mathematics

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Credit Risk Assessment of Heavy-Polluting Enterprises: A Wide-ℓ_p *Penalty* and Deep Learning Approach

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Abstract: Effective credit risk assessment of heavy-polluting enterprises can achieve a balance between environmental and economic benefits. It requires the consideration of risk indicators for both the carbon information dimension and the compliance dimension. However, as the feature dimensions of the model continue to increase, so does the irrelevant feature or noise. Therefore, we investigate the use of non-integers for regularization from high-dimensional data under the conditions of a large number of irrelevant features. In this paper, a novel Wide-ℓ_p *Penalty* and Deep Learning (WPDL) method for credit risk assessment is proposed, which could provide a sparse solution. The Wide-ℓ_p *Penalty* component allows feature selection using a linear model with an ℓ_p *Penalty* regularization mechanism, where $0 < p \leq 2$. The deep component is a DNN that can generalize indicator features from the credit risk data. The experimental results show that the minimum prediction error occurs at a non-integer ℓ_p *Penalty*. Furthermore, the WPDL outperforms other models such as KNN, DT, RF, SVM, MLP, DNN, Gradient Boosting, and Bagging.

Keywords: wide and deep learning; ℓ_p *Penalty*; feature selection; non-integer regularization; credit risk assessment

MSC: 91G40; 68T07; 68T20; 62P20

Citation: Song, W.; Min, J.; Yang, J. Credit Risk Assessment of Heavy-Polluting Enterprises: A Wide-ℓ_p *Penalty* and Deep Learning Approach. *Mathematics* **2023**, *11*, 3462. https://doi.org/10.3390/math11163462

Academic Editor: Anatoliy Swishchuk

Received: 10 July 2023
Revised: 6 August 2023
Accepted: 8 August 2023
Published: 9 August 2023

1. Introduction

Effective credit risk assessment of heavy-polluting enterprises is critical to the growth of green lending by commercial banks and sustainable economic development. The objective of credit risk assessment for heavy-polluting enterprises is to reduce the carbon emissions of these enterprises while effectively predicting their credit default status, so as to protect commercial banks' green credit returns and achieve a balance between environmental and economic benefits. Previous studies have shown that there is a positive correlation between a company's environmental performance and its business performance, i.e., the better a company's environmental performance, the lower its environmental risk and the lower its credit risk.

From the perspective of enterprises' resource investments in carbon emission reduction, the cost of low-carbon transformation for heavy polluters is high, and the short-term benefits are low, so commercial banks lack the incentive to provide green credit to them without policy support factors. Credit resources are less likely to flow to such enterprises, which have a weaker ability to sustain commercial bank financing and a higher credit risk. At the same time, increased environmental regulation may weaken the financial position of companies, which in turn may lead to a higher default risk for commercial banks. In the long run, carbon emissions could threaten the sustainability of highly polluting companies and increase their left-wing and credit risks [1,2]. The regulatory uncertainty associated with high carbon emissions is perceived as a significant risk by investors, especially institutional investors [3], and carbon emissions have been identified as a significant risk to credit markets, affecting the ability of firms to raise debt finance.

From the perspective of the enterprises' carbon reduction performances, poor corporate environmental performance is often associated with lower credit ratings and higher bond yield spreads [4,5]. Siddique [6] argued that the disclosure of carbon footprint information would benefit companies. Trinks [7] found that lower carbon emissions increase resource efficiency, which supports financial performance. Velte [8] found that carbon performance reduces information asymmetries and increases firm value. Gallego [9] highlighted that achieving carbon neutrality increases the likelihood that firms will have higher recovery rates, thus lower default losses [10]. Firms' carbon reduction performances were negatively correlated with corporate bond default rates and systematic risk factors, and they were positively correlated with PE and PN ratios [11]. Attig [12] found that rating agencies tend to assign higher credit ratings to socially performing firms, which reduces corporate credit risk. Guangming [13] found a negative relationship between corporate social responsibility disclosure and corporate bond costs.

