LEVERAGING DEEP LEARNING METHODS ON CREDIT SCORING IN THE FINANCIAL SECTOR IN KENYA

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ABSTRACT

Financial institutions in Kenya are cornerstones of financial inclusion, yet they face increasing non-performing loans (NPLs) and risks due to reliance on manual, subjective, or simplistic traditional credit scoring methods. Evaluating credit risk is a crucial responsibility in the financial sector to assess the probability of borrowers failing to repay loans. Traditional credit scoring methodologies need to be augmented in order to accurately assess creditworthiness due to the growing complexity of financial data and the emergence of non-traditional lending platforms. Moreover, the increasing complexity and volume of financial and behavioral data present significant challenges to traditional credit scoring methods. While some financial institutions have mainly digitized, others still struggle to assess clients' creditworthiness with thin credit files or informal income sources. This paper examined the application of deep learning model to leverage credit scoring system in the financial sector. The paper has reviewed past studies on deep learning models to ascertain their veracity in credit scoring assessment. It is apparent that application of deep learning models is superior in evaluating credit worthiness. This application of the models makes it easier to input financial data and analyze it in order to display the anticipated credit scores. Hence, the paper concludes that the application of the deep learning model is essential in minimizing financial distress, bankruptcy, credit card fraud detection and inclusion of macro-economic variables. This is effectively done by integrating traditional and behavioral data into credit scoring models to improve the interpretability and performance of the models. In order to fully integrate the traditional and behavioral data, it is imperative that greater emphasis be placed on gathering more extensive and varied datasets that fairly represent a wide range of socioeconomic backgrounds and demographic categories of clients.

Key words: Behavioral Data, Traditional Credit Data, Deep Learning Model, Data Preprocessing, Alternative Data, Credit Scoring, Financial Intuitions, Hybrid Deep Learning Models.

INTRODUCTION

Appropriate customer selection is a key element of risk management in the financial sector, yet achieving accuracy is considered a difficult task. Thus, techniques such as logistic regression and neural networks (NNs) can be used to estimate the borrower's probability of default. To manage financial risks, financial institutions often collect information from customers and other financial institutions to distinguish safe borrowers from risky ones. However, current automated lending risk evaluation methods are imperfect, and the failure of credit scoring algorithms to accurately assess loan recipients can result in considerable losses. Thus, from the perspective of the financial institutions, appropriate assessment of credit applicants is crucial. As a result, credit scoring has been at the forefront in the fields of finance and economics in applying machine learning techniques such as decision trees (DTs), NNs and Support Vector Machines (SVMs). The performance of various classification algorithms for credit scoring has been intensively researched yet the accuracy gains of these methods for the assessment of creditworthiness appear to be limited. Nonetheless, the application of deep learning (DL) has attracted considerable research attention. Kraus (2026) revealed that DL is a feasible and effective method that can outperform its traditional counterparts in terms of predictive accuracy making its development a major area of focus for financial institutions. DL has been successfully used in many real-world applications, especially for credit scoring in the financial institutions.

Credit scoring is a data-driven, statistical method used to assess a borrower's risk and creditworthiness, replacing subjective loan officer judgments to improve accuracy, efficiency and financial inclusion (Xiaomin, 2019). According to Onsongo, Miroga and Otinga (2025) financial institutions often evaluate the 5Cs of credit namely character (credit history), capacity (ability to repay), capital (net worth), collateral (assets), and conditions (loan purpose). This means that credit scoring uses historical, behavioral and alternative data to predict default probabilities. This reduces bad debt and enable faster processing, lower operating costs, and increased access to credit (Abduganiyevich, 2025). It is apparent that credit scoring serves as a cornerstone of the modern financial sector, providing a systematic, data-driven approach for institutions to evaluate the creditworthiness of loan applicants. By analyzing factors such as repayment history, income stability and debt levels, financial institutions can classify applicants as either good (creditworthy) or bad (high-risk) to minimize Non-Performing Assets and secure profitability.

