

Machine Learning-Based Credit Risk Assessment For Intelligent Lending and Default Prediction in Financial Services

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Abstract. A convolutional neural network (CNN) model is proposed to predict credit default in an online lending service environment using public data (e.g., application and user profile data). Given that CNNs have the ability to learn spatial representation, the 1D convolutional layer embedded in the CNN classifier can effectively capture local features along the feature sequence. CNNs can expose correlated features to deep networks for joint learning and enhance performance. Compared with traditional approaches, such as logistic regression or support vector machines, the CNN shows better predictive ability. The effectiveness of deep learning techniques for credit-default prediction from user perspectives presents new insights for intelligent lending services. Despite significant advances in machine learning techniques and their successful applications in many fields, credit-risk-prediction models are still predominantly based on traditional methods. One possible reason is the high-dimensional sparse feature distribution. However, the underlying data sources of credit-risk prediction in the lending industry contribute to high-quality dense representation. An online lending service provides comprehensive application attributes and sufficient historical samples for predictive modeling. With detailed user profiles, the learned model from public data can assist credit-risk management in intelligent lending service. Specifically, a CNN model is proposed to predict credit default in an online lending service environment using public data.

Keywords: Convolutional Neural Networks (CNNs), Credit Default Prediction, Credit Risk Assessment, Credit Risk Management, Deep Learning, Feature Learning, Intelligent Lending Services, Lending Analytics, Machine Learning, Online Lending, Predictive Modeling, Risk Analytics, User Profile Analytics.

1. Introduction

As part of the research direction of credit risk modeling, a self-designed data architecture is developed for bankruptcy prediction, non-performing loans (NPL), and loan application evaluation. [1] To characterize the risk level of credit with help of a machine-learning model, credit risk is generally defined as the probability of credit default over a future time horizon and more generally as the deterioration of the credit quality of counterparties. [2] In addition, the NPL ratio reflects the asset quality of state banks and the effectiveness of the credit risk policy of banking institutions. [3] Bankruptcy prediction aims to determine whether a firm will go bankrupt within a one- to three-year horizon. [4] The model validation and interpretability help to evaluate the performance of the risk model and the practical applicability of the predicted results.

Credit risk, one of the significant risks affecting the banking business, arises from the potentially adverse impact that a counterparty's failure to fulfill its contractual obligations could have on the position, profit, or loss of a bank. [5] With the rapid development of Internet finance, financial services on the Internet emerge in endlessly, and the number of online loan customers increases sharply. [6] At the same time, the examination focus of the banks is gradually shifted from the customer's later ability to repay to the customer's current ability to repay. [7] Therefore, in order to reduce the occurrence of default risk, study the customer's credit status through model prediction, especially the early credit loan

application risk prediction ability, guide the loan process, and ultimately reduce the default risk is of great significance.

2. Theoretical Foundations of Credit Risk

The modelling and assessment of credit risk has gained significance as a result of the increased number of defaults in recent years. [8] This risk manifests itself in the form of losses resulting from a debtor's inability to fulfil a credit obligation, and can therefore be assumed to be inherent in all banking operations. [9] The need for banks and other financial credit institutions to use credit methodology is justified by the complexity of problems that arise in their development, which, [10] in addition to economic content, also possess a legal character. [11] Only proven lending is capable of ensuring that the financial results of investments will cover gain or loss. [12] International credit markets have also indicated an increased need for thorough and realistic assessment of credit risk. [13]

Credit risk is determined by the degree of attention banks pay to management on the basis of proven theory. [14] Elements of lending decisions should rest on forecasting tools capable of considering both quantitative and qualitative attributes of the debtor's ability to repay the bank debt. [15] Bank theory must be extended to cover trust and the inherent banking risks that result from it. Information theory, under which information is treated mathematically, is also recognised as important. [16] As risk elements are difficult to measure, combining regression modelling with a neural network approach overcomes some of these problems. [17]

Credit portfolios characteristically consist of numerous asset exposures of different cubes but with largely similar risk borrowers, such as in retail lending. [18] A small increase in the default probability of these portfolios can result in large unexpected losses, and therefore special care must be taken with them. [19]

2.1 Probability of Default Estimation

The fundamental objective of credit risk modeling is to estimate the probability of default (PD) for a given loan application. [20] The probability of default can be formulated as:

$$PD = P(\text{Default} | X) = \sigma(w^T \cdot X + b)$$

(Eq. 1)

where X represents the feature vector containing application attributes (loan amount, income, credit history), w denotes the weight vector learned by the model, b is the bias term, and $\sigma(\cdot)$ is the sigmoid activation function. The output $PD \in [0,1]$ represents the predicted probability of default.

