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Evaluating the Performance of Deep Convolutional Neural Networks and Support Vector Regression for Creditworthiness Prediction in the Financial Sector

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Abstract

Creditworthiness prediction plays a crucial role in the financial sector, where accurate assessments of individuals' credit risk are essential for making informed lending decisions. In recent years, the use of advanced machine learning algorithms, such as Deep Convolutional Neural Networks (DCNNs) and Support Vector Regression (SVR), has gained traction for creditworthiness prediction tasks. These algorithms offer unique capabilities for analyzing complex financial data and extracting valuable insights to effectively assess credit risk. This study develops and compares credit risk prediction models using DCNNs and SVR, leveraging two real-world financial datasets: the Bank Churners Dataset (10,127 records, 23 features) from Kaggle and a Personal Loan Dataset (5,000 records, 14 features) with a significant class imbalance. The datasets include variables such as income, credit limit, transaction history, and loan acceptance, which are critical for assessing financial behavior. Given the imbalance in both datasets (e.g., only 16.1 % of customers churned in the Bank Churners Dataset and 10 % accepted loans in the Personal Loan Dataset), we apply the Synthetic Minority Over-sampling Technique (SMOTE) to balance the classes and improve model performance. Evaluation metrics, including accuracy, precision, recall, and F1-score, demonstrate that SVR outperforms DCNN across key parameters, achieving an accuracy of 0.92, F1-score of 0.95, precision of 0.93, and recall of 0.97 on Dataset 1. In comparison, DCNN achieved an accuracy of 0.88, F1-score of 0.89, precision of 0.86, and recall of 0.91. On Dataset 2, while DCNN's accuracy improved to 0.93, SVR excelled with 0.98. These findings underscore the superiority of SVR in scenarios demanding high accuracy and precision, while DCNN offers a more balanced trade-off between precision and recall. This study provides actionable insights into selecting optimal models for credit risk evaluation, contributing to the development of reliable, data-driven financial systems.

Resumen

La predicción de la solvencia crediticia desempeña un papel crucial en el sector financiero, donde las evaluaciones precisas del riesgo crediticio de los clientes son esenciales para tomar decisiones crediticias bien fundadas. En los últimos años, el uso de avanzados algoritmos de aprendizaje automático, como las redes neuronales convolucionales profundas (Deep Convolutional Neural Networks, DCNN) y la regresión de vectores de soporte (Deep Convolutional Neural Networks, SVR), ha ganado terreno en las tareas de predicción de la solvencia crediticia. Estos algoritmos ofrecen capacidades únicas a la hora de analizar datos financieros complejos y extraer informa-

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ción valiosa para evaluar eficazmente el riesgo crediticio. Este estudio desarrolla y compara modelos de predicción del riesgo crediticio utilizando DCNN y SVR, aprovechando dos conjuntos de datos financieros del mundo real: el conjunto de datos de abandono bancario (10.127 registros, 23 características) de Kaggle y un conjunto de datos de préstamos personales (5.000 registros, 14 características) con un desequilibrio de clases significativo. Los conjuntos de datos incluyen variables como ingresos, límite de crédito, historial de transacciones y aceptación de préstamos, que son fundamentales para evaluar el comportamiento financiero. Dado el desequilibrio en ambos conjuntos de datos (por ejemplo, solo el 16,1 % de los clientes abandonaron la cuenta en el conjunto de datos de clientes que abandonaron la cuenta bancaria y el 10 % aceptó préstamos en el conjunto de datos de préstamos personales), aplicamos la técnica de sobremuestreo sintético de minorías (SMOTE) para equilibrar las clases y mejorar el rendimiento del modelo. Las métricas de evaluación, que incluyen exactitud, precisión, recuperación y puntaje F1, demuestran que SVR supera a DCNN en parámetros clave, logrando una exactitud de 0,92, una puntuación F1 de 0,95, una precisión de 0,93 y una recuperación de 0,97 en el Conjunto de datos 1. En comparación, DCNN logró una exactitud de 0,88, una puntuación F1 de 0,89, una precisión de 0,86 y una recuperación de 0,91. En el Conjunto de datos 2, mientras que la exactitud de DCNN mejoró a 0,93, SVR destacó con 0,98. Estos hallazgos subrayan la superioridad de SVR en escenarios que exigen alta exactitud y precisión, mientras que DCNN ofrece un mejor equilibrio entre precisión y recuperación. Este estudio proporciona información útil para seleccionar modelos óptimos para la evaluación del riesgo crediticio, contribuyendo al desarrollo de sistemas financieros confiables y basados en datos.

Keywords: Deep Convolutional Neural Network, Support Vector Regression, Synthetic Minority Oversampling Technique, Imbalanced dataset, Machine Learning, Creditworthiness Prediction.

1. Introduction

In the financial sector, accurate creditworthiness prediction is critical for informed lending decisions and risk management. Traditional statistical models, such as logistic regression, often fall short in capturing the non-linear patterns inherent in financial data. A comprehensive approach is needed that addresses users' attitudes and external factors to promote electronic banking services [1]. Machine learning (ML) approaches, including Deep Convolutional Neural Networks (DCNNs) and Support Vector Regression (SVR), offer promising alternatives for addressing these challenges. However, imbalanced datasets—where creditworthy borrowers vastly outnumber high-risk ones—pose significant challenges for these models, potentially skewing predictions and reducing reliability. Traditional statistical models, such as logistic regression, lack the capacity to capture complex non-linear patterns. Machine learning (ML) approaches, including tree-based algorithms, ensemble methods, and neural networks, have shown significantly higher accuracy and robustness in financial applications [2].

This study investigates the performance of DCNNs and SVR in predicting creditworthiness, focusing on their ability to manage imbalanced datasets. Synthetic Minority Over-sampling Technique (SMOTE) is employed to correct class imbalances, while advanced feature selection and preprocessing ensure robust model training. DCNNs excel in extracting intricate patterns from financial data, making them valuable for tasks such as fraud detection and credit risk forecasting. Conversely, SVR demonstrates robustness in handling noisy data and modeling complex relationships, offering a compelling alternative for credit risk assessment. By comparing the performance of DCNNs and SVR, the study aims to identify the more effective model for credit risk prediction with imbalanced datasets. These methodologies are analyzed for their impact on financial outcomes and performance metrics, leading to more precise credit risk assessments, especially in scenarios where most clients are classified as non-defaulters [3]. Despite these strengths, SVR's limitations include sensitivity to noisy features and lower adaptability to dynamic data. Additionally, its computational demands increase exponentially with the size of the feature space, which can hinder scalability in large-scale financial applications [4]. Using real-world datasets, this research evaluates the two models against key metrics, including accuracy, precision, recall, and F1-score, to determine their relative strengths. Results demonstrate that SVR achieves higher accuracy and precision in certain scenarios, while DCNN offers a more balanced trade-off between precision and recall. The findings provide actionable insights for financial institutions seeking to implement advanced machine learning techniques for reliable and efficient credit risk assessment, contributing to more stable and responsible lending practices.

