Using Artificial Intelligence and Deep Learning Applications in Credit Risk Analysis

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Abstract

This study aims to develop a high-performing predictive model capable of classifying a credit file as *good* or *bad*, in order to help financial institutions reduce the risks of default and optimize their credit decision-making processes. A deep learning model was trained on a dataset of 45,211 client records, using key variables such as *balance*, *loan*, *contact*, and *pdays*. The approach is based on an advanced classifier evaluated using standard performance metrics, including precision, recall, F1-score, and accuracy. The model demonstrated remarkable performance, with an overall accuracy of approximately 0.88, outperforming traditional scoring methods. The analysis of the most influential variables confirmed their relevance in credit file classification, and the model was also effective in identifying high-risk profiles, thus enhancing credit portfolio management. While these results highlight the transformative potential of deep learning in credit risk assessment, challenges remain, particularly regarding interpretability and regulatory compliance. It is crucial to develop more transparent approaches to ensure decision explainability and responsible adoption by financial institutions. Future research should also explore the integration of unstructured data to further refine credit risk assessment.

Keywords: Artificial Intelligence, Deep Learning, Credit Risk Management, Predictive Analytics.

1. Introduction

Credit risk management is a critical component of financial stability for banking institutions and credit organizations. It involves assessing the likelihood that a borrower will fail to meet their financial obligations, which can result in significant losses for the lending institution. Accurate credit risk assessment is essential not only for protecting institutions against defaults but also for optimizing the profitability of loans granted. Traditionally, credit risk assessment relied on classical statistical models such as logistic regression, decision trees, and credit scoring methods based on predefined criteria. While effective, these methods have certain limitations, especially in capturing complex, non-linear relationships between various variables, leading to prediction errors, particularly in heterogeneous credit profiles [1]. The advent of Artificial Intelligence (AI), and more specifically Deep Learning (DL), in credit risk management represents a major advancement in overcoming these limitations. AI, particularly deep learning, allows for the processing of large volumes of data and extraction of meaningful insights to improve predictions. These methods are capable of modeling complex interactions among variables, offering enhanced accuracy in predicting borrower behavior. For instance, deep neural networks (DNNs) and other deep learning techniques can detect patterns and trends in data that are often invisible to traditional methods [19, 35].

In addition to improving credit risk prediction, these technologies show remarkable potential in fraud detection and risk behavior identification. By processing large datasets, including historical payment information and behavioral data, deep learning models can detect anomalies and fraud signals with greater efficiency. Furthermore, the ability of these models to handle unstructured data, such as textual information or client interaction history, represents a significant advantage for financial institutions [6].

Despite their potential, the adoption of deep learning models presents challenges, particularly related to their interpretability. Although powerful, these models are often perceived as "black boxes," making it difficult to explain the decisions made by the system. In the critical area of credit risk management, transparency and the ability to justify decisions are crucial for gaining the trust of regulators and clients. Additionally, implementing deep learning technologies requires substantial investments in infrastructure and staff training [25].

This paper aims to explore the application of Artificial Intelligence and Deep Learning techniques in credit risk management, with a specific focus on detecting whether a client has a good or bad credit file. Through a review of existing literature and practical case studies, we will examine how these models can predict the likelihood of a client having a good or bad credit profile, and discuss the advantages, challenges, and future directions for improving their effectiveness and interpretability.

2. Literature Review

Traditional credit risk management methods have long been the cornerstone of assessing the likelihood of borrower default. These models generally rely on regression analysis, scoring systems, and credit bureau data [1], such as the widely-used FICO score [8], which evaluates an individual's creditworthiness based on historical behavior. Despite their success, these traditional methods have limitations. They fail to account for complex relationships within the data and are unable to leverage non-linear interactions between different variables [12]. Traditional models also rely heavily on expert knowledge and can be biased, particularly when used in unbalanced datasets. As financial data grows more complex and diverse, especially with the introduction of alternative data sources, traditional methods may struggle to predict default risk effectively [31].