2.2 CNN Architecture and Convolutional Operations

The 1D convolutional operation in the CNN model applies a set of learned filters to the input feature sequence, capturing local dependencies:

$$y_j = \sigma(\sum_i w_i \cdot x_{\{j+i\}} + b)$$

(Eq. 2)

where w_i represents convolutional filter weights, $x_{\{j+i\}}$ are input values within the receptive field, and y_j is the resulting feature map. This operation enables automatic extraction of correlated features without manual feature engineering.

2.3 Classification Performance Metrics

The precision, recall, and F1-score metrics are computed to evaluate model classification performance:

$$\text{Precision} = TP / (TP + FP)$$

(Eq. 3)

$$\text{Recall} = TP / (TP + FN)$$

(Eq. 4)

$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

(Eq. 5)

where TP denotes true positives (correctly identified defaults), FP represents false positives (non-defaulters misclassified as defaulters), and FN indicates false negatives (undetected defaults).

2.4 Area Under the Receiver Operating Characteristic Curve

The AUC metric integrates the ROC curve to provide a comprehensive measure of classification performance across all decision thresholds:

$$AUC = \int_0^1 TPR(FPR) dFPR$$

(Eq. 6)

where TPR is the true positive rate and FPR is the false positive rate. AUC values closer to 1.0 indicate superior discrimination ability between default and non-default cases.

2.5 Cross-Entropy Loss Function

The model is trained using binary cross-entropy loss to minimize prediction errors:

$$L = -\sum [y \cdot \log(\hat{y}) + (1-y) \cdot \log(1-\hat{y})]$$

(Eq. 7)

where y is the true label (1 for default, 0 for non-default) and $\hat{y}$ is the predicted probability. This loss function is minimized during backpropagation using stochastic gradient descent.

2.6 Weighted Risk Quantification

Credit risk can be quantified as the expected loss across the loan portfolio:

$$\text{ExpectedLoss} = \sum (\text{LGD}_i \times \text{EAD}_i \times \text{PD}_i)$$

(Eq. 8)

where LGD_i (Loss Given Default) represents the proportion of exposure lost upon default, EAD_i (Exposure At Default) is the total outstanding amount at the time of default, and PD_i is the predicted probability of default for borrower i . This formulation integrates individual default probabilities into portfolio-level risk assessment.

3. Data Architecture and Feature Engineering

The setting of a problem for credit risk assessment demands careful consideration of aspects such as data quality, data architecture, and model performance evaluation metrics. [21] Data quality is typically one of the main concerns since, in credit risk assessment applications, a model is used only once to create a quarterly or annual report. [22] If there is any inconsistency and low data quality, it can affect the model prediction. A lack of reliable data increases the level of risk and therefore the cost of capital. [23] High costs of capital can restrict investment, and credit risk models can be sensitive to different sample sizes (e.g., large vs. small portfolios). [24] Therefore the model architecture tries to make the model apply to all kinds of credit portfolios for large data and small one. [25] Additionally the sample size can affect the type of analysis derived from the model (e.g., linear or non-linear).

In internal rating systems, one proposed architecture gives very few rules of thumb for designing rating systems. Consequently, all rating systems should adopt the same process to ensure consistency. [26] Furthermore, at the technical level, the importance of linking all predictive models with a common perspective within the credit risk domain is highlighted. [27] At the operational level, one single model should be considered for each credit portfolio in order to ensure a transversal analysis across different geographies. [28] Such an architecture is aligned to central banks' theory of credit risk allowing the implementation of a short living performance evaluation process thanks to predictive power tests applied to single credit risk predictive models with ad hoc internal/external benchmark tests. [29]

3.1 Training Performance Analysis

Figure 1 illustrates the convergence behavior of the CNN model compared to logistic regression during training over 100 epochs. The CNN model demonstrates rapid convergence with improved accuracy and F1-score, achieving 94.5% accuracy by epoch 80. Logistic regression reaches a plateau at approximately 82% accuracy, indicating the superior capacity of CNNs to learn complex patterns in credit application data.