The structure of this work is organized as follows. Subsection 2 reviews relevant literature on the application of DCNNs and SVR in credit risk prediction. Section 3 details the proposed methodology, including data preprocessing steps, the application of SMOTE for class balancing, and the architectures of the models. In Section 4, the experimental setup is described, followed by a comparative performance evaluation of the models using two real-world datasets. Section 5 discusses the model evaluation, presents the comparative performance of two machine learning models, evaluated across two datasets Deep Convolutional Neural Network (DCNN) and Support Vector Regression (SVR), and shows the performance metrics, highlighting the implications of precision, recall, and F1-score metrics for model selection. Finally, Section 6 summarizes the conclusions drawn and suggests future research directions, such as exploring hybrid approaches and ensemble models to enhance prediction accuracy and robustness.

2. Literature review

A sophisticated neural network-based model for predicting credit card loan risk has been developed. This model is highly suitable for commercial banks assessing borrower creditworthiness [5]. Incorporating a Deep Convolutional Neural Network (DCNN), allows for efficient feature reuse and multi-calibration, improving the precision of credit risk prediction, even with imbalanced data. Additionally, the Focal Loss function addresses disparities between sample data and challenging instances, further enhancing prediction accuracy. However, SVR, a regression technique, may be less effective with imbalanced datasets compared to DCNN [6]. Therefore, it is highly recommended to use DCNN methods for the prognosis of credit risk in datasets showing an imbalance.

Banks and financial institutions are investing heavily in improving algorithms and employing data analysis technologies to detect and combat fraudulent activity. A live system using deep neural network technology for credit card fraud detection has demonstrated significant improvements in accuracy, recall rates, and precision over existing solutions [7]. The prediction of credit risks is of substantial importance within the realm of finance, and machine learning techniques are increasingly being employed to tackle this dilemma. Notable advances have been made, such as the proposal of deep learning models, including Convolutional Neural Networks (CNNs) and Support Vector Machines (SVM), which aim to improve the overall effectiveness in predicting credit risk outcomes.

[8] proposed a hybrid ensemble learning model combining Convolutional Neural Network (CNN) and Agile Temporal Convolutional Network (ATCN). The Conditional Tabular Generative Adversarial Network (CTGAN) is a concept introduced in this study to identify potential defaults or bad debts in the finance sector. It suggests using a CNN-ATCN hybrid ensemble learning model to simultaneously extract static and dynamic features. While the TCGN extracts temporal dependencies, CNN is used for finance attribute learning. Two real-world datasets were used to validate the model, and results demonstrated that CTGAN outperforms other deep learning models in multiple metrics and effectively addresses the issue of data imbalance.

An SVM with a polynomial kernel achieved an accuracy rate of 87 % on the original dataset. However, when trained on a high-dimensional dataset transformed by a pretrained DNN, its accuracy improved to 97.05 %. According to related reviews, this prediction model exhibits exceptional performance, reaching an accuracy rate of 97 %. This machine learning strategy is highly effective and adaptable to similar tasks. It not only demonstrates excellent performance in related works but also exceeds expectations in reviewed cases [9].

[10] proposed an unsupervised technique for detecting credit card fraud using autoencoders and cluster analysis. They implemented three hidden layers and used k-means clustering on a European dataset to test their approach. The effectiveness of the suggested model is compared to conventional detection techniques using a large dataset of credit card transactions. The outcomes show that the autoencoder-based clustering strategy reduces false positive rates and greatly improves detection accuracy. This study advances the field by demonstrating the promise of deep learning, providing a robust framework for real-time fraud detection.

[10] also compared deep neural networks and gradient boosting machines (GBMs) for credit score prediction. The results demonstrated that GBM exhibited faster processing capabilities and greater effectiveness than DNNs due to its relatively lower computational demands [11]. Additionally, a comparison of Bayesian networks with artificial neural networks (ANNs) for predicting credit operation recovery va-

lues found that ANNs are more efficient tools for predicting credit risk than the Naive Bayesian (NB) approach [12]. The SVM model with a polynomial kernel shows the highest accuracy and AUC value, making it effective for classifying prospective customers into good or bad credit classes, helping banks reduce bad credit risk [13]..

The Wisconsin Breast Cancer Database illustrates issues with imbalanced classes, where precision benefits the majority class, neglecting the minority class. To address class imbalance, oversampling methods like the Synthetic Minority Oversampling Technique (SMOTE) and Random Oversampling are employed. Tree-based machine learning methods such as Random Forest, Adaptive Boosting, and Extreme Gradient Boosting are used to improve performance. These methods enhance the performance of the XGBoost algorithm in breast cancer prediction, achieving a 10-fold cross-validation accuracy of 0.98 [14].

Other research compares the performance of ensemble deep learning methods based on decision trees with traditional logistic regression and benchmark machine learning methods, such as support vector machines, finding boosted decision trees to be the most successful [15].

ATCN introduces advances that surpass traditional temporal convolutional neural networks by incorporating residual connections to enhance depth and accuracy, along with separable depth-wise convolution to optimize computational complexity. ATCN demonstrates remarkable results in various embedded and cyber-physical applications, maintaining accuracy while significantly improving execution time. ATCN is notable for being the first time-series classifier based on deep learning techniques that can be executed on embedded microcontrollers with limited computational performance and memory capacity. Despite these limitations, ATCN achieves state-of-the-art accuracy levels. Comparative analyses highlight that while DCNNs excel in recall, making them suitable for detecting rare defaulters, SVR provides superior precision, which is critical for minimizing false positives. Baharani and Tabkhi noted that SVR demonstrates consistent performance across datasets with varying structures, while DCNNs may struggle with noisy or sparse features. The choice of model often depends on the application's priorities, whether reducing false positives or ensuring comprehensive detection of at-risk borrowers [16].

3. Proposed methodology

Deep learning techniques have proven to be more effective than traditional machine learning and statistical methods in various domains, particularly in the field of credit risk assessment. However, to fully harness the potential of these approaches, several key considerations must be addressed. First, novel techniques are required to mitigate data imbalances that frequently occur in financial datasets. Second, there is a need for comprehensive legal frameworks to address default cases and ensure efficient resolution through method-specific interventions, especially in situations where data inconsistencies exist. Third, improvements to machine learning strategies are necessary when working with specific data scenarios, ensuring that the models adapt to various conditions. Finally, it is crucial to rigorously test enhanced deep learning models in the context of credit risk classification tasks, ensuring their practical applicability and robustness in real-world settings [19].

The methodology for this study is outlined in Fig. 1, which presents a clear, step-by-step approach to processing the dataset, training the models, and evaluating the results for accurate credit risk predictions.

1. Input Data (Dataset): Raw credit-related data is collected, including financial attributes like credit history, income, and outstanding debt.

2. Data Preprocessing: Data is cleaned, relevant features are selected, missing values are handled, and normalization/standardization is applied to prepare the dataset for machine learning.

3. Class Balancing (SMOTE): To address the imbalance between creditworthy and high-risk borrowers, the Synthetic Minority Over-sampling Technique (SMOTE) generates synthetic samples for the minority class.

4. Model Training: Two models are trained:

[1]Data archives, https://pages.stern.nyu.edu/ adamodar/New_Home_Page/dataarchived.html

Cuadro 1: Summary table of literature reviews.