Nevertheless, in an increasingly turbulent and digitized economic landscape, the reliance on traditional, linear credit scoring models has become a limiting factor, often resulting in misclassification and significant financial losses (Ahmed, 2025). The traditional credit scoring systems often struggle to capture the dynamic and nonlinear nature of consumer financial patterns in the digital economy (Afolabi, Chukwurah & Abieba, 2025) as they are often restricted by their linear assumptions and inability to process non-traditional, unstructured data, such as behavioral patterns or real-time transactional data. Furthermore, these systems frequently struggle with data imbalance, failing to accurately assess individuals with thin or no credit histories, thereby restricting financial inclusion for young adults and underserved populations (Villarreal, 2025).

According to Mienye (2024) there is a compelling need to explore and evaluate DL models that offer greater predictive accuracy and adaptability in credit scoring applications (Mienye, 2024). DL is a subset of artificial intelligence (AI) and machine learning that uses multi-layered artificial neural networks (Recurrent Neural Networks (RNNs) and Deep Neural Networks (DNNs)) to simulate human-like decision-making (Bhutta, Hizmo & Ringo 2025).

DL offers a robust solution for capturing complex, non-linear relationships within vast datasets-patterns that traditional, rule-based systems often overlook. DL techniques have demonstrated superior performance in analyzing high-dimensional, behavioral and time-dependent data, such as longitudinal financial histories. Specifically, techniques like Long Short-Term Memory (LSTM) networks have shown remarkable accuracy in capturing temporal dependencies in financial behavior, achieving higher Area Under the Curve (AUC) and recall rates compared to traditional methods (Mienye, 2024).

Neural networks, especially RNNs and CNNs facilitate automatic feature extraction from sequential or high-dimensional data like transaction records or time series (Zhu, Zhou, Xie, Wang & Nguyen, 2019). These models provide enhanced performance by modeling nonlinearity, temporal sequences and interactions across diverse data sources (Dumitrescu, Hué, Hurlin & Tokpavi, 2022). Neural networks are effective when linked to pre-training on a massive, general dataset and adapting it to a specific task. This approach leverages existing, high-level feature knowledge to boost accuracy and reduce training time on smaller, custom datasets. However, DL approaches encounter difficulties regarding interpretability, computational expenses and regulatory compliance. Overcoming these challenges involves a combination of Explainable AI (XAI) frameworks, model optimization techniques, and structured governance (Pallathadka, 2021). The goal is to offer a robust, scalable, and interpretable deep learning framework tailored to the unique demands of credit scoring in the financial sector.

DL is increasingly being applied in the financial sector to enhance credit scoring by processing vast, non-traditional datasets, offering higher accuracy than traditional linear models, especially for members with limited credit history (Salaton, 2020). Since loan repayment and delinquency are matters that continue to be a challenge, combining DNNs with RNNs or LSTM units can be effective in achieving high predictive AUC-ROC scores (Marino, 2018). With the current high rate of default, leveraging DL (RNN/DNN) can minimize default rate by leveraging deep learning models to allow the financial institutions to assess members' creditworthiness more accurately, reducing NPLs and expanding financial inclusion (Amunabi & Koori, 2024). Abduganiyevich (2025) has emphasized that financial institutions can no longer rely on traditional models in assessing the behavior of the clientele as far as credit lending is concerned. However, besides strict measures being taken to minimize credit risk, the rate of defaulting remains high even with strict control measures put across by the institutions. Hence, this paper scrutinized past studies on leveraging DL in the financial sector to foster and advance credit to the customers in Kenya.