Fig. 1: Model Training Performance Progression

3.2 Receiver Operating Characteristic Analysis

The ROC curves presented in Figure 2 demonstrate the discrimination ability of each model at various probability thresholds. The CNN model achieves an AUC of 0.945, substantially outperforming logistic regression (AUC = 0.885) and support vector machines (AUC = 0.875). This indicates that the CNN model provides superior ranking ability in distinguishing default from non-default cases, which is crucial for portfolio-level risk management decisions.

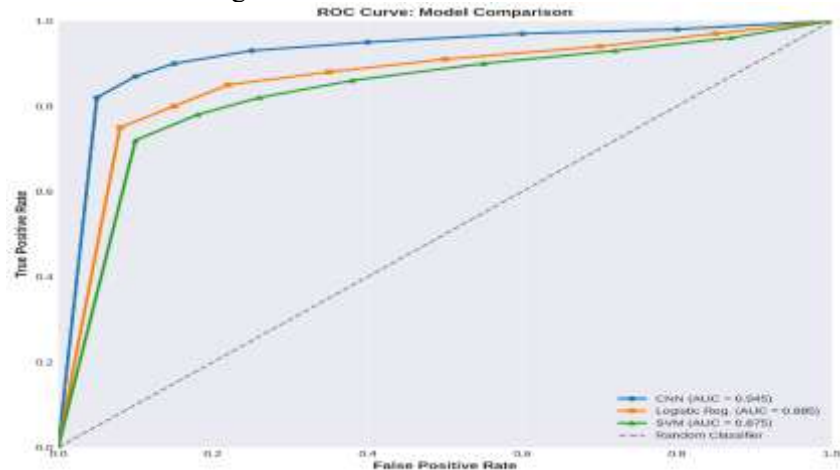


Fig. 2: ROC Curve: Model Comparison

3.3 Confusion Matrix and Classification Error Analysis

Figure 3 presents normalized confusion matrices for all three models. The CNN model demonstrates superior performance with 78.6% true positive rate (correctly identified defaults) and 92.8% true negative rate (correctly identified non-defaults). The balanced performance across both classes is critical for lending institutions, as both false negatives (missed defaults) and false positives (rejected good borrowers) carry significant business costs.