Author	Problem Addressed	Machine Learning Methods	Accuracy	Limitations	Dataset Types
[8]	Credit scoring model in imbalanced data based on CNN-ATCN	Agile temporal convolutional network (ATCN), Convolutional neural network (CNN)	CNN 91 % TCN 80 %	Lack of data dimensions	Chinese commercial bank, UCI dataset
[17]	Deep Learning-Based Model for Financial Distress Prediction	Adaptive whale optimization algorithm (AWOA), Deep neural network (DNN)	AWOA 95 % DNN 89 %	AWOA convergence speed is poor	Australian (DuaGraff, 2017), Analecta[1]
[9]	Cascade of Deep Neural Network & Support Vector Machine for Credit Risk Prediction	Deep Neural Networks (DNN), Support Vector Machine (SVM)	DNN 94 % SVM97 %	Classification problem	Kaggle dataset
[18]	Review of Performance of support vector machine approaches classifying defaulters & non-defaulters of a credit dataset	Support Vector Machine (SVM)	German 74.3 %, Australian 89.1 %, German 80.0 %, Australian Nil	Needs improvements in prediction accuracy	Australian, German, and Japanese from UCI
[19]	A Model Based on Convolutional Neural Network for Online Transaction Fraud Detection	Convolutional neural network (CNN)	CNN 94 %	Requires additional data on transaction sequences for better fraud detection	data support for this study is derived from the commercial bank B2C, internal data
[20]	Application of Deep Learning for Credit Card Approval: A Comparison with Two Machine Learning Techniques	Logistic Regression Model (LR), Support Vector Machine (SVM), Deep Learning (DL)	LR 86 % SVM 86 % DL 87 %	Limited dataset reduces accuracy and applicability	UCI dataset
[21]	To minimize risk assessment using support vector machine	Support Vector Machine (SVM), Logistic regression (LR), Ensemble	Australian: LR 84.1 %, SVM 85.5 %, Ens. 87.4 %; German: LR 73.9 %, SVM 74.1 %, Ens. 73.2 %	High cost in space and computation time for Ensemble methods	Australian and German dataset from UCI dataset
[22]	Credit card frauds scoring model based on deep learning ensemble	Convolution neural network (CNN), Auto-Encoder (AE), Recurrent Neural Networks (RNN), Ensemble Learning.	CNN 91 %, AE 93 %, RNN 91 %, ENSEMBLE 97 %	Long training and learning time, handling imbalance issue	Kaggle dataset
[23],	Credit card fraud scoring model based on deep learning ensemble	Random Over sampling + Random Forest, Random Forest + Random Over-Under sampling	90.1 %, 76 %	Output accuracy can be increased	German Credit dataset
[24]	Credit card fraud detection using artificial neural network	k-Nearest Neighbor (KNN), Machine learning (ML) and support vector machine (SNM)	KNN 99 %, ML 99 %, SVM 93 %	Imbalanced dataset.	N/A
[25]	An improved bank credit scoring model: a naïve Bayesian approach	Naives Bayesian algorithm	83.3 %	Number of instances was 690, too low for prediction accuracy	N/A

- Deep Convolutional Neural Networks (DCNNs): Automatically extracts features, applies ReLU for non-linearities, and uses backpropagation to minimize errors.
- Support Vector Regression (SVR): Maps input data to higher-dimensional space using kernel functions, optimizing margin width and minimizing errors.

5. Model Evaluation: Performance is assessed using metrics like accuracy, precision, recall, and F1-score, with cross-validation to ensure consistency and stability.

6. Output (Predictions): The trained models generate predictions classifying borrowers as creditworthy or high-risk, aiding financial institutions in lending decisions.

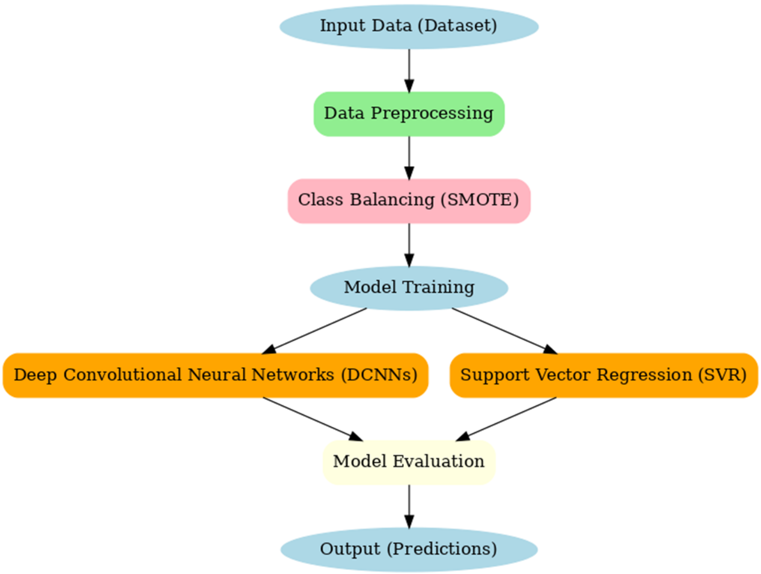

Figura 1: Methodoly.

3.1. Preprocessing data

To maintain data integrity and improve model performance, a comprehensive preprocessing strategy was implemented, addressing missing data, feature selection, normalization, and class imbalance.

3.1.1. Handling Missing Data

To prevent biases and ensure dataset consistency, missing values were identified and treated using appropriate imputation techniques:

- Numerical Variables: Mean imputation was applied to preserve the statistical distribution.
- Categorical Variables: Mode substitution replaced missing values with the most frequently occurring category, maintaining consistency.
- K-Nearest Neighbors (KNN) Imputation: Used in cases where feature relationships were significant, estimating missing values based on similarity among existing data points.

This methodology ensured dataset stability without introducing artificial variability.

3.1.2. Feature Selection and Engineering

To enhance computational efficiency and improve predictive accuracy, a systematic feature selection approach was employed:

- Correlation Analysis: Highly correlated features were removed to prevent redundancy and mitigate multicollinearity.
- Recursive Feature Elimination (RFE): An iterative process was utilized to retain only the most relevant predictors.
- Principal Component Analysis (PCA): Applied where necessary to reduce dimensionality while preserving essential variance.

Additionally, feature engineering was performed to create new, meaningful attributes, further enhancing the model's predictive capability.

3.1.3. Data Normalization and Standardization

Machine learning models are sensitive to variations in feature scales. To ensure numerical stability and efficient training, the following transformations were applied:

- Min-Max Normalization: Scaled numerical features to a standardized range [0,1] for uniformity.
- Z-score Standardization: Applied particularly for Support Vector Regression (SVR) to maintain a zero mean and unit variance, improving convergence.

3.1.4. Class Imbalance Handling with SMOTE

SMOTE is a powerful approach for addressing class imbalance in machine learning datasets. It creates artificial instances of the minority class by interpolating among existing examples.

The SMOTE algorithm follows these steps:

1. Identify class imbalances by comparing the distributions of minority and majority class instances.
2. Select each minority class instance and find its k-nearest neighbors.
3. Generate synthetic samples along the line segment between an instance and one of its neighbors, mathematically expressed as in Equation 1:

$$x_{new} = x_i + \lambda(x_j - x_i), \quad \lambda \in [0, 1] \tag{1}$$

This method creates synthetic examples along the line segment between x_i and x_j, effectively balancing the dataset. This ensures that the synthetic sample lies between the selected points, maintaining data diversity.