Considering the aforementioned issues, the main contributions to the current scientific knowledge can be summarized as follows:

- We integrate carbon elements into the credit risk assessment of heavy-polluting enterprises and combine compliance dimension risk indicators to effectively assess credit risks. It provides technical and strategic support for commercial banks to develop green credit. Meanwhile, it achieves a balance between the ecological benefits of enterprises and the economic benefits of commercial banks.
- With the increase in the feature dimensions of risk assessment models, the amount of task-irrelevant feature data or noise will also increase, which reduces the efficiency of models. This study proposes a method to implement feature selection based on a neural network framework using the ℓ_p *Penalty*. In previous algorithms, the regularization parameter was predetermined, i.e., the default $p = 1$ or $p = 2$, while the method we proposed in this study can take $0 < p \leq 2$. Feature selection can improve the interpretability of the model without changing the physical properties and data structure of the original features. Therefore, the method identifies key risk features and selects the optimal subset of features, providing decision support for firms to prevent and control credit risk.

The remainder of this paper is organized as follows. Section 2 describes the related work and research status in the credit risk assessment domain. Section 3 presents the details of the proposed Wide-ℓ_p *Penalty* and Deep Learning (WPDL) method. Section 4 describes multidimensional datasets, data description and processing, evaluation metrics, and experiment design. In Section 5, several experiments were conducted to comprehensively evaluate the proposed method. We display experimental results together with analysis in detail. Section 6 summarizes the paper and explores further research.

2. Related Work

2.1. Heavy-Polluting Enterprises Credit Risk Indicators

Scholars attempted to enrich and refine new elements based on the Basel Accord's credit risk monitoring indicators. For example, some scholars proposed concentration indicators and loan quality indicators [14,15], some proposed financial and non-financial indicators [16,17], and others proposed core and non-core indicators [18]. However, most of the studies were conducted mainly on financial institutions [19] and a few on enterprises [20]. Chen [21] examined the lenders' credit levels, asset structures, related party transactions, and financing [22] based on a combination of the behavioural strategies of government departments, financial institutions, enterprises, and other stakeholders.

Zhou [23] argued that the reasons for carbon credit risk are the international and domestic environmental protection policies, innovation of enterprises' low-carbon technologies, changes in enterprises' management objectives, and the influence of market demand. Referring to Yao [24], Yang [25] argued that financial capability, technological capability, governance structure, and external environment affect the ability of firms to reduce carbon emissions. Based on Chen [26], Tong [27] selected the indicator variables that affect the credit risk of enterprises from seven dimensions: enterprise carbon reduction capability, enterprise debt servicing capability, enterprise profitability, enterprise operational capability, enterprise development capability, enterprise-scale strength, and asset management capability. Rodrigo Zeidan [28] selected risk indicators in terms of economic growth, environmental protection, social progress, socio-economic development, eco-efficiency, and socio-environmental development.

Many banks now use the Equator Principles (Eps), which take account of environmental and social risks to assess the risks of project finance. Adams and Frost [29] found that companies are increasingly incorporating social and environmental indicators into their strategic planning. Weber [30] used environmental sustainability as a predictor of future financial performance and argued that banks should use it in their credit risk models. Capasso [31] analyzed carbon emissions, and Jung [32] analyzed the disclosure of carbon emissions on corporate credit risk.

2.2. Heavy-Polluting Enterprises Credit Risk Assessment Methods

The credit risk assessment model has evolved from expert judgement to artificial intelligence. The metric model is continuously enriched, and the metric mechanism evolves towards intelligence. It can be divided into three stages: first, models based on expert judgment and extensive analysis; second, models based on mathematical statistics; and third, models based on artificial intelligence.

At the stage of credit risk assessment models based on expert judgement and comprehensive analysis, enterprise credit risk assessment has just started. Risk assessment mainly uses the 5C analysis method, 5W analysis method, 5P analysis method, univariate analysis method, multivariate analysis method, credit scorecard, and other methods. The methods at this stage mainly use qualitative indicators and expert-assigned scoring methods, and the credit risk assessment mechanism lacks objectivity.