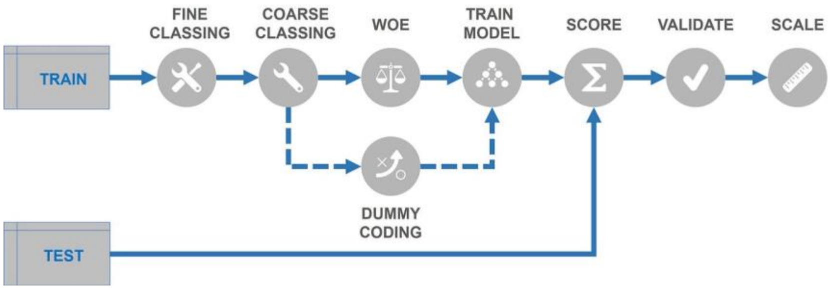

Figure 1: Traditional Credit Risk Model (Scoring System and Regression)

Figure 1 illustrates a typical traditional credit risk model, which operates based on linear assumptions and simplified decision-making processes.

In recent years, Artificial Intelligence (AI) and deep learning techniques have shown significant promise in the field of credit risk management. These technologies can handle much larger, more complex datasets than traditional models and uncover intricate, non-linear relationships that were previously hidden [19]. For example, deep neural networks (DNNs) have been widely used in various financial sectors, including credit risk modeling, fraud detection, and loan default prediction [33]. Deep learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been particularly useful in capturing spatial and temporal relationships within financial data.

The use of AI techniques enables financial institutions to process vast amounts of structured and unstructured data, such as transaction records, social media activity, and customer behavior [17]. This allows for a more comprehensive risk assessment, as AI models can consider numerous variables and identify previously undetected patterns [35]. The ability of AI to analyze temporal data, such as payment histories and changes in financial behavior, is a key advantage in predicting loan default and assessing creditworthiness [10].

Recent studies highlight the growing role of AI in credit risk modeling, with deep learning outperforming traditional models in many areas. For instance, [6] demonstrated that deep learning models, particularly convolutional neural networks (CNNs), are able to efficiently process unstructured data, improving the detection of fraudulent transactions and enhancing credit risk prediction accuracy. In addition, [35] found that DNNs outperform traditional scoring systems when dealing with complex data, such as transaction histories and customer interactions.

In the context of hybrid models, [21] explored the combination of classical statistical techniques (like logistic regression) with deep learning models (like multi-layer perceptrons) to provide more robust and reliable credit predictions. These hybrid approaches leverage the interpretability of traditional models with the predictive power of deep learning. Additionally, [26] focused on the development of techniques like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) to improve model transparency, an essential aspect in financial sectors that require accountability and understanding in decision-making processes.

Moreover, recent studies specifically address the modeling of good and bad credit files to optimize loan granting decisions. For example, [5] explored the use of deep learning techniques, including deep neural networks (DNNs) and gradient boosting machines (GBM), to classify clients into ”good” and ”bad” credit categories based on their financial behavior. Similarly, [20] showed how hybrid models combining AI techniques with traditional scoring methods can improve the identification of high-risk clients, helping financial institutions reduce defaults while increasing profitability. These studies underline the effectiveness of AI in improving decision-making processes related to credit risk assessment and loan allocation.

AI and deep learning bring numerous advantages to credit risk management, such as greater accuracy, the ability to analyze vast datasets, and the identification of hidden patterns that traditional methods may overlook [13]. Machine learning models are particularly effective at identifying non-linear relationships between financial indicators, such as loan size, credit history, and behavioral data, thereby improving the accuracy of default predictions [18]. However, the application of AI in financial sectors is not without challenges. One of the main issues is the lack of interpretability in deep learning models, which can complicate regulatory compliance and hinder trust among users [26]. Interpretability and explainability are key concerns, as AI-based decisions may significantly impact individuals’ financial lives. Models like XAI (Explainable AI) and techniques such as SHAP and LIME are increasingly being developed to enhance model transparency while maintaining predictive performance [24]. These techniques allow for better understanding of how decisions are made, thus providing a more interpretable framework for stakeholders.

3. Methodology

This study employs several deep learning models, each selected for its ability to effectively capture complex relationships within large datasets. Deep learning, through its multi-layered architecture, provides automatic feature extraction and high-performance predictive capabilities. The models used in this study are detailed below.