After applying SMOTE, the enriched dataset was used to train machine learning models, enhancing their ability to capture patterns while minimizing bias caused by skewed class distributions. By integrating these preprocessing techniques, the dataset was optimized for model training, ensuring accuracy and robustness in financial risk prediction.

3.2. Deep Convolutional Neural Networks (DCNNs)

Deep Convolutional Neural Networks (DCNNs) are a sophisticated class of artificial neural networks designed to effectively identify and learn complex patterns, features, and hierarchies from raw data. This capability makes them highly effective across a wide range of applications and extends their potential beyond traditional computer vision tasks. In particular, DCNNs show promising potential in structured data analysis, relevant to fields like finance and risk assessment. The structure of DCNN, as illustrated in Fig. 2, demonstrates the progression from raw input to classification.

Basic features of DCNNs

1. Convolutional Layers: DCNNs are built upon convolutional layers that apply trainable filters to input data. These filters systematically scan the input, capturing localized patterns, edges, and features. Initially, they detect basic features such as edges and progressively identify more complex structures.

2. Pooling Layers: Pooling layers in DCNNs downsample the feature maps generated by preceding convolutional layers. For example, max pooling selectively retains significant attributes while reducing spatial resolution. This approach helps preserve crucial information while reducing computational complexity.

3. Fully Connected Layers: Beyond convolution and pooling layers, DCNNs typically include one or more fully connected layers. These layers are responsible for making predictions or classifications based on the learned features. In financial domains, they can be used to assess credit risks based on predefined models.

4. Enabling Functions: Enabling functions, such as the Rectified Linear Unit (ReLU), introduce non-linearities into the network, allowing it to detect complex relationships within the data.

5. Training with Backpropagation: DCNNs are trained using backpropagation and gradient descent algorithms. These methods adjust the network's parameters (weights and biases) to minimize the difference between predicted and actual results during training;
$(OutputFeatureMap) = (InputFeatureMap) * (Filter) + Bias$
$ReLU(x) = max(0, x)$
$Output = Activation(Weight * Input + Bias)$

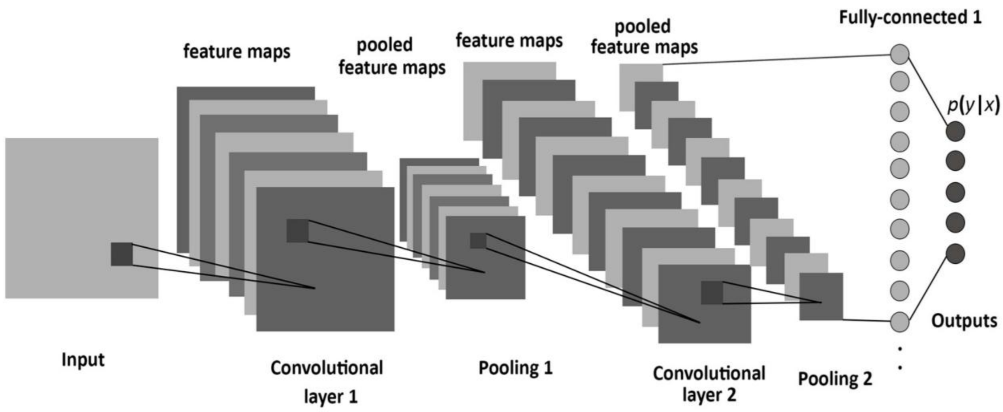

Figura 2: The structure of a DCNN, consisting of convolutional, pooling, and fully connected layers.

3.3. Support Vector Regression (SVR)

Support Vector Regression involves finding a regression function while maintaining a tolerance margin around the predicted values. The SVR problem is typically formulated as an optimization problem.

Basic Features of SVR

1. Margin Maximization: SVR aims to find a regression function that minimizes prediction errors within a specified margin while maximizing the width of this margin. This concept is similar to Support Vector Machines (SVM) for classification but is adapted for regression tasks.

2. Kernel Functions: SVR employs kernel functions (e.g., linear, polynomial, or radial basis function) to map input data into a higher-dimensional space. This mapping can make complex relationships between features more apparent, allowing SVR to capture non-linear dependencies in the data.

3. Support Vectors: In SVR, only a subset of data points, called support vectors, significantly influences the model. These support vectors are the data points closest to the margin and determine the structure of the model.

4. Regularization: SVR includes a regularization parameter that helps control the trade-off between the precise fitting of the training data and the maintenance of a simpler model. This is crucial to avoid overfitting, especially in financial applications, where noisy data can be prevalent.

Basic formulation Given a dataset of input-output pairs (x_i, y_i) where $i \in [1..N]$, x_i is the input vector of features and y_i is the corresponding output, the SVR problem aims to find a regression function $f(x)$ that minimizes the prediction error while allowing a tolerance ϵ for data points to fall within a margin.

Non-linear SVR (Kernel SVR) In the case of non-linear SVR, a kernel function is used to map the input data into a higher dimensional space. The SVR problem is then formulated in this transformed space, enabling the capture of more complex relationships within the data.

The regression function can be expressed as in Equation 2:

$$f(x) = \sum(\alpha_i \cdot K(x, x_i)) + b \tag{2}$$

where:

- $f(x)$ is the predicted output.
- α_i are the Lagrange multipliers.
- $K(x, x_i)$ is the kernel function that calculates the similarity between the input x and the training data point x_i.
- b is the bias term.

The optimization problem for non-linear SVR aims to find the Lagrange multipliers (α_i) and the bias term (b) that minimize the objective function of Equation 3:

$$\frac{1}{2} \cdot \sum(\sum(\alpha_i \cdot \alpha_j \cdot K(x_i, x_j))) - \sum(\alpha_i \cdot (y_i - b)) \tag{3}$$

Restricted to: $0 <= \alpha_i <= C \ \ \forall i$ and $\sum(\alpha_i \cdot (y_i - b)) = 0$

In this context, the regularization parameter C assumes a significant role in determining the balance between minimizing error and maximizing the margin.

The selection of different kernels, such as linear, polynomial, or RBF can greatly impact the performance of SVR. The optimal values of the Lagrange multipliers, denoted α_i, are derived by solving a quadratic programming problem. Once these values have been obtained, it becomes feasible to compute the regression function to make predictions.

Fig. 3 provides a visual representation of the SVR's approach to regression using non-linear kernel functions. The focus is on the use of kernel functions to handle non-linear relationships in the data. Concepts such as support vectors, margin maximization, and the role of regularization parameters are detailed.

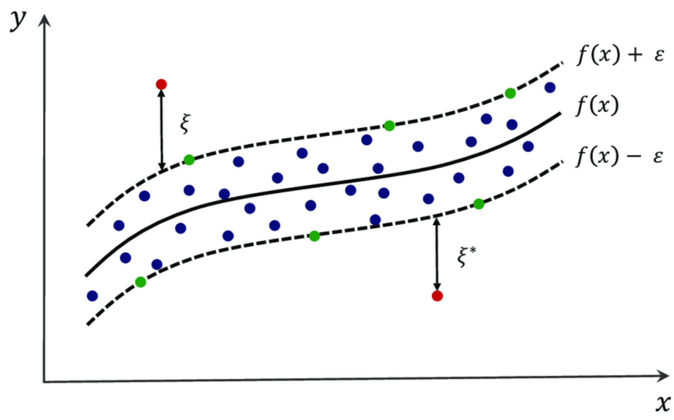

Figura 3: The structure of non linear support vector regression.