LITEREATURE REVIEW

Credit Scoring in the Financial Sector

Credit scoring is an essential aspect of modern financial systems, where the goal is to predict the likelihood of a borrower defaulting on a loan based on their financial history, personal information, and other related factors (Cornaggia, Cornaggia & Israelsen, 2018). The accuracy of credit scoring models directly influences lending decisions, risk management and customer satisfaction. In recent years, the application of machine learning techniques, including supervised learning algorithms such as logistic regression, decision trees and neural networks has revolutionized the credit scoring process. The process typically involves collecting vast amounts of data, including the applicant's credit history, income and other financial indicators, which are then transformed into features suitable for model training. These features are used by a predictive model to classify applicants into different risk categories, which can be used to determine whether to approve or reject a loan application. The application of machine learning models for credit scoring has garnered significant interest, driven by the increasing complexity of financial datasets and the heightened need for accurate risk evaluation. Advanced deep learning approaches, such as artificial neural networks (ANNs), CNNs and RNNs, have shown marked advantages in capturing non-linear dependencies and processing high dimensional inputs (Ahmed, 2025). Among DL models, RNNs are highly proficient at managing sequential or time-dependent data, such as longitudinal credit histories. By taking into account the chronological progression of financial activity and borrowing behavior, these models can uncover dynamic patterns that inform more reliable credit risk predictions. The automatic feature extraction capabilities of DL models, along with their capacity to learn hierarchical data representations, position them as valuable tools for financial institutions seeking to refine and streamline the credit scoring process (Calabrese, Dong & Shi, 2021). The overall performance of such models is heavily influenced by the integrity and representativeness of the input data. However, financial datasets are often plagued by issues such as missing values, anomalous entries and imbalanced class distributions. Because DL algorithms are particularly susceptible to data irregularities, tailored preprocessing techniques are essential to ensure reliable training outcomes (Aleksandrova, 2021).

Deep Learning and Credit Score in the Financial Sector

Several studies have highlighted that DL methods are one of the major achievements put in place by financial technology (FinTech) in gaining a competitive advantage. Mumbua (2018) concurred that borrower's characteristics are significant to loan repayment default in financial sector. In their study on Explainable Enterprise Credit Rating via Deep Feature Crossing Network, Weyu (2018) argued that the credit rating methods of use should be dependent on the capability of the borrower. Moscato (2021) asserted that lack of lenders' experience and missing or uncertain information about borrower's credit history can increase risks in social lending platforms, requiring an accurate credit risk scoring. Ershadi (2019) asserted that client appraisal as well as credit monitoring is essential in ensuring minimization of risks and loan default. In comparing Bayesian networks with artificial neural networks for predicting recovered value in a credit operation, Teles (2020) found that ANNs are a more efficient tool for predicting credit risk than the Naıve Bayesian (NB) approach. In studying DL models for bankruptcy prediction using textual disclosures, Mai (2019) constructed a comprehensive bankruptcy database of 11,827 U.S. public companies and showed that DL models yield superior prediction performance in forecasting bankruptcy using textual disclosures. When textual data are used in conjunction with traditional accounting-based ratio and market-based variables, DL models can further improve the prediction accuracy (Mai, 2019). In examining the need to increase accuracy in financial sector, Ashwani (2021) posited that technology innovations and strategies played a vital role in raising the standards of financial institutions.

Loan advancing being one of the risk factors in the financial sector, automation alone cannot mitigate on such challenges (Lestari, 2023). According to Sriram (2025) traditional modeling techniques and the emerging AI and machine learning techniques for risk modeling applications can make it possible to lower the overall cost of credit risk assessment while deepening both positive customer experiences and financial inclusion. According Shi (2025) Hybrid Financial Risk Predictor (HFRP) model have demonstrated the values of the revenue, net income and earnings per share.