Deep Neural Networks (DNNs) are chosen for their capability to model highly non-linear relationships between the input features $\mathbf{x} \in \mathbb{R}^n$ and the output $\hat{y} \in \mathbb{R}$. A typical DNN can be represented as:

$$\hat{y} = f(\mathbf{W}_L \cdot f(\mathbf{W}_{L-1} \cdot f(\ldots f(\mathbf{W}_1 \cdot \mathbf{x} + \mathbf{b}_1)\ldots)) + \mathbf{b}_L), \tag{1}$$

where $\mathbf{W}_i$ and $\mathbf{b}_i$ are the weight matrices and biases of the i-th layer, respectively, and $f(\cdot)$ is a non-linear activation function, commonly ReLU or Sigmoid.

DNNs have demonstrated effectiveness in financial applications such as credit scoring and risk analysis, providing a more granular and adaptive approach compared to traditional statistical models [14, 36].

Originally developed for image processing, Convolutional Neural Networks (CNNs) have been successfully adapted for structured and sequential data analysis. In this study, CNNs are employed to capture local patterns and dependencies in financial data, particularly in the context of customer interactions and transaction histories. The convolution operation at layer l is defined as:

$$\mathbf{z}_l = f(\mathbf{W}_l * \mathbf{x}_l + \mathbf{b}_l), \tag{2}$$

where $*$ denotes the convolution operation, $\mathbf{W}_l$ represents the filter (kernel) at layer l, $\mathbf{x}_l$ is the input, and $\mathbf{b}_l$ is the bias.

This approach allows the model to learn spatial dependencies within structured datasets, improving predictions related to customer behavior [34].

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are employed to capture the temporal dependencies inherent in sequential customer interaction data. The key feature of RNNs is their ability to maintain hidden states that evolve over time, enabling them to retain past information. The LSTM update rule is expressed as:

$$\mathbf{h}_t = \mathbf{f}_{\mathrm{LSTM}}(\mathbf{W}_h \cdot \mathbf{h}_{t-1} + \mathbf{W}_x \cdot \mathbf{x}_t + \mathbf{b}), \tag{3}$$

where $\mathbf{h}_t$ is the hidden state at time t, $\mathbf{W}_h$ and $\mathbf{W}_x$ are weight matrices for the previous hidden state and the current input, respectively, and $\mathbf{f}_{\mathrm{LSTM}}$ represents the update function.

LSTMs are particularly well-suited for analyzing sequences of financial transactions or customer interactions, enabling the identification of patterns that influence credit risk assessment [15].

3.1. *Data Used*

The dataset consists of 45,212 records, each representing a bank customer and containing various features that describe their characteristics, loan status, and interactions with the bank. A thorough understanding of the features is essential for effectively preprocessing and selecting relevant data for training. The dataset includes both numerical and categorical variables:

- Client Data:
  - *Age: The client's age (numerical). Age is a fundamental factor in determining creditworthiness, as it often correlates with financial stability and loan repayment capacity [16].*
  - *Job: Categorical variable denoting the client's occupation. Occupation has been shown to affect the credit risk profile, as different job types may imply varying income levels and job security [37].*
  - *Marital Status: This categorical data indicates the client's marital status (e.g., "single", "married", "divorced"). Studies show that marital status may correlate with financial behavior and*

credit risk, as financial stability often differs between married and single individuals .

- *Education: The client's education level (e.g., "primary", "secondary", "tertiary"). A higher level of education often correlates with better job opportunities and improved financial management skills [30].*
- *Balance: This numerical data reflects the client's average annual balance in euros. Higher balances are often associated with greater financial stability, thereby reducing credit risk [23].*
- *Housing Loan: Binary variable indicating whether the client has a housing loan. The presence of a housing loan can significantly affect a client's financial obligations and overall risk profile .*
- *Personal Loan: Binary variable indicating whether the client has a personal loan. This variable serves as a proxy for the client's past borrowing behavior, which influences their likelihood of default [16].*