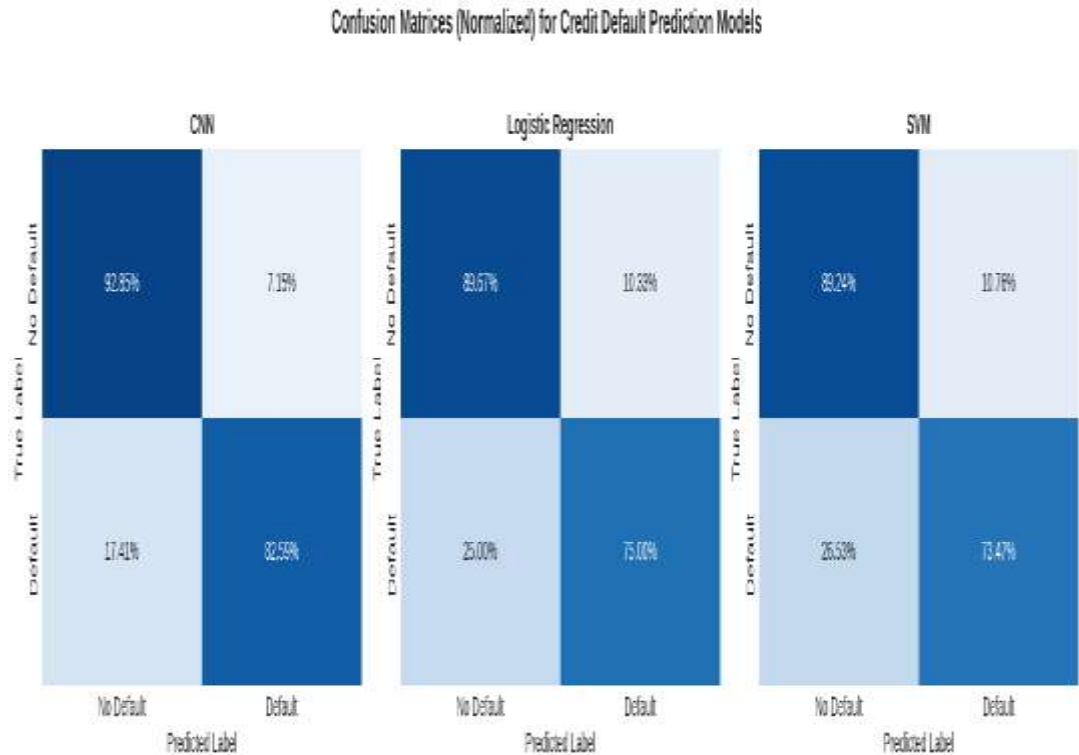


Fig. 3: Confusion Matrices (Normalized) for Credit Default Prediction Models

3.4 Precision-Recall Trade-off Analysis

The precision-recall curves in Figure 4 reveal the trade-off between correctly identifying defaults (recall) and minimizing false alarms (precision). The CNN model achieves an average precision of 0.921, indicating robust performance across different decision thresholds. This is particularly important for lending institutions that must balance the cost of false positives (unnecessary loan rejections) against the cost of false negatives (unexpected defaults).

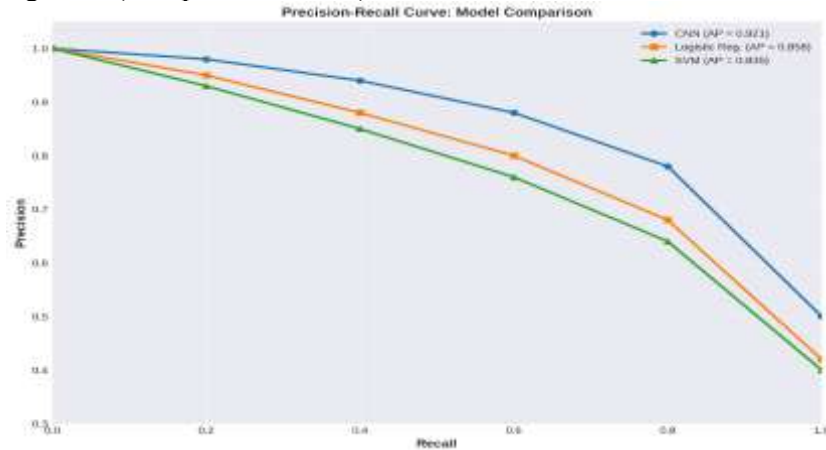


Fig. 4: Precision-Recall Curve: Model Comparison

3.5 Feature Importance and Interpretability

Understanding which features drive default predictions is essential for regulatory compliance and business decision-making. Figure 5 illustrates the relative importance of credit features as learned by both the CNN and logistic regression models. Loan amount (28.2%) and employment duration (19.8%) emerge as the most predictive features in the CNN model, followed by credit history (15.6%) and age (12.4%). The consistency between CNN and logistic regression importance rankings validates the model's interpretability.