At the stage of credit risk assessment, based on mathematical and statistical models, the main models include discriminant analysis, hierarchical analysis, grey correlation analysis, Z-score model, principal component analysis, Fisher's discriminant analysis, fuzzy clustering, variable precision rough set, logistic model, KMV model, Credit Metric model, Credit Risk + model, VAR model, etc. These methods are computationally intensive and mainly use structured quantitative indicators, which are difficult to fully and objectively reflect corporate credit information. Previous studies used hierarchical analysis [33], hybrid grey correlation degree-TOPSIS [34], VAR models [35], and Credit Metric models [36] to assess the credit risk of firms.

Artificial intelligence-based credit risk assessment models make risk assessment more intelligent. These methods are based on computer intelligence that learns inference rules among data, constantly reducing metrics and prediction errors. As a result, these methods are more suitable for high-dimensional, complex problems. Decision tree [37,38], IDGSO-BP [39], belief rule-based (BRB) method [40], DCC-GARCH [41], SA-DP forest [42], SVM [43], DNN [44], ensemble and hybrid models with neural networks, and SVM [45] were used to improve the accuracy of risk assessment.

In practice, real-world datasets are used to develop credit risk assessment models, and such datasets may contain noisy data, missing values, redundant or irrelevant features, and complex distributions [46]. Data quality has a significant impact on predictive accuracy [47]. Most credit risk assessment studies have used a feature selection step as a preprocessing step to clean their data from any noise that may interfere with the training process [48–59]. Some scholars have also designed models based on highly noisy data. Orlova [50] developed new models for clustering and classification using digital footprint data. She proposed a borrower clustering model based on the k-means method and a borrower classification model based on the stochastic gradient boosting (SGB) method. Perko [51] proposed behaviour analysis methods for identifying patterns and assessing affinity.

Table 1 shows the advantages and disadvantages of the methods presented and their area of applicability.

Table 1. Comparison of credit risk assessment models.

Method		Advantages	Disadvantages	Applicability Area
Expert Judgement Methods	5C analysis method, 5W analysis method, And 5P analysis method	Initiated systematic work on credit risk assessment and developed a relatively stable assessment experience based on past information and historical data.	(1) Factors cannot be analyzed quantitatively. (2) Judgements are subjective.	Credit risk assessment based on qualitative indicators and expert scores
Comprehensive Analysis Methods	Univariate analysis method, Multivariate analysis method, and Credit scorecard			
Linear Analytical Methods	Discriminant analysis, Hierarchical analysis, Grey Correlation analysis, Z-score model, Principal Component analysis, Fisher's discriminant analysis, Fuzzy Clustering, and Logistic model	(1) Credit risk metrics have gradually established a metric system focused on default risk. (2) Overcomes the arbitrariness and subjectivity of expert system ratings.	(1) Computational complexity. (2) Relying on financial statement book data for simple linear analysis.	Credit risk assessment based on financial statement book data
Mathematical Methods	KMV model, Credit Metric model, Credit Risk + model, and VAR model	(1) Introduction of a wide range of mathematical and statistical methods for measuring credit risk. (2) Consideration of external factors.	The actual distribution of real credit risk data does not conform to the normal distribution assumption in most models.	Credit risk assessment based on a complete default database
Artificial Intelligence Methods	Random Forest, Decision Trees, SVM, Bayesian Networks, BP Neural Networks, and Deep Neural Networks	(1) Variables are not subject to strict assumptions. (2) Strong non-linear modelling capability. (3) High prediction accuracy.	(1) Prone to overfitting when dealing with noisy data. (2) Weak interpretability.	Accurate credit risk assessment based on large samples of high-dimensional data

In summary, most of the previous studies are ex post studies that focus on whether and how environmental factors affect corporate credit risk, but few scholars have conducted an ex ante early warning of corporate credit risk or proposed targeted carbon credit risk prevention strategies from an interpretable perspective. Meanwhile, early warning research on environmental credit risk at the corporate level faces the following challenges. First, there is a lack of reliable and continuous data sources [45]. Second, it is still difficult to quantify the environmental factors involved in the operation of companies, and there is a lack of consistent and comparable evaluation criteria between environmental and financial factors. Third, a comprehensive early warning indicator system for the credit risk of heavy-polluting companies has not yet been established.