To perform a comparative analysis between SVR and DCNN for credit risk prediction purposes, an extensive dataset containing historical credit information is divided into training and testing subsets. Both models undergo training in identical datasets, with their performance subsequently evaluated using standard metrics, including accuracy, precision, recall, and F1-score.

The notion of accuracy encompasses the general correctness in a comprehensive manner. Precision, on the other hand, embarks on scrutinizing the faithfulness within affirmative forecasts. Meanwhile, recall concentrates its attention towards capturing each and every positive occurrence with utmost efficacy. Lastly, the F1-score delicately strikes a balance between precision and recall. All of these metrics serve as invaluable tools to understand and assess the efficiency of a classification model, particularly when discrepancies between false positives and false negatives carry dissimilar consequences.
$Accuracy = (NumberofCorrectPredictions/TotalNumberofPredictions) * 100$
$Precision = TruePositives/(TruePositives + FalsePositives)$
$Recall = TruePositives/(TruePositives + FalseNegatives)$
$F1 - score = 2 * (Precision * Recall)/(Precision + Recall)$

3.4. Model-Specific Considerations

While DCNNs and SVR are effective for credit risk assessment, they face specific challenges that impact their performance.

- DCNN Challenges: Prone to overfitting on imbalanced data, requires high computational power, and lacks interpretability. Mitigation strategies included SMOTE for class balancing, dropout regularization, and feature visualization techniques (Grad-CAM, LRP) to enhance transparency.
- SVR Challenges: Sensitive to noisy features, computationally expensive for large datasets, and struggles with imbalanced data. Solutions included feature selection (RFE, PCA), kernel optimization (RBF kernel), and SMOTE for data balancing.

Addressing these challenges improved accuracy, scalability, and interpretability, optimizing both models for robust credit risk prediction.

4. Result analysis and findings

4.1. Data collection

To identify the most accurate model for predicting financial distress, we utilized two distinct datasets to evaluate its performance. Initially, both datasets underwent loading and exploratory analysis to understand their structure and content. Data cleaning procedures included addressing missing values, removing irrelevant columns, and encoding categorical variables. Exploratory Data Analysis (EDA), through correlation heatmaps, was conducted to identify relationships among the features. Subsequently, the datasets were divided into training and testing subsets to facilitate effective model performance evaluation. We constructed pipelines to streamline the preprocessing and model training processes, and hyperparameter tuning was applied to optimize the model's performance. These preprocessing steps are vital for preparing the data for machine learning applications, ultimately enhancing the models' ability to accurately predict customer behavior.

The first dataset, Bank Churners Dataset[2], sourced from Kaggle, contains information on 10,127 customers with 23 features, such as age, salary, marital status, credit card limit, and credit card category. In this dataset, 16.1 % of customers have churned or become inactive, while 83.9 % remain active. The challenge posed by this dataset is its imbalance, making it difficult to train a model that accurately predicts customer loyalty.

To further examine the model's performance, we tested it on a second dataset comprising 5,000 observations with 14 variables, categorized into four measurement types. Notably, about 90 % of the customers in this dataset did not accept the personal loan offered in the last campaign, creating a significant class imbalance. This imbalance presents a challenge for the model, similar to the first dataset, as it must be able to accurately predict outcomes in a skewed distribution.

By applying the model to this second dataset, we aim to assess whether the model generalizes well to different data structures, variable types, and imbalanced classes, providing a broader evaluation of its predictive capabilities. To provide a clear understanding of the datasets, Tables 2 and 4 present the summary statistics of key numerical features, including their mean, standard deviation, minimum, and maximum values :

Cuadro 2: Descriptive statistics for key numerical features for dataset 1

Feature	Mean	Std Dev	Min	Max
Customer_Age	46.3	8.0	26	73
Months_on_book	36.9	7.9	13	56
Credit_Limit	8634.9	9087.2	1438	34516
Total_Revolving_Balances	1162.8	815.2	0	2517
Total_Trans_Ct	64.9	23.4	10	139
Total_Trans_Amt	3994.4	2276.3	510	18484
Total_Ct_Chng_Q4_Q1	0.76	0.22	0.0	3.71

Cuadro 3: Frequency distribution of categorical features for dataset 1

Feature	Categories	Frequency (%)
Gender	Male / Female	52.5 / 47.5
Marital_Status	Married / Single / Others	57.4 / 35.4 / 7.2
Education_Level	Graduate / High School / Others	53.7 / 27.3 / 19.0
Income_Category	<$40K / $40K-$80K / >$80K	23.3 / 33.4 / 43.3

4.2. Feature selection and engineering

Selecting and engineering the most relevant features is crucial for predicting creditworthiness or churn. This can be achieved using statistical methods, domain knowledge, or machine learning algorithms. In our study, a correlation matrix was employed to illustrate the relationships between different variables in the dataset.

Correlation coefficients help interpret these relationships: values close to 1 indicate a strong positive correlation, values close to -1 suggest a strong negative correlation, and values near zero imply little or no linear correlation between the variables.

[2]https://www.kaggle.com/code/josh1337/bankchurners/input

Cuadro 4: Descriptive statistics for key numerical features for dataset 2

Feature	Mean	Std Dev	Min	Max
Age	45.34	11.46	23.0	67.0
Experience	20.10	11.47	-3.0	43.0
Income	73.77	46.03	8.0	224.0
CCAvg	1.94	1.75	0.0	10.0
Mortgage	56.50	101.71	0.0	635.0
Personal Loan	0.10	0.29	0.0	1.0
Securities Account	0.10	0.31	0.0	1.0
CD Account	0.06	0.24	0.0	1.0
Online	0.60	0.49	0.0	1.0
CreditCard	0.29	0.46	0.0	1.0

As depicted in Fig. 4, the features “Avg_Open_To_Buy” and “Credit_Limit” exhibit the highest correlation. “Total_Transaction_Amount” has a correlation of 0.81 with “Total_Transaction_Count”, reflecting that the transaction amount typically increases with the number of transactions. “Customer_Age” and “Months_on_Book” show a correlation of 0.79, indicating that younger customers are more likely to have recently acquired a credit card. Conversely, “Avg_Utilization_Ratio” and “Avg_Open_To_Buy” have an inverse correlation of -0.54.

By analyzing these correlations, we can more effectively select and engineer features that enhance the predictive power of our model for assessing financial distress. This process ensures that the model focuses on the most significant variables, thereby improving its accuracy and robustness in real-world applications. Understanding these relationships allows for a more targeted approach in feature selection, which is crucial for developing reliable and efficient predictive models in the financial sector.