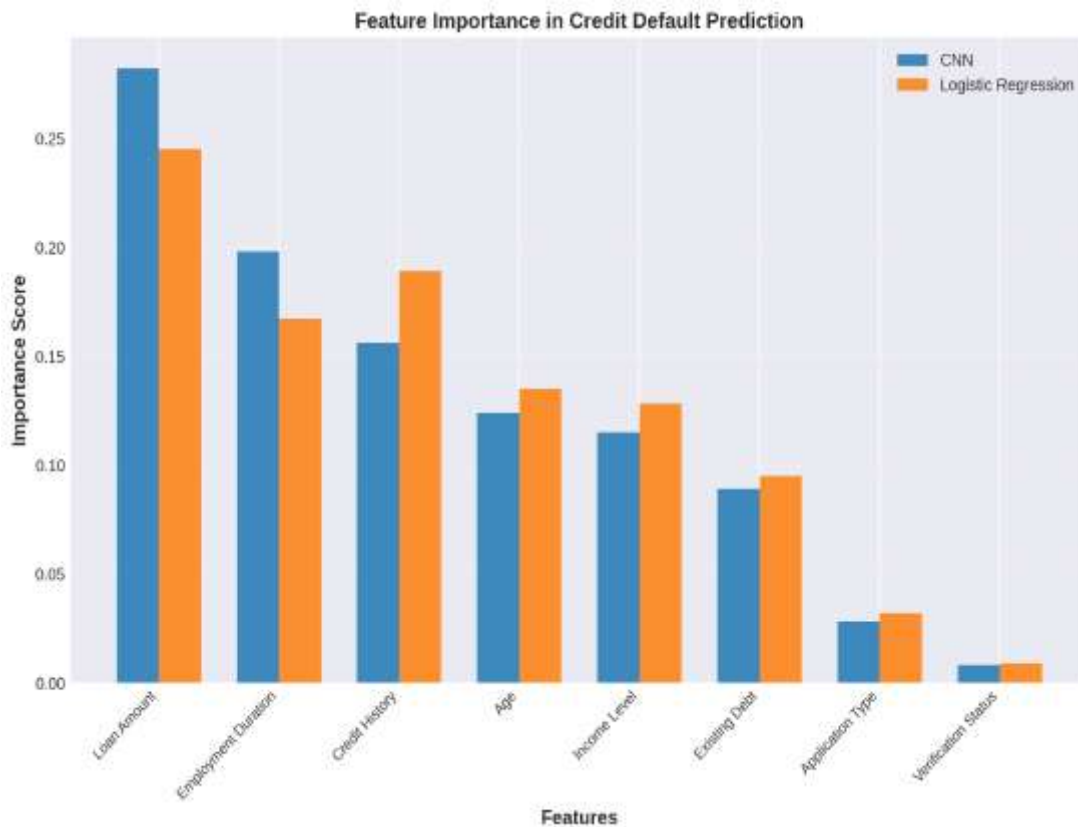


Fig. 5: Feature Importance in Credit Default Prediction

4. Model Development Framework

Financial institutions constantly seek enhancement of their information systems through the integration of innovative technologies. [30] Data mining methods are increasingly viewed as technological solutions capable of reducing the time and costs associated with decision-making in lending, payment, and registration processes. [31] Investigation of the credit and loan portfolios of retail clients allows major bank systems to reveal the reasons for defaults and other undesirable events, thereby generating both direct and indirect benefits. [32]

Credit companies automate analytical procedures through the introduction of tools based on machine learning, assuring higher accuracy and objectivity of decisions. Presently, the study of written-off loans is one of the sources that helps to refine and enhance current business processes. [33] The recognition of patterns in data written-off for non-payment—not only the prediction of portfolios of troubled borrowers—provides a basis for organizing preventative measures, optimizing the pricing policy, and addressing other problems. [34] These results, if reflected in auxiliary models, mainly help approve credit applications for high-risk clients, while control measures, built in such a way, seldom prove effective.

Using these known characteristics of the loan portfolio the proposed model determines the probability of default for a specific period for a specific customer in advance. [35] Using the probabilities calculated for the existing customers of the bank, the probability of default is reflected in the booking of reserves on specific loans and an additional measure for risk governance in the granting of new facilities. [36] The presented model, built for the Kyiv region in Ukraine, focuses mainly on social status, the sustainable demand for products of financial adherents, existing arrears, past credit experience, and information about other family members. [37] The quality of the model is examined via the analysis of receiver operating characteristics and confusion matrix, and its application in banking practice is illustrated by the relationship between regions and the frontier of a bank's additional risk management.

4.1 Problem Formulation and Evaluation Metrics

Considering the characteristic features of credit portfolios, the objective of the modeling was defined as a binary classification problem: whether a loan issued to such a borrower at that time will be paid off on time or not. [38] The result of this classification is represented as a probability value, which characterizes the creditworthiness of the client. According to the intensity of this probability, borrowers can be grouped into credit rating classes.