Gunnarsson, vanden Broucke, Baesens, Óskarsdóttir and Lemahieu (2021) evaluated whether DL provided significant performance improvements over traditional methods (logistic regression, RF, XGBoost) on ten retail credit datasets. However, the key findings were that deep learning did not consistently outperform state-of-the-art tree-based models and was more computationally expensive. Bussmann, Giudici and Facchinetti (2020) examined the application of deep learning models on credit data from Peer-to-Peer (P2P) lending platforms, comparing them with standard machine learning approaches. It was established that DL could effectively handle complex, non-linear data structures, offering potential for improved predictive power in P2P datasets. Papouskova and Hajek (2019) applied Deep Belief Networks (DBNs) to credit data sets, comparing them to standard neural networks and found that DBNs effectively used unsupervised learning for pre-training, enhancing the model's ability to extract deep features. Rida (2024) challenged the regulatory status-quo by applying Deep Learning and Gradient Boosting machines to validate Basel II/III compliance for a European bank's auto loan applicants. It was apparent that advanced DL techniques could drastically improve default capture rates while potentially adhering to European regulatory standards.

Bussmann (2021) investigated credit risk modeling for small and medium enterprises (SMEs) using standard logistic regression and machine learning XGBoost algorithms. The study highlighted the significance of precise default probability estimation and model assessment techniques and offered insights into the factors affecting individual organizations' default probability. The study emphasized the efficacy of machine learning methods in evaluating credit risk for SMEs by showcasing the usefulness of Shapley values for interpreting models. Bao (2019) examined how incorporating unsupervised learning methods could improve credit-scoring models. By comparing model performances on three credit datasets and using different algorithm combinations, the study concluded that integrating at any step enhanced model performance, with the combined strategy producing the most favorable outcomes. Bhatore (2022) provided an extensive overview of current research methodologies and machine learning approaches in credit risk assessment by conducting a thorough literature review of 136 publications between 1993 and 2019 to analyze how hyper-parameters affect machine learning models used in credit risk evaluation. The analysis highlighted the restricted availability of extensive public datasets, offering valuable insights into the present condition and upcoming trends in credit risk assessment while also recognizing areas for future research and enhancement. Davis (2022) addressed the development of machine learning models to predict home equity credit risk using real-world data and proposed methods to enhance the interpretability of the models for various stakeholders. The study assessed the explainability of the models for loan companies, regulators, loan applicants and data scientists, taking into account their specific needs for understanding model outputs. The ultimate goal was to facilitate the adoption of machine learning techniques in domains where explanations of predictions are crucial. Zhou (2019) introduced an advanced hybrid ensemble machine learning model called RS-MultiBoosting, which merged the random subspace (RS) and MultiBoosting methods to boost the precision of predicting credit risk for SMEs. The study used data from 46 SMEs and seven core enterprises (CEs) in the Chinese stock market from March 31, 2014, to December 31, 2015, to evaluate the feasibility and effectiveness of the RS-MultiBoosting method. RS-MultiBoosting showed strong performance with limited sample sizes, emphasizing the significance of conventional financial metrics like current and quick ratios and supply chain finance (SCF) specific factors, such as trade goods characteristics and CE profit margins, in improving SMEs' access to financing. The study showcased the potential of RS-MultiBoosting method for credit risk prediction and offered insights into the factors that affect SME funding.

