Credit Default Status Prediction

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Literature Review

Financial risk management needs accurate credit default prediction which allows companies to determine whether debt-paying borrowers will default on their obligations. Financial institutions can reduce risks while allocating funds effectively to preserve economic stability because of precise predictions. Since its inception this field shifted from basic statistical approaches to sophisticated machine learning methods because of enhanced financial system complexity and data access.

Traditional Statistical Approaches

The start point for constructing credit default predictions relies on statistical models. Discriminant analysis and logistic regression served as early methods which used financial ratios along with indicators to spot defaulting entities from non-defaulting ones. Such models were easy to interpret but failed to detect the non-linear connections across the data. The models faced performance limitations during predictions especially when operating in complex financial situations (Markov, A., Seleznyova, Z., & Lapshin, V. (2022)).

Advent of Machine Learning Techniques

The ineffective performance of traditional models created an opportunity for using ML techniques to enhance credit risk assessment. The three popular ML alternatives for large-scale data analysis included Support Vector Machines (SVMs), decision trees, and artificial neural networks (ANNs) because of their capability in discovering complex non-linear patterns. Advanced prediction methods led to enhanced default estimation through their competence in working with large datasets and identifying sophisticated variable connections. The problems of overfitting and interpretability issues still needed improvement in addition to further advancements (Kimani, G. W., Mwai, J. K., & Mwangi, E. (2024)).

Ensemble Methods and Hybrid Models

Multiple algorithms were combined through ensemble methods by researchers to address individual model weaknesses because predictive performance suffered from their limitations. LightGBM and XGBoost have become popular because they efficiently process large credit data with high accuracy. Multiple decision trees are integrated in these models to achieve better generalization and minimize overfitting problems. The combination of statistical approaches with ML techniques through hybrid models has emerged as a proposed solution to use both paradigms while finding an equilibrium between interpretability and predictive capabilities (Yao, J., et al., (2022)).

Deep Learning Applications

Deep learning has introduced additional transformations to the credit default prediction process. The multilayer structure of deep neural networks allows them to extract hierarchical data representations which suits their use in processing complex credit behavior sequencing. Deep learning models have shown better results than traditional ML algorithms in two specific use cases: unstructured data analysis and situations where feature engineering proves difficult. The opaque internal functioning of advanced models creates important challenges regarding explainability since financial institutions need complete transparency for proper decision making (Dastile, X., & Celik, T. (2021)).

Feature Selection and Engineering

Every modeling method depends heavily on the quality of its input features for producing effective credit default prediction models. The process of feature selection and engineering consists of selecting and developing meaningful variables which represent the financial health along with creditworthiness of potential borrowers. Adding macroeconomy signals together with transaction activities combined with consumer behavioral patterns enables better model predictions. The implementation requires specialists in the field together with thorough evaluation to prevent problems of bias and overfitting (Shukla, D., & Gupta, S. (2024)).

The prediction of credit default has undergone dramatic transformations as traditional statistical models shifted to elaborate implementations of ML and deep learning approaches.

Literature Gaps

Dastile, X., & Celik, T. (2021). A deep learning model for credit scoring needs to develop its predictions with explainable information. The paper appears in IEEE Access: Practical Innovations, Open Solutions volume 9 with page numbers 50426–50440. It is accessible at https://doi.org/10.1109/access.2021.3068854.

The proposed research implements 2D CNNs to perform credit scoring operations through a tabular-to-image conversion while maintaining a primary goal to construct an explainable robust deployable classification system which evaluates credit risk. A baseline establishment through classical ML models represents a main deficiency before adopting deep learning in the proposed work. The first part of this solution will use traditional approaches for benchmarking purposes. Standard transparency tools such as SHAP/LIME will be integrated for explanation despite missing from the current work approach. A web-based dashboard development represents the only deployment strategy described in this work.

Kimani, G. W., Mwai, J. K., & Mwangi, E. (2024). The authors present a deep learning hybrid system to construct superior credit score prediction models. International Journal of Research and Innovation in Applied Science, IX(VII), 250–262. https://doi.org/10.51584/ijrias.2024.907024

A hybrid RNN+DNN model used to improve credit scoring within the existing study partially achieves its main goals. The analysis increases classification performance yet lacks specific goals for reaching 85% precision in high and low risk borrower identification. Model interpretability needs improvement since the adoption of SHAP or LIME explainable AI techniques would remedy this problem. Real-world deployment of a secure web-based dashboard would provide better practical usability since the current research design lacks such elements. The analysis lacks real-world dataset and industry standard benchmarks as part of its assessment. The proposed improvement strategy involves hyperparameter optimization followed by explainable AI integration and the deployment of an interactive interface and the conduct of performance benchmarks relative to industry standards.