2.3. Goals

Therefore, this paper's goals are as follows, which are different from previous studies:

- Goal 1: The risk assessment indicators highlight the carbon elements. By incorporating the concept of sustainable development, the carbon element is highlighted in the risk indicator system. It is built by integrating the carbon information dimension and the compliance dimension to enhance the relevance and practicality of risk assessment for heavy-polluting companies.
- Goal 2: Develop a novel ensemble model combining ℓ_p *Penalty* regularization with wide and deep learning. Obtain verification of the proposed solution based on the

credit risk assessment. Based on the credit risk indicator system that includes carbon elements, it achieves a high-accuracy risk assessment.

- Goal 3: The risk assessment model strikes a balance between accuracy and interpretability. We propose the WPDL method to select highly relevant indicators and trigger warning rules. The method improves the quality of risk data and reduces feature redundancy, solving the problem of risk feature over-dimensionality and model over-fitting. It guides organizations to understand the internal mechanism of risk assessment rules.

3. Materials and Methods

3.1. Main Assumptions

The main assumptions are as follows:

- Assumption 1: Conducted an experiment using the real-world dataset in order to objectively compare the proposed method to the current results.
- Assumption 2: Applied the non-integer ℓ_p *Penalty* into wide and deep learning.
- Assumption 3: By using the Default Distance (DD) estimated from the KMV model, the credit risk of heavy-polluting enterprises was carried out.

3.2. Dataset

The dataset consists of 974 samples, which are from listed Chinese companies in heavy-polluting industries during 2000–2022. Ministry of Ecology and Environment of the People's Republic of China has published the Environmental Information Disclosure Guidance for Listed Companies. It classifies 16 types of industries—including thermal power, iron and steel, cement, electrolytic aluminum, coal, metallurgy, chemicals, petrochemicals, construction materials, paper, brewing, pharmaceuticals, fermentation, textiles, tanning, and mining—as heavy-polluting industries. We excluded sample companies with ST, insolvent, more missing data, and extreme outliers, and we selected over 10,744 samples. The real dataset is described below:

- The frequency of the dataset is annual in order to assess the credit status of enterprises from a macro perspective;
- The data sources are the WIND database at https://www.wind.com.cn/ (accessed on 30 May 2023) and CSMAR database at https://www.gtarsc.com/ (accessed on 30 May 2023);
- For the data type, there are 32 categorical variables, such as green invention patent authorization, green utility model patent authorization, waste gas emission reduction and treatment, etc. from four dimensions: carbon emissions dimension, carbon performance dimension, carbon disclosure dimension, and carbon regulation dimension. The other indicators are numeric variables. The data type of the indicator system is shown in Table 2.

Table 2. Data type of credit risk indicator system.

Data Type	Indicator Dimension
Categorical Variables	6 indicators of carbon emission dimension, carbon performance dimension, carbon disclosure dimension, and carbon regulation dimension
Numeric Variables	8 indicators of carbon emission dimension, carbon investment dimension, solvency dimension, profitability dimension, operating capacity dimension, growth capacity dimension, cash flow levels dimension, and operations management dimension

3.3. Methods

In this section, we proposed the Wide-ℓ_p *Penalty* and Deep Learning (WPDL) method. Figure 1 shows the framework of the WPDL method:

