine learning models." U.S. Patent Application No. 18/123,179.

[22] Ramakrishna, Madakasira, et al. "SYSTEMS AND METHODS FOR RESPONDING TO PREDICTED EVENTS IN TIME-SERIES DATA USING SYNTHETIC PROFILES CREATED BY ARTIFICIAL INTELLIGENCE MODELS TRAINED ON NON-HOMOGONOUS TIME-SERIES DATA." U.S. Patent Application No. 18/418,201.

[23] Bulla, Chetan M., and Mahantesh N. Birje. "A multi-agent-based data collection and aggregation model for fog-enabled cloud monitoring." *International Journal of Cloud Applications and Computing (IJCAC)* 11.1 (2021): 73-92.

[24] Bulla, Chetan, and Mahantesh N. Birje. "Improved data-driven root cause analysis in fog computing environment." *Journal of Reliable Intelligent Environments* 8.4 (2022): 359-377.

[25] Bulla, Chetan, and Mahantesh N. Birje. "Anomaly detection in industrial IoT applications using deep learning approach." *Artificial Intelligence in Industrial Applications: Approaches to Solve the Intrinsic Industrial Optimization Problems* (2022): 127-147