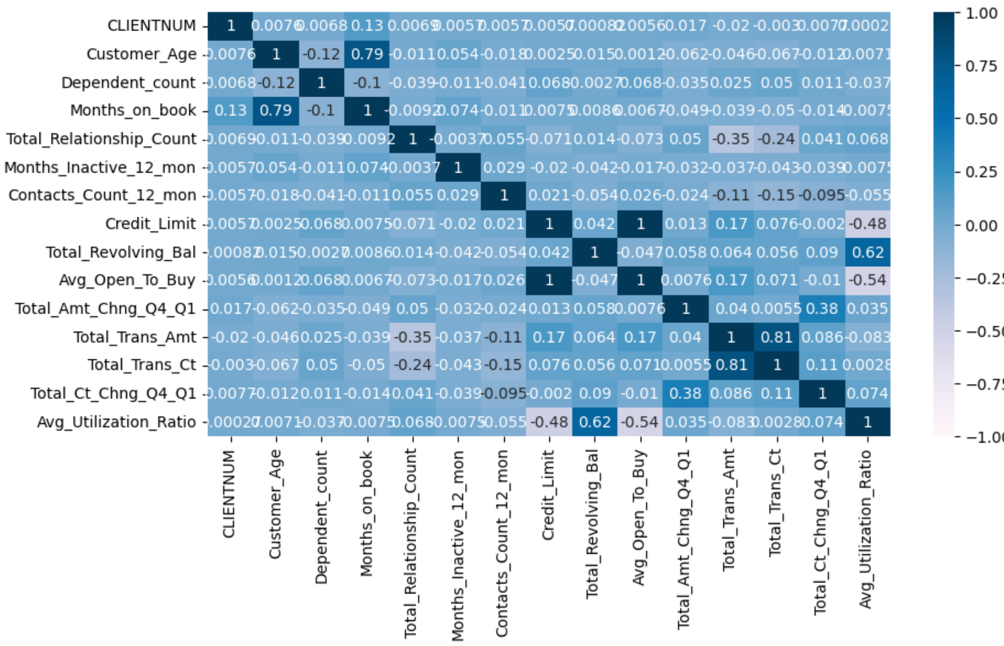

Figura 4: The correlation matrix for dataset1.

In the context of the Bank Personal Loan Modeling dataset[3], analyzing the correlation matrix (Fig. 5) provides valuable insights into how different features are related to each other and to the target variable, “Personal Loan” (which signifies whether a customer accepted a personal loan).

“Income” exhibits the highest positive correlation with “Personal Loan” (0.55), suggesting that income

[3]https://www.kaggle.com/code/farzadnekouei/imbalanced-personal-bank-loan-classification

is a significant determinant in whether a customer opts for a loan. This indicates that individuals with higher income levels are more likely to accept a personal loan offer.

Similarly, the variable “CCAvg” (credit card average spending) shows a positive correlation with “Personal Loan” (0.40), implying that customers with higher credit card spending are also more inclined to take out loans. This suggests that spending habits, reflected by credit card usage, can influence the likelihood of accepting loan offers.

“Education” demonstrates a moderate positive correlation with “Personal Loan” (0.35). This indicates that more educated customers may be more willing or financially capable of accepting personal loans, possibly due to better financial literacy or access to credit.

Lastly, “Mortgage” has a weak but positive correlation (0.15) with “Personal Loan”. Although the relationship is not strong, it suggests that customers with existing mortgages may still consider personal loans. However, this feature appears to be a relatively minor factor in the decision-making process for accepting loans.

This correlation analysis underscores the importance of income, spending behavior, and education level in predicting a customer’s likelihood to accept a personal loan, while mortgage status plays a more limited role.

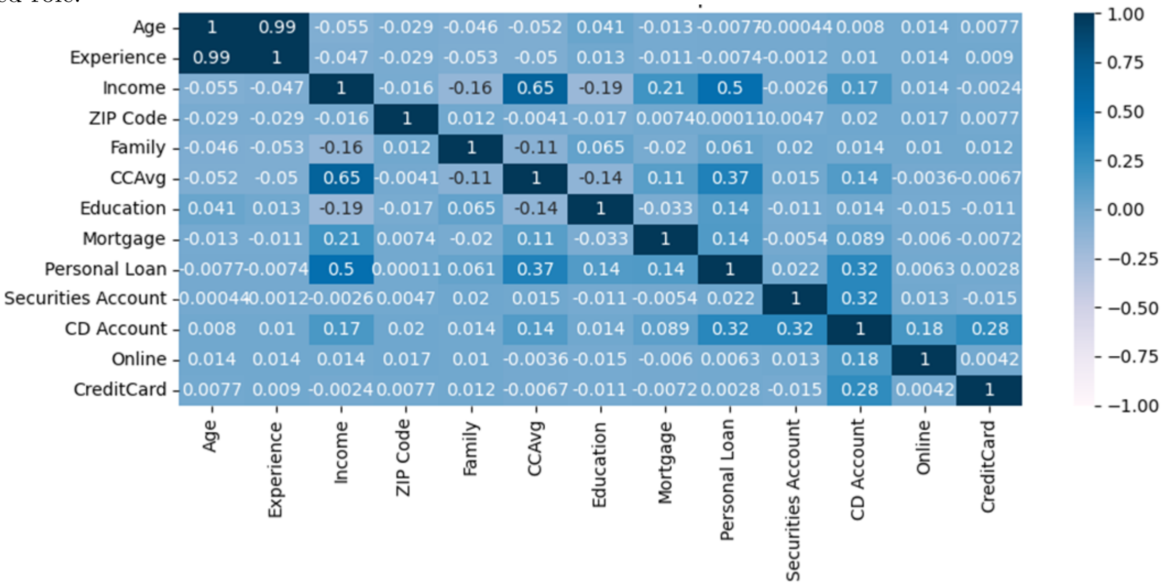

Figura 5: The correlation matrix for dataset2.

4.3. Data preprocessing and balancing

In this study, we employed two separate datasets: the Bank Personal Loan dataset and the Bank Churners dataset.

Bank Personal Loan Dataset This dataset was imported from an Excel file utilizing the Pandas library in Python. The initial data loading revealed insights into the dataset’s structure and provided descriptive statistics, aiding in the comprehension of feature distributions. We carried out essential data integrity checks to identify missing values and duplicate records, ensuring the dataset’s quality for further analysis.

To prepare the dataset for modeling, categorical variables such as “Family” and “Education” were converted to integer format. The feature matrix X was formed by omitting the target variable “Personal Loan” and the non-informative “ZIP Code” column. The target variable y indicated whether an individual accepted a personal loan.

Bank Churners Dataset Similarly, the Bank Churners dataset was obtained from a CSV file. We performed checks to detect missing values and duplicates, thus maintaining data integrity. Relevant features were selected, and categorical variables were transformed into integer values to create a suitable dataset for modeling. The target variable for this dataset, “Attrition_Flag,” was established as the dependent variable, while the remaining features were retained in X.

Both datasets exhibited class imbalance, a prevalent issue in financial datasets where the frequency of the target class is often much lower than that of the non-target class. To address this challenge, we implemented the Synthetic Minority Over-sampling Technique (SMOTE), which produces synthetic samples for the minority class. This oversampling technique ensured balanced representation of both classes, thereby enhancing the training process and improving model performance.

4.4. Model selection and evaluation

Deep Convolutional Neural Networks (DCNN) Convolutional Neural Networks (CNNs) are renowned for their superiority over other artificial neural networks due to their capability to process visual, textual, and audio data efficiently. The “to categorical” function transforms class vectors, typically represented by integers, into a binary matrix encoding each class in a one-hot format.