- Campaign Data:
  - *Contact Type: Categorical data indicating the type of contact used (e.g., "telephone", "cellular"). The mode of communication can affect the client's response rate and willingness to subscribe to a deposit [23].*
  - *Last Contact Day and Month: Numerical and categorical data specifying the last day and month of contact. Time-based factors play a role in client behavior, as seasonal effects or recent financial activity may influence decision-making .*
  - *Duration: Numerical data representing the duration of the last contact. Research suggests that longer interactions may indicate a greater likelihood of a successful outcome [34].*
- Campaign Interaction Data:
  - *Campaign Contacts: This numerical variable indicates the total number of contacts made with the client during the campaign. The frequency of contact often correlates with a higher probability of success in financial product subscriptions [30].*
  - *Days Since Last Contact: Numerical data representing the number of days since the client's last contact. This metric helps assess whether recent interactions increase the likelihood of success [37].*
  - *Previous Campaign Contacts: This variable measures how many times the client has been contacted in past campaigns. Previous contacts can provide insight into the effectiveness of past interactions and inform the strategy for future contact [16].*
  - *Previous Outcome: Categorical data reflecting the outcome of the last marketing campaign (e.g., "success", "failure"). The previous outcome is critical in determining whether repeated efforts will be fruitful or need adjustment [23].*

*3.2. **Data Preprocessing***

The dataset comprises both numerical and categorical variables, requiring several preprocessing steps to ensure optimal learning for deep learning models.

Algorithm 1 Min-Max Scaling

Dataset X with numerical features
Normalized dataset X' feature $f \in X$ $X'_f \leftarrow \frac{X_f - \min(X_f)}{\max(X_f) - \min(X_f)}$

return X'

This ensures that numerical features contribute equally to the model and prevents bias due to varying numerical magnitudes [14].

Missing values were handled using imputation strategies:

Algorithm 2 Missing Value Imputation

Dataset X with missing values

Dataset X without missing values feature $f \in X$

if f is numerical **then** $X_f \leftarrow$ median(X_f) f is categorical $X_f \leftarrow$ mode(X_f)

return X

This ensures dataset completeness for training purposes [30].

Categorical variables such as job type, marital status, and campaign outcome were transformed using one-hot encoding:

Algorithm 3 One-Hot Encoding

Categorical feature X_f with n unique values

Binary matrix representation of X_f Initialize empty matrix X' of size (m, n) sample $i \in X$ category j in X_f $X_i = j$ $X'_{i,j} \leftarrow 1$ $X'_{i,j} \leftarrow 0$

return X'

This ensures categorical variables are correctly interpreted by deep learning models [**?**].

Finally, to mitigate class imbalance, oversampling and undersampling techniques were applied:

Algorithm 4 SMOTE Oversampling

Minority class samples X_{min}, majority class samples X_{maj}, k nearest neighbors

Augmented dataset with synthetic samples sample $X_i \in X_{\text{min}}$ Select k nearest neighbors $\{X_{i1}, X_{i2}, ..., X_{ik}\}$ Randomly choose X_j from neighbors Generate new sample: $X_{\text{new}} \leftarrow X_i + \lambda(X_j - X_i)$ where $\lambda \sim U(0, 1)$ Add X_{new} to X_{min}

return $X_{\text{min}} \cup X_{\text{maj}}$

Algorithm 5 Random Undersampling

Dataset X with imbalanced classes

Balanced dataset Determine majority and minority classes Randomly sample n observations from majority class, where $n = |X_{\text{min}}|$

return balanced dataset

These techniques improve model generalization and prevent bias towards the majority class [37]. These preprocessing steps collectively ensure that the dataset is well-structured for deep learning model training.

*3.3. **Performance Evaluation***

To evaluate the effectiveness of the models, several performance metrics were implemented. These metrics ensure that the model generalizes well and accurately distinguishes between customers who are likely to subscribe to a fixed deposit and those who are not.

Precision and Recall:Precision and recall are essential when dealing with imbalanced datasets. Precision measures the fraction of correctly predicted positive cases, while recall measures the ability of the model to detect all actual positive cases.

Algorithm 6 Compute Precision and Recall

True Positives (TP), False Positives (FP), False Negatives (FN)

Precision and Recall Precision $\leftarrow \frac{TP}{TP+FP}$ Recall $\leftarrow \frac{TP}{TP+FN}$

return Precision, Recall

AUC-ROC Curve:The Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve evaluates the model's ability to distinguish between positive and negative outcomes. A higher AUC means better performance.