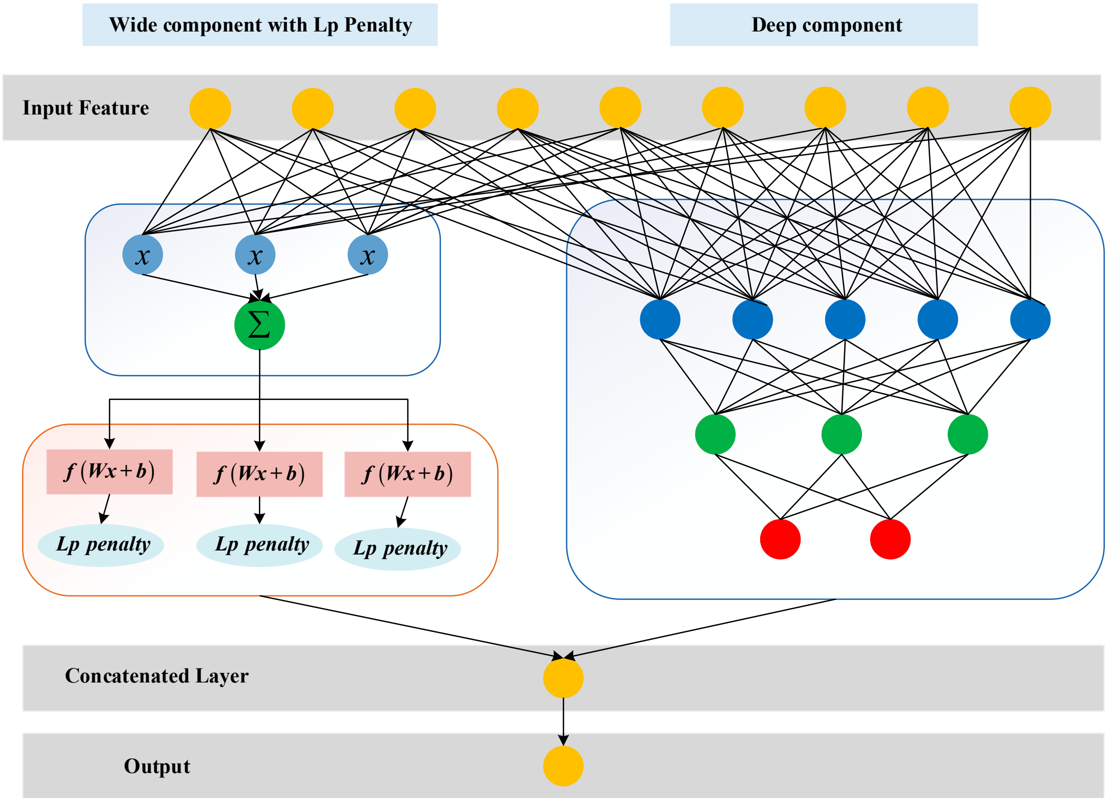

Figure 1. The WPDL framework.

Step 1: We constructed the enterprise credit risk assessment indicator system.

Step 2: We added the ℓ_p *Penalty* to the wide component to achieve interpretability of the model.

Step 3: A deep neural network was used as the deep component of the model.

Step 4: The concatenated layer combines the outputs of the wide component with ℓ_p *Penalty* and the deep component.

Step 5: We chose the Default Distance (DD) calculated using the KMV model as a measure of corporate credit risk.

This study constructs a mapping relationship between the credit risk index system X_t of heavy polluters and the credit risk (DD) Y_{t+1} of heavy polluters in the future period, and the WPDL method achieves the credit risk assessment of heavy polluters through learning and feature fitting of sample data.

3.3.1. Input: Credit Risk Indicator System

The current credit risk assessment indicators for heavy-polluting enterprises are mostly based on financial indicators. However, due to the industry characteristics of heavy-polluting enterprises and the characteristics of the carbon element of the research problem, the traditional financial information evaluation lacks advantages. Therefore, this study focuses on the carbon information element to reflect the impact of carbon emission reduction behaviour and green technology innovation on the credit risk of heavy-polluting enterprises. We highlight the carbon element in the risk indicator system and sort out the carbon information indicators of enterprises.

Specifically, we reflect the carbon information of heavy polluters from carbon investment, carbon emission, carbon performance, carbon disclosure, and carbon regulation, and we combine them with a large number of financial dimension indicators to build an early warning indicator system for the credit risk of heavy polluters.

Among the compliance dimension, we selected indicators including solvency, profitability, operating capacity, growth capacity, cash flow levels, and operations management. Solvency is the ability of an enterprise to pay its debts in previous periods, thus reflecting its creditworthiness. Profitability is the ability of an enterprise to use current resources to generate profits. Operating capacity indicates the operating efficiency of an enterprise, which mainly refers to the efficiency and utility of its operating assets. Growth capacity reflects the speed of development of the enterprise and expectations for the future. Cash flow levels reflect a company's cash holdings and represent the level of short-term debt service. Operations management represents the strategic planning of the company.