The Deep Convolutional Neural Network (DCNN) architecture comprises three primary layers: convolutional layers, pooling layers, and fully connected (FC) layers. The model architecture for Dataset 1 includes a single ‘Conv1D‘ layer with 20 filters, a kernel size of 1, and ReLU activation, designed to directly capture essential patterns from the data. This single convolutional layer allows for detection of simple feature dependencies within the dataset, making it suitable for data with minimal hierarchical complexity. Following this, a max pooling layer reduces the dimensionality of the feature map, prioritizing primary features while controlling computational demands. As a result of using a single convolutional layer, this model emphasizes primary feature detection, rather than extracting layered or complex hierarchies. The Fully Connected Layers component of this architecture comprises two dense layers with 100 and 50 neurons, respectively, culminating in a softmax output layer for classification. This configuration supports efficient feature learning, balancing computational efficiency with accuracy, though its simpler structure may limit the identification of more intricate patterns within the data.

In contrast, the model architecture for Dataset 2 integrates two ‘Conv1D‘ layers with 32 and 64 filters, respectively, and a kernel size of 2. This additional convolutional layer facilitates progressive feature extraction, enabling the model to capture complex patterns present in the dataset. Each convolutional layer is followed by a max pooling layer, which compresses spatial dimensions and enhances feature abstraction. This sequential design aids in identifying higher-order patterns within Dataset 2, which may involve more complex or hierarchical feature interactions. The Fully Connected Layer component in this model includes a single dense layer with 64 neurons before the softmax output layer. This structural choice increases the model’s ability to learn intricate patterns within the dataset while maintaining computational efficiency. To achieve a balanced class distribution essential for accurate model training, the dataset was divided into a training set (75 %) and a test set (25 %).

Model training was performed over 100 epochs with early stopping applied based on validation loss; training was halted when no improvement was observed over five consecutive epochs, thereby minimizing overfitting and ensuring the retention of optimal model weights.

To comprehensively assess the model’s classification performance, several metrics were employed, including precision, recall, F1-score, and ROC AUC score. These metrics were chosen for their ability to provide nuanced insights into model performance, particularly in binary classification contexts where class imbalance might impact predictive accuracy. ROC AUC (Receiver Operating Characteristic - Area Under the Curve) is a performance measurement for classification problems at various threshold settings. It provides a comprehensive evaluation of a model’s ability to distinguish between classes, specifically focusing on the trade-off between sensitivity (true positive rate) and specificity (true negative rate).

Support Vector Regression (SVR) The objective of Support Vector Regression (SVR) is to find a function that approximates the relationship between input variables and a continuous target variable while minimizing prediction error. To achieve optimal performance, a grid search method is employed. This method constructs a grid of hyperparameter values and assesses model performance for each combination.

To enhance the performance of the model, a grid search approach is implemented to systematically explore a range of hyperparameters. The primary parameters under consideration include:

- C: This is the regularization parameter that governs the trade-off between minimizing training error and reducing testing error.

- Kernel: This parameter specifies the type of kernel function utilized in the algorithm, including options such as sigmoid, radial basis function (RBF), and polynomial.

- Gamma: This parameter determines the extent of influence exerted by a single training example; lower values indicate a broader influence, while higher values suggest a more localized effect.

The grid search process incorporates 5-fold cross-validation, which is critical for ensuring that the model generalizes effectively to previously unseen data. Accuracy is utilized as the primary evaluation metric to guide the optimization process.

Binary transformation is a common practice when dealing with regression models that produce continuous values but need to be interpreted in a binary classification context. It allows for decisions based on whether the predicted value indicates a positive or negative outcome. The dataset is split into features and the target variable. A stratified train-test split is performed to maintain the distribution of the target variable, resulting in a training set comprising 70 % of the data and a testing set of 30 %.

The model is trained and evaluated five times, with each fold serving as a rotational test set. The cross-validation score, combined with the Accuracy, a metric used to measure real-world efficacy, helps determine the balance between false positives and true positives. Accuracy provides an independent assessment using a completely new set of data.

Both the cross-validation score and Accuracy are crucial for evaluating the overall performance and generalization ability of the SVR model. These metrics ensure the model's reliability and effectiveness in real-world applications

5. Model Evaluation

In summary, the performance metrics present the comparative performance of two machine learning models, **Deep Convolutional Neural Network (DCNN)** and bf Support Vector Regression (SVR), evaluated across two datasets using key metrics, namely **Validation Loss, Accuracy, F1 Score, Precision**, and **Recall**. Table5 shows the performance evaluation of the Deep Convolutional Neural Network and Support Vector Regression Models.

Cuadro 5: Performance Comparison of DCNN and SVR Across Two Datasets.

dataset	Model	Val-loss	Accuracy	F1 score	Precision	Recall	ROC AUC
1	DCNN	0.34	0.88	0.89	0.86	0.91	0.86
1	SVR	0.19	0.92	0.95	0.93	0.97	-
2	DCNN	0.17	0.93	0.92	0.94	0.91	0.93
2	SVR	0.06	0.98	0.87	0.92	0.82	-

Dataset 1:

- **DCNN**: Achieved a satisfactory performance, registering an accuracy of 0.88 and an F1 score of 0.89. The model maintained close values for precision (0.86) and recall (0.91). An AUC of 0.86 suggests that there is a good level of confidence in the model's predictions, meaning that when randomly selecting one positive instance and one negative instance, the model has an 86 % chance of correctly identifying which is which.

- **SVR**: Outperformed DCNN on most fronts, achieving higher accuracy (0.92), a superior F1 score (0.95), and greater precision (0.93) and recall (0.97). Additionally, SVR exhibited a significantly lower validation loss (0.19 versus 0.34 for DCNN).

Dataset 2:

- **DCNN**: Demonstrated a performance improvement, recording a higher accuracy (0.93) and a marginally reduced F1 score (0.92) compared to Dataset 1. The model also showed enhanced precision (0.94) and recall (0.91). An AUC of 0.93 reflects a higher level of predictive power and indicates that the model is likely to make better predictions than on Dataset 1.

- **SVR**: Attained a remarkable accuracy of 0.98 with a very low validation loss (0.06). However, despite its high precision (0.92), the F1 score dropped to 0.87 due to a noticeable decline in recall (0.82), suggesting some imbalance between precision and recall.