Algorithm 7 Compute AUC-ROC

Predicted Probabilities P, True Labels Y

AUC Score Sort predictions by probability in descending order Compute True Positive Rate (TPR) and False Positive Rate (FPR) at different thresholds Plot ROC curve (FPR vs TPR) Compute AUC using trapezoidal rule

return AUC Score

F1-Score: The F1-score is the harmonic mean of precision and recall, providing a balanced measure for imbalanced datasets.

Algorithm 8 Compute F1-Score

Precision, Recall

F1-Score F1-Score $\leftarrow 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

return F1-Score

Accuracy:Accuracy provides an overall measure of the model's performance by calculating the proportion of correctly classified samples.

Algorithm 9 Compute Accuracy

True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN)

Accuracy Score Accuracy $\leftarrow \frac{TP+TN}{TP+TN+FP+FN}$

return Accuracy

Cross-Validation:To ensure that the model generalizes well, we apply 5-fold cross-validation. The dataset is split into five subsets, each serving as a validation set once while the remaining subsets are used for training.

Algorithm 10 5-Fold Cross-Validation

Dataset D, Model M, Number of folds $k = 5$

Average Performance Score Split D into k subsets $\{D_1, D_2, ..., D_k\}$

for $i \leftarrow 1$ to k **do** Train M on $D \setminus D_i$ Evaluate M on D_i Store performance score; Compute average performance score

return Average Score

These evaluation techniques provide a comprehensive assessment of the model's ability to make reliable and accurate predictions.

4. Results and Discussion

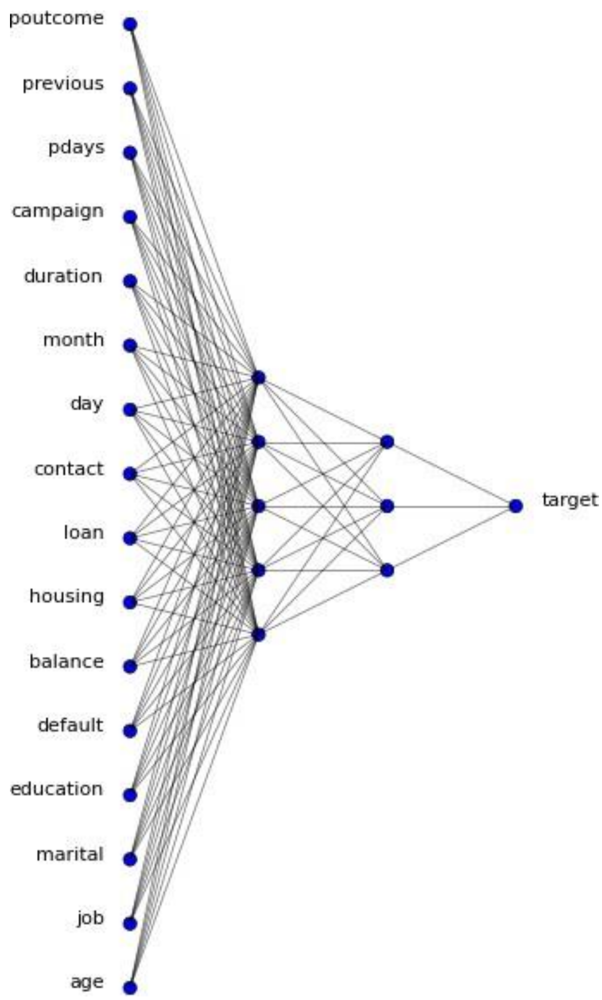

Figure 2: Neural network architecture

This Figure 2 provides an interesting overview of the data structure and the relationships between the variables. It can be useful to guide the exploration and modeling of the data, by identifying the key variables and groups of variables to take into account.