Markov, A., Seleznyova, Z., & Lapshin, V. (2022). The implementation of credit scoring techniques requires attention to present trends and fundamental factors. The Journal of Finance and Data Science, 8, 180–201. https://doi.org/10.1016/j.jfds.2022.07.002

Research from this source conducts a systemized review of credit scoring studies whereas it omits detailed guidance for predictive model development. The field lacks experimental methods that could be used to create and validate a credit default prediction system. The proposed solution fills the research gaps through machine learning model development combined with deep learning enhancement and explainable AI implementations using SHAP or LIME methods. The project introduces a web-based dashboard designed for financial institutions as its practical implementation component. A framework framework goes through benchmark testing with real-world datasets for confirming its suitability to industry standards.

Shukla, D., & Gupta, S. (2024). Strategic manipulations of credit-related features lead to enhanced performance levels of scoring models. In 2024 6th International Conference on Electrical, Control and Instrumentation Engineering (ICECIE) (pp. 1–5). IEEE.

Originally the reviewed work studied machine learning-based approaches to feature engineering for credit risk assessment though it fails to deliver essential elements specified in the objectives. The research does not construct an explicit credit default prediction model and omits performance enhancing deep learning techniques. Model interpretability suffers because the article lacks explainable AI techniques like SHAP/LIME. There is no web interface for risk assessment in real time while industry performance standards are not considered for benchmarking purposes. This research establishes a classification system that uses neural networks while adding explanation capabilities to it for website-based risk assessment support and testing against different systems.

Table 1: Literature Gaps

Objective	Identified Gaps in Reviewed Studies	Proposed Solution to Address Gaps
Objective 1: Build a classification model for predicting credit default status with at least 85% accuracy.	Studies like Shukla & Gupta (2024) and Markov et al. (2022) discuss credit risk assessment but do not develop a dedicated classification model for predicting default status. Kimani et al. (2024) introduce deep learning but do not explicitly target an 85% precision goal.	Develop a robust machine learning classification model, using feature engineering and hyperparameter tuning, ensuring it achieves at least 85% accuracy for classifying borrowers as high or low risk.
Objective 2: Improve classification performance with a deep learning model (Neural Networks).	The studies incorporate deep learning (Dastile & Celik, 2021; Kimani et al., 2024) but lack baseline classical ML benchmarking before implementing deep learning. Hybrid models (RNN+DNN) in Kimani et al. (2024) show improvements but lack hyperparameter optimization.	Use baseline traditional ML models for benchmarking, followed by fine-tuning and training deep learning architectures such as CNNs and hybrid models to enhance classification performance. Optimize hyperparameters for improved accuracy.
Objective 3: Introduce explainable AI (SHAP/LIME) to understand model predictions.	Some studies (Dastile & Celik, 2021; Kimani et al., 2024) acknowledge the importance of explainability but do not integrate SHAP/LIME for transparency. Markov et al. (2022) proposes SHAP/LIME but lacks practical implementation details.	Implement SHAP/LIME for model interpretability, allowing financial institutions to understand why a borrower is classified as high or low risk, improving trust in AI-driven decisions
Objective 4: Deploy a secure web-based credit risk assessment dashboard.	Most studies (Dastile & Celik, 2021; Kimani et al., 2024) do not focus on deployment, except for Markov et al. (2022), which proposes a dashboard but lacks technical implementation details.	Develop a secure web-based dashboard for financial institutions, enabling real-time borrower risk assessment and seamless model deployment.
Objective 5: Benchmark the framework against real-world datasets and industry standards.	Studies such as Kimani et al. (2024) and Shukla & Gupta (2024) lack performance benchmarking with real-world datasets and industry standards.	Conduct empirical evaluations using real-world datasets and compare model performance with existing credit risk assessment methods to validate effectiveness.

Dataset

The dataset established by Lipin Pappachen, Aditya Raj Kashyap, and Jay Dixit delivers quality material for classification models in credit default forecasting. The diverse dataset requires analysis with machine learning models including Random Forest, Decision Tree and Gaussian Naïve Bayes and K-Nearest Neighbors (KNN) to reveal both useful features and obstacles when attempting to develop predictive models.

The dataset will be used to construct a classification model aimed at estimating credit default status conditions under Objective 1. The target accuracy exceeds the former research outputs by 85% since the current study focuses on attaining better classification results than the recorded 72.6% from Random Forest and 68.3% from KNN. The successful implementation of these methods will accomplish the objective by optimizing hyperparameters while implementing advanced feature engineering and handling classes appropriately.

A set of deep learning models including Neural Networks will be brought into Objective 2 to achieve better classification successes beyond standard models. The dataset's variable precision and recall performance in previous work implies that deep learning methods such as ANNs, CNNs and LSTMs are suitable for detecting borrower patterns in the data.

SHAP values and LIME will serve as the explainable AI components for Objective 3. The previous models suffered from a lack of interpretability which made it difficult to determine the factors that led a borrower to be classified as a defaulter. Acceptable explanations from AI techniques will generate meaningful credit insights which financial institutions may use.

A real-time assessment system through the development of a credit default risk dashboard represents the fourth objective of this project. This dashboard provides better decision-making than static results by allowing the examination of borrower data in real time.

An assessment based on industry benchmarks will be executed for Objective 5 to confirm that the model proves superior to current risk evaluation systems in the market.

The proposed work changes academic research into an operational solution that performs credit risk assessment for practical deployment.