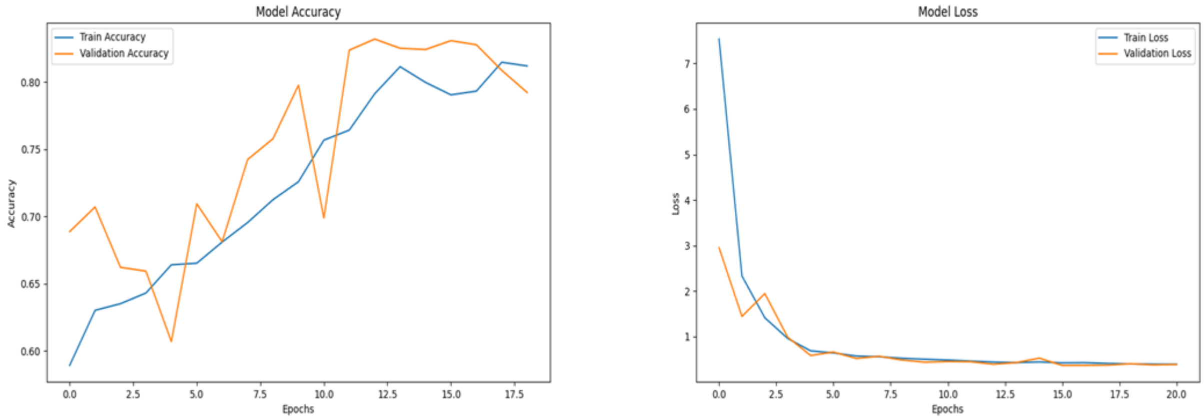

Figura 6: DCNN Model accuracy and model loss for dataset 1.

The Fig. 6 suggests the model is well-trained, with both training and validation accuracy improving and stabilizing over time. The convergence of training and validation metrics demonstrates good generalization to unseen data. The model shows steady improvement in accuracy and a consistent decrease in loss, both stabilizing after around 10 epochs. The validation accuracy's fluctuations in earlier epochs may indicate initial sensitivity to data variance but are resolved with further training.

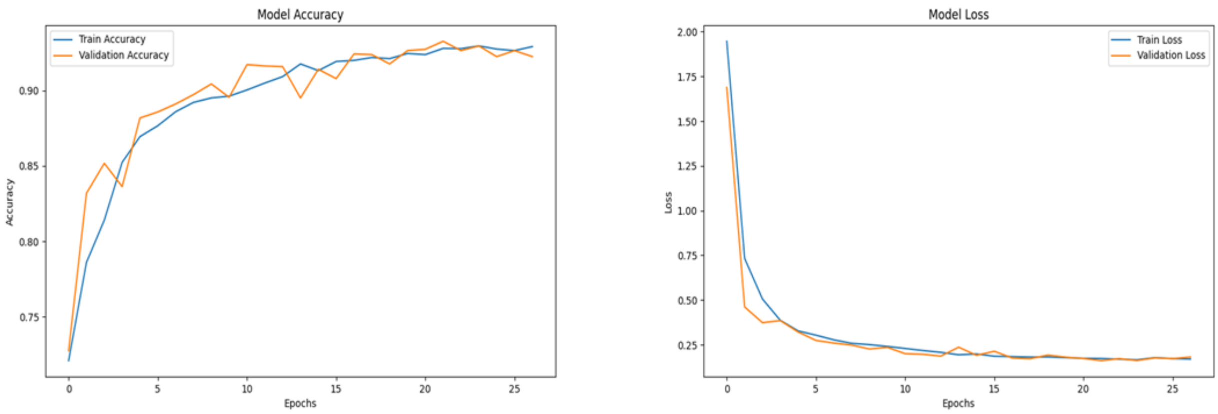

Figura 7: DCNN Model accuracy and model loss for dataset 2.

As can be seen in Fig. 7, the model exhibits strong performance, with training and validation accuracy converging and reaching over 90 %. Both training and validation loss decrease steadily and stabilize, indicating no overfitting or underfitting. The alignment of training and validation metrics suggests that the model generalizes well to unseen data.

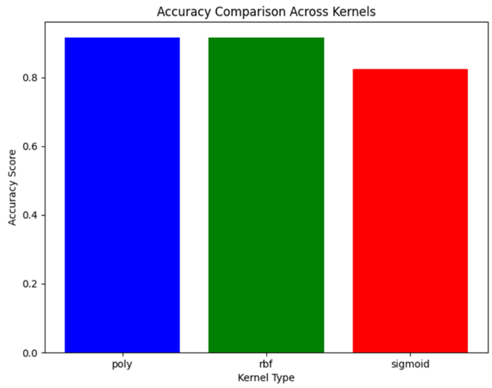

Figura 8: SVR accuracy comparison of kernels for dataset 1.

Fig. 8 shows that the poly and rbf kernels performed similarly and achieved high accuracy, while the sigmoid kernel had a slightly lower accuracy score. This suggests that the poly and rbf kernels are better suited for the dataset or problem at hand compared to the sigmoid kernel.

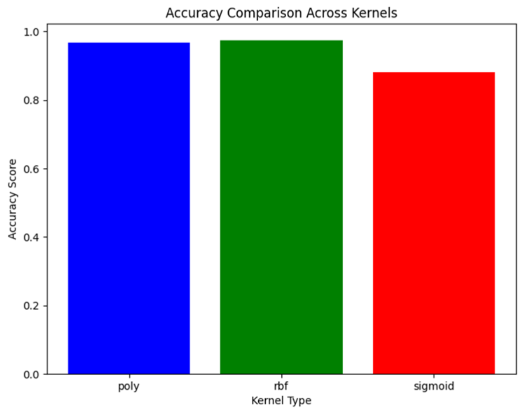

Figura 9: SVR accuracy comparison of kernels for dataset 2.

Fig. 9 suggests that Poly and RBF kernels are the top-performing options for the model in this context, with Sigmoid being a less optimal choice.

6. Conclusions and future work

This article evaluates the performance of Deep Convolutional Neural Networks (DCNNs) and Support Vector Regression (SVR) in addressing challenges posed by imbalanced datasets in credit risk assessment. The objective was to identify the most effective model for this scenario. Overall, SVR showed better performance in terms of validation loss and accuracy across both datasets. However, DCNN demonstrated a more consistent balance between precision and recall, particularly on Dataset 2, where SVR's recall declined despite maintaining high accuracy. This suggests that while SVR is more accurate overall, DCNN is better suited for applications that require a balanced trade-off between precision and recall.

Both models were assessed on a real-world dataset representing various creditworthiness characteristics, with data preprocessing steps such as Synthetic Minority Over-sampling Technique (SMOTE) applied to mitigate class imbalance. DCNNs, known for their ability to extract complex patterns from data, were compared with SVR, which excels in regression and classification tasks relevant to credit risk prediction.

While both models demonstrated strong performance with high validation and test scores, the choice between them depends on the problem's specific attributes and the precision-recall trade-off. SVR showed superior precision, whereas DCNNs outperformed in recall. This comparison underscores SVR's advantage in overall accuracy, but DCNN's strength lies in handling imbalanced datasets where recall is crucial.

The results have significant implications for the financial sector, particularly in predicting credit risk with imbalanced datasets. However, the selection of the kernel function in SVR can significantly impact its performance, though this choice is not always straightforward. DCNNs are prone to overfitting, especially with small, imbalanced datasets, which can impair generalization and accuracy. Careful regularization and architectural decisions are essential to mitigate this risk. Moreover, the quality of training data is critical, as imbalanced datasets may contain noise or anomalies that affect model performance.

Future research could explore ensemble methods and hybrid models that combine the strengths of DCNNs and SVR to enhance credit risk prediction further. Particularly in environments where timely response and precise identification are essential for online transactions, it is important to recognize that different sequences of characteristics can have varying impacts on model efficacy. Future efforts can focus on exploring sequence attributes within transactions and incorporating the Long Short-Term Memory (LSTM) algorithm to improve the model's capacity to identify transactions more accurately.

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