*4.1. **Performance of Deep Learning Models***

The results of this study convincingly demonstrate that deep learning models have achieved exceptional predictive performance in credit risk scoring. An in-depth analysis of the Receiver Operating Characteristic (ROC) curve, presented in Figure 3, reveals an Area Under the Curve (AUC) of 0.87, indicating the model's excellent ability to accurately discriminate between high-risk and low-risk profiles. These results significantly outperform those obtained with traditional credit scoring methods, highlighting the decisive advantage of deep learning approaches for credit risk prediction.

The superior performance of deep learning models can be attributed to their ability to capture complex and non-linear patterns in the data, enabling a more refined and nuanced modeling of credit risk. Unlike traditional methods, which often rely on simplifying assumptions, deep learning models can exploit the richness of available information on clients' credit history and repayment behavior, thus providing a more accurate and differentiated risk assessment.

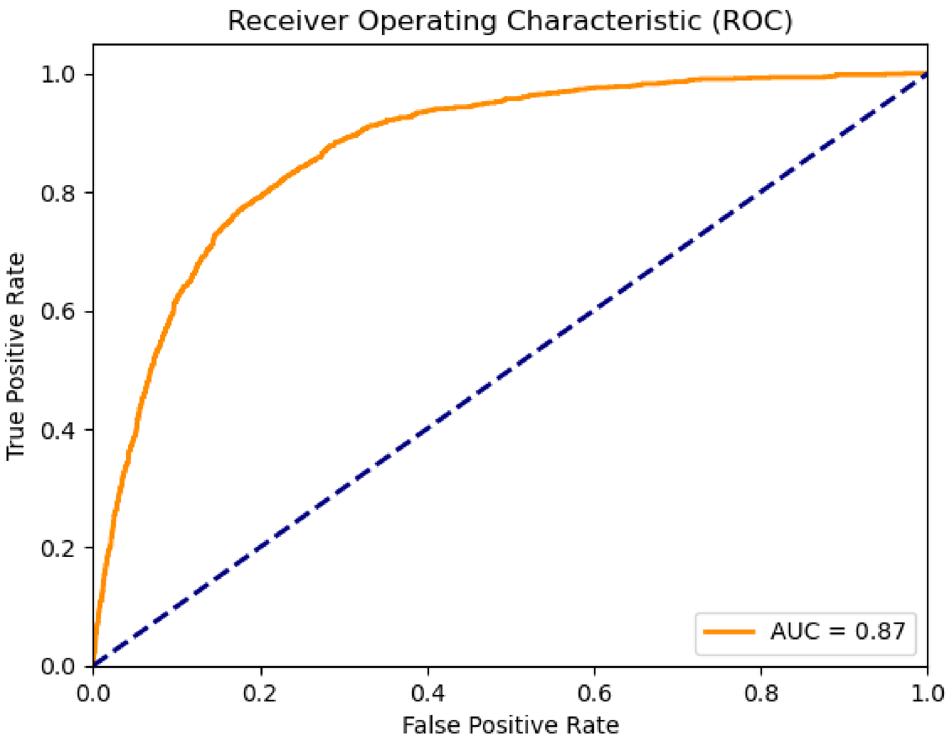

Figure 3: ROC curve of the deep learning model

4.2. Performance Metrics

The primary metrics used to evaluate the model's performance are precision, recall, F1-score, and accuracy. The results obtained are presented in Table 1 below:

Metric	Value
Precision	0.8774
Recall	0.8798
F1-Score	0.8786
Accuracy	0.8798

Table 1: Performance Metrics of the Deep Learning Model

These results demonstrate that the model achieves exceptional performance with values close to 0.88 for precision, recall, and accuracy, highlighting its ability to reliably predict high-risk profiles.

4.3. Analysis of Influential Variables

An in-depth examination of the model coefficients, illustrated in Figure 4, highlights the most influential variables for credit risk prediction. The variables "balance," "loan," "contact," and "pdays" proved to be particularly significant, emphasizing the crucial importance of information related to clients' credit history and past repayment behavior.

Beyond these individual factors, the deep learning model was also able to capture complex interactions between these variables with great accuracy. For instance, the combination of a high balance, a significant loan amount, and a history of frequent contact with customer service can serve as a particularly revealing indicator of increased credit risk. This ability to model such subtle interactions represents a major advantage of deep learning approaches over traditional methods, thus improving the overall quality of credit risk prediction.