Munkhdalai (2019) used machine-learning algorithms and feature-selection strategies to construct credit-scoring models. The trials used a 10-fold cross-validation method to assure reliability and the assessment metrics were averaged for comparison. The primary goals were to evaluate the efficacy of various algorithms and identify the most superior one. The tested models were LR, MARS, SVM, RF, XGBoost, and MLP, with hyper-parameters optimized individually. The MLP model with sigmoid activation function demonstrated superior AUC and h-measure metrics performance. The RF and XGBoost models exhibited superior performance regarding True Positive Rate, False Positive Rate and accuracy. The NAP feature-selection strategy often outperformed TSFFS, especially regarding AUC, TPR, FPR, and accuracy. Dumitrescu (2022) presented a new credit scoring method called penalized logistic tree regression, which combines decision tree data to improve logistic regression accuracy while maintaining interpretability. It was apparent that PLTR effectively captured non-linear effects in credit scoring data by combining rules from short-depth decision trees with penalized logistic regression while keeping the interpretability of logistic regression. PLTR outperformed standard logistic regression and achieved similar accuracy to the random forest method through Monte Carlo simulations and empirical evaluations. Agyemang (2022) analyzed the performance of advanced data mining techniques and machine learning approaches (including ensemble and neural net techniques) against traditional methods within the Ghanaian banking sector to improve lending decisions. The analysis heavily leveraged mobile phone usage, transactions and behavioral data due to limited credit bureau coverage. It was apparent that **c**ombining DL with genetic algorithms or traditional models to solve interpretability issues could provide credit scores to the unbanked population by automating the evaluation process. In Kenya, Kimani (2024) developed a hybrid model combining DNN and RNN to analyze financial and behavioral data for credit scoring, aiming to enhance prediction accuracy, particularly for unbanked individuals while Onyimbo (2021) compared traditional logistic regression against machine learning models, including Multi-layer Perceptron Neural Networks, to identify defaulters using data from the credit market. Ahmed (2025) examined the broader sector-wide implications, particularly in terms of regulatory compliance and market stability with key findings revealing that predictive analytics not only improved the precision and adaptability of risk management practices but also facilitated more accurate, timely, and dynamic risk assessments.

Research Gaps

From the foregoing discussion, it is apparent that DL models are widely applied for credit scoring using both structured and unstructured data. While appreciating previous studies in deep learning, there exist various gaps as far as credit score in financial sector is concerned. A number of models reviewed have scanty literature in regards to features related to credit score. However, the application of DL in the finance sector is significant especially in the area of credit score where machine learning sometimes fail as a result of human intervention. Credit process is associated with nature of datasets both structured and unstructured particularly in areas where it offers distinct advantages over traditional methods. Significant adoption has seen financial institutions rapidly integrate DL into their operations (Idhalama, 2024). Further, Idhalama (2024) highlights that leveraging the capabilities of DL present a significant progress in achieving sustainability. For instance, Olubusola (2024) noted that DL has significantly revolutionized financial forecasting, offering improved precision in market trend analysis and asset price predictions through innovations in DL, reinforcement learning and hybrid models. Olukoya (2023) reiterated that the accuracy and risk assessment are critical components for organizational resilience and decision-making. While the models formulated and tested revealed the predictive capability of the DL techniques, what is apparent is that majority of studies have used fundamental statistical techniques such as descriptive and inferential statistical methods. Furthermore, studies did not concentrate on determining the many kinds of validity for the models to guarantee the precision and quality of the findings. However, it is apparent that superior performance in DL models consistently outperforms traditional statistical methods in tasks involving complex, non-linear, and high-dimensional data such as risk assessment during credit scoring.

CONCLUSION

From the review of literature it can be concluded that DL methods have been applied to leverage on credit scoring in financial sector. DL needs to prioritize the highest accuracy using complicated rules that enhance consisting of considerably large images. Hence, it can be concluded that there is a need to actively aim towards not only predictive accuracy, but also in interpretability in credit scores. The introduction of DL for credit scoring is essential in minimizing financial distress, bankruptcy, peer-to-peer (P2P) lending, credit card fraud detection, and inclusion of macro-economic variables. This is useful for the financial institutions that seek to integrate traditional and behavioral data into credit scoring models, using rigorous feature selection and data cleaning procedures to improve the interpretability and performance of the models. This emphasizes the need of combining behavioral and traditional financial measures in predictive modeling to determine creditworthiness using interest rates, credit utilization ratios, and outstanding debt. By offering thorough insights into borrower risk profiles through a methodical analysis, a hybrid DL model is required to predict credit scores by smoothly integrating traditional and behavioral data. By allowing stakeholders to interactively assess credit score forecasts and comprehend the underlying causes impacting decisions, DL models can improve accessibility and transparency. However, there is need to include alternate neural network topologies and sophisticated preprocessing techniques in order to further improve predictive modeling capabilities across a variety of domains and applications.

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