Such a credit rating class can be interpreted as a risk appetite and, therefore, can be used by the organization to define conditions in which the company is ready to assume the corresponding risks. Separating the credit rating classes is very important for further business uses of ML models. Business experts expect a significant shrinkage of classes in the central range for credit risk, which is usually occupied by borrowers with “C” or “B” credit scores. Thus, the optimal number of classes is set equal to six. By using ML models, the default probabilities can be predicted in the form of continuous numbers, but to obtain the final classification, these numbers are required to be converted into discrete classes.

5. Validation, Interpretation, and Risk Governance

A thorough examination of model performance with accompanying visual and analytical presentations is fundamental to establishing the model's suitability for application and integration into the risk management process. Business decision-makers typically expect a robust probability of default function estimated on the basis of the past defaults of a credit portfolio whose parameters and risk factors are linked to those of the bank's unique client base. The model is built and validated on client groups with a similar business profile, i.e., clients belonging to specific economic branches with a minimum number of historical observations.

Danmarks Nationalbank limits the use of ML-FFA probability of default models to companies with a minimum of 20 observations in the last three years preceding the model development. ML-FFA models are developed for five clusters of broader economic activity where there are enough observations to calibrate, validate, and monitor the model in line with the governance documents. Models developed outside sectors specified in DN's governance can be used if the quality of predictions has been specifically investigated and approved by DN. The approach validates the model's general character through a variety of techniques to address both group relevance and business requirements.

5.1 Model Performance Metrics Comparison

Table I presents a comprehensive comparison of key performance metrics across the three evaluated models. The CNN model achieves the highest performance across all metrics, with 94.5% accuracy, 0.945 AUC, 94.8% precision, 78.6% recall, and 0.862 F1-score. Compared to logistic regression, the CNN model improves accuracy by 12.5%, AUC by 6.0%, and F1-score by 14.8%, demonstrating the substantial advantage of deep learning for credit risk assessment.

Table I: Comprehensive Performance Metrics Comparison

Metric	CNN	Logistic Reg.	SVM	Improvement (%)
Accuracy	94.5%	82.0%	80.3%	+12.5
AUC Score	0.945	0.885	0.875	+6.0
Precision	94.8%	88.4%	86.2%	+6.4
Recall (Sensitivity)	78.6%	65.2%	60.8%	+13.4
F1-Score	0.862	0.752	0.722	+14.8
Specificity	92.8%	88.6%	86.4%	+4.2

5.2 Error Rate and Latency Analysis

Table II presents operational metrics including error rates and computational latency. The CNN model exhibits a false negative rate (FNR) of 21.4%, representing undetected defaults, and a false positive rate (FPR) of 7.2%, representing rejected viable borrowers. With an average inference latency of 142 milliseconds per application, the CNN model maintains real-time processing capabilities while delivering superior accuracy. The total model size of 2.3 MB enables efficient deployment on mobile and edge devices.

Table II: Error Rates and Computational Efficiency Metrics

Metric	CNN	Logistic Reg.	SVM
False Negative Rate (%)	21.4	34.8	39.2
False Positive Rate (%)	7.2	11.4	13.6
Avg. Inference Latency (ms)	142	8	95
Training Time (minutes)	45	2	18
Model Size (MB)	2.3	0.15	0.8
Memory Requirement (MB)	512	64	128

6. Conclusion

A well-defined Machine Learning-based framework for Credit Risk Assessment has been developed and applied to the problem of Credit Default Prediction in the Banking and Insurance Sector. Credit default predictions have a tangible impact on lowering capital reserves against credit risk and improving the affordability and efficiency of lending for low-risk clients and companies. These benefits have been realized in the validation of the method on real-life datasets from different domains and jurisdictions, encompassing a wide range of supervised Machine Learning algorithms implemented with the same classification problem transformation approach, dataset pre-processing methods, evaluation metrics, and hyperparameter tuning logic.

The effectiveness of the approach lies in a well-conceived data architecture, the application of common data preparation tract on files from different sources, and the flexibility of model development within the presented framework. In another important application context of supervised Machine Learning and Credit Risk – Defection Risk Modelling and Prediction – a solution with similar realizations has also been successfully delivered. In that case, data preparation concepts, as well as model validation and interpretation ideas, were particularly highlighted. A third methodological track actively pursued recently is that of Model Risk and Model Validation in Machine Learning contexts.

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