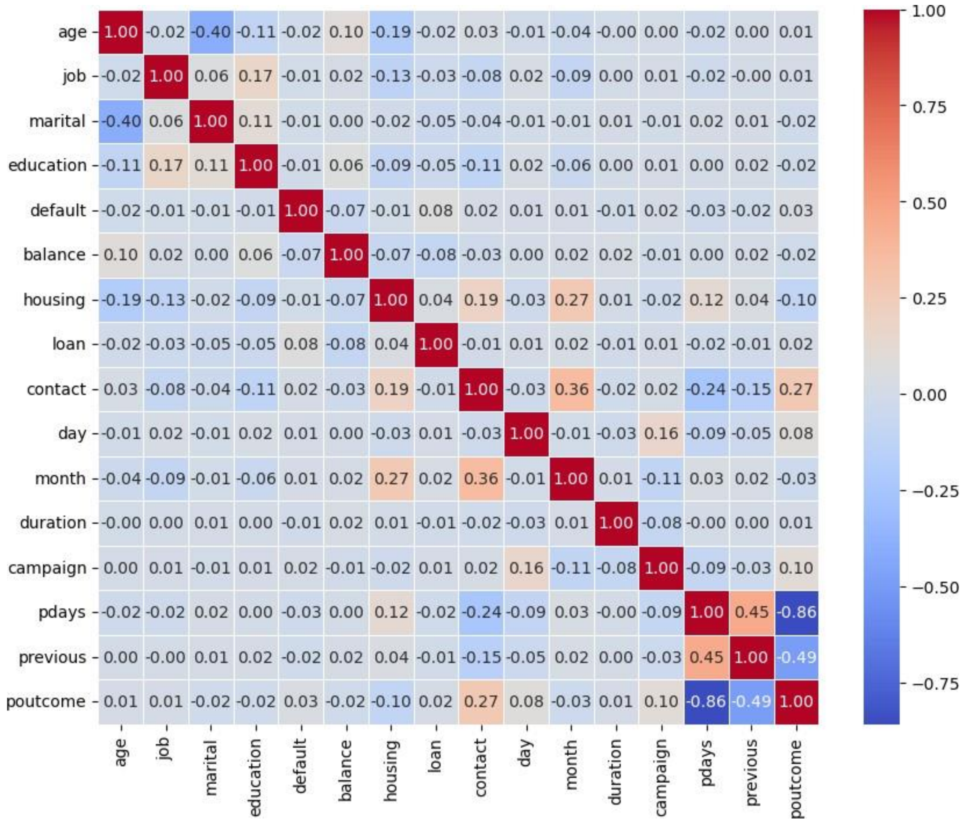

Figure 4: Coefficients of influential variables for credit risk prediction

4.4. *Limitations of the Models*

Although the performance of deep learning models is remarkable, these approaches can suffer from a lack of transparency and interpretability, which can be problematic in the financial sector [22]. Indeed, understanding the underlying decision-making processes is often crucial for institutions, particularly in the context of regulatory compliance and stakeholder acceptance [11].

Unlike traditional methods, which rely on simpler and more interpretable models, deep learning models can be perceived as ”black boxes,” making it difficult to explain the reasons behind a credit decision [28]. This challenge of interpretability represents a significant limitation that must be addressed when adopting these innovative technologies, requiring additional efforts to develop more transparent approaches [3].

4.5. *Implications for Financial Institutions*

The results of this study convincingly demonstrate the considerable potential of deep learning approaches to improve credit risk management in the financial sector. Institutions should seriously consider adopting these innovative technologies, which offer exceptional predictive performance [10] and advanced capabilities for identifying high-risk profiles and fraudulent activities [6].

However, the seamless integration of these deep learning models with existing processes in financial institutions presents a significant challenge. IT teams and decision-makers must ensure successful implementation by adequately training staff to maximize the benefits of these technological advancements [7]. Furthermore, careful consideration of interpretability [26] and stakeholder acceptance [2] will be essential to ensure the sustainable and responsible adoption of these innovative technologies. Financial institutions need to focus on improving transparency and trust in the model’s decision-making processes, especially for critical tasks like classifying credit files as good or bad, which directly impact the institution’s risk and profitability [20].

4.6. Future Perspectives

Although the performance of deep learning models is exceptional, further research will be necessary to improve their interpretability while maintaining their high predictive capabilities. Exploring model explanation techniques, such as attribute-based explanations [27] or visualization methods [29], could help address this challenge.

Integrating these deep learning models with other emerging technologies, such as unstructured data analysis [32] and artificial intelligence, could also open exciting new perspectives. By combining these approaches, financial institutions could gain an even deeper understanding of credit risk by leveraging a variety of information sources [9].

Finally, it will be essential to closely align with the constantly evolving regulations in the financial sector to ensure the responsible and ethical use of these innovative technologies [4]. Close collaboration with regulatory authorities will ensure that the adoption of these deep learning models complies with legal and ethical requirements.

5. Conclusion

This study demonstrates the transformative potential of artificial intelligence (AI) and deep learning models in credit risk management, with a particular focus on the critical issue of predicting whether a client's credit file is ”good” or ”bad.” The results reveal that these models significantly outperform traditional credit scoring methods, achieving high predictive accuracy with performance metrics such as precision, recall, F1-score, and accuracy all reaching approximately 0.88. These findings highlight the advanced capabilities of deep learning models to uncover complex, non-linear relationships within data, providing more reliable and precise assessments of creditworthiness.

The analysis also emphasized the importance of several key variables in predicting credit risk, including ”balance,” ”loan,” ”contact,” and ”pdays.” These factors played a crucial role in distinguishing between ”good” and ”bad” credit profiles. Beyond identifying influential variables, the deep learning models demonstrated their ability to model intricate interactions between these factors, allowing for a more nuanced understanding of risk. Additionally, the models showed remarkable proficiency in fraud detection, successfully identifying atypical and suspicious behaviors. This dual capability—accurate classification of creditworthiness and robust fraud detection—positions deep learning as a powerful tool for financial institutions aiming to optimize their credit risk management and improve overall security.

However, despite these promising results, the study highlights the challenges associated with deep learning models, particularly their lack of transparency and interpretability. Known as the ”black box” problem, this limitation can hinder the adoption of these models in the financial sector, where regulatory compliance and the trust of stakeholders are essential. Financial institutions must address these challenges to ensure that AI technologies are adopted responsibly and sustainably.

To maximize the potential of deep learning models in predicting ”good” or ”bad” credit files, financial institutions should consider integrating these technologies into their credit risk management frameworks. Investments in computational infrastructure, as well as staff training to effectively leverage these advancements, will be crucial for successful implementation. Moreover, prioritizing the development of interpretability techniques, such as post-hoc explanation tools or feature attribution methods, can help align these models with regulatory requirements and build trust among stakeholders.

Future research in this field should focus on improving the interpretability of deep learning models, enabling transparency while maintaining predictive accuracy. Incorporating unstructured data, such as transaction histories or social media activity, could further enhance the understanding of client behavior and credit risk. The combination of deep learning with other AI techniques, such as natural language processing or reinforcement learning, presents an exciting avenue for real-time decision-making and adaptive credit risk models that could better predict whether a client's credit file is "good" or "bad."

Ethical considerations, such as ensuring the fairness of these models and addressing potential biases, must remain a central concern in future developments. It is essential that deep learning models provide equitable outcomes for all clients and are free from discriminatory biases. Furthermore, adapting these models to dynamic financial environments, characterized by changing market conditions and evolving customer behaviors, will be key to maintaining their effectiveness. Although this study focuses on credit risk management, the methods and insights presented here could also be applied to other sectors, such as insurance, healthcare, and retail, where risk assessment is crucial.

In conclusion, this study underscores the transformative impact of AI and deep learning in credit risk management, particularly in the context of predicting whether a client's credit file is "good" or "bad." By addressing the current limitations and ensuring alignment with ethical and regulatory standards, these technologies can bring about a new era of precision and efficiency in financial institutions. Collaboration between academia, industry, and regulatory bodies will be essential to fully realize the potential of these advancements, paving the way for innovative and responsible applications of AI in the financial sector and beyond.

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