For space reasons, some indicators are presented in Table 3, and the full indicator system is in Appendix A.

Table 3. Credit risk assessment indicator system (abbreviated version).

Dimension		Indicator
Carbon Information Dimension	Carbon Investment	environmental input
	Carbon Emissions	CO_2 emissions from coal, CO_2 emissions from coke, CO_2 emissions from crude oil, CO_2 emissions from gasoline, CO_2 emissions from paraffin, CO_2 emissions from diesel, CO_2 emissions from fuel oil, CO_2 emissions from natural gas, total CO_2 emissions, wastewater emissions, CO_2 emissions, SO_2 emissions, soot and dust emissions, and industrial solid waste generation
	Carbon Performance	green invention patent authorization, green utility model patent authorization, waste gas emission reduction and treatment, wastewater emission reduction and treatment, dust and smoke treatment, solid waste utilization and disposal, noise and light pollution and radiation treatment, and clean production implementation
	Carbon Disclosure	environmental protection philosophy, environmental protection objectives, environmental protection management system, environmental education and training, environmental protection special operations, environmental incident response mechanism, environmental protection honors or awards, "three simultaneous" system, disclosure of annual reports of listed companies, disclosure of social responsibility reports, and disclosure of environmental reports
	Carbon Regulation	whether it is a key pollution monitoring unit, whether the pollutant emissions meet the standards, sudden environmental accidents, environmental violations, environmental petition cases, whether it has passed ISO14001 [52] certification, and whether it has passed ISO9001 [52] certification
Compliance Dimension	Solvency	current ratio, quick ratio, quick ratio, cash ratio, working capital to borrowings, working capital, and net cash flows (NCF)/current liabilities, etc.
	Profitability	return on assets, net profit margin on total assets, net profit margin on current assets, net profit margin on fixed assets, and return on net assets (ROE), etc.
	Operating Capacity	accounts receivable to revenue, accounts receivable turnover, accounts receivable turnover days, inventory to revenue, and inventory turnover, etc.
	Growth Capacity	capital preservation rate, capital preservation rate of parent company, capital accumulation rate, and capital accumulation rate of parent company, etc.
	Cash Flow Levels	net cash content of net profit, cash content of operating income, net cash content of operating income, and net cash flow to creditors from financing activities, etc.
	Operations Management	interest cover multiple, cash asset ratio, asset receivables ratio, working capital to current assets ratio, working capital requirement (WCR), working capital, etc.

3.3.2. Wide Component with ℓ_p *Penalty*

In previous algorithms, the regularization parameter was predetermined, i.e., the default $p = 1$ or $p = 2$. However, different datasets are suitable for different orders of regularization. In this paper, we propose a ℓ_p *Penalty* regularization, which allows the algorithm to choose the order p ($0 < p \leq 2$) of the regularization parametrization.

In order to make the model more suitable for the regression task, we use the MSE as the loss function of the neural network.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Yi - \hat{Y}i)^2 \tag{1}$$

To introduce the ℓ_p *Penalty* into the neural network and guide its learning process, the ℓ_p *Penalty* is added to the loss function of the network layer, so that the loss function is modified to [53]

$$L(y_k, \hat{y}_k) = \frac{1}{\text{n}}\sum_{i=1}^{n}(Yi - \hat{Y}i)^2 + \lambda\|\mathbf{W}\|_p \tag{2}$$

where, λ is the strength parameter.

The ℓ_p *Penalty* is defined as [54]

$$h(\mathbf{w}) = \|\mathbf{w}\|_p = \left[\sum_{j=1}^{n}|w_j|^p\right]^{\frac{1}{p}} \tag{3}$$

Note, with $p = 1$ or $p = 2$, this is an L1- or L2-regularized logistic regression, respectively. Here, we seek to extend their study to the case of $p \in (0, 2]$, which we refer to as ℓ_p *Penalty*.

Therefore, the final solution to the model is expressed as [55]

$$\min L(y_k, \hat{y}_k) = \min\frac{1}{\text{n}}\sum_{i=1}^{n}(Yi - \hat{Y}i)^2 + \lambda\|\mathbf{W}\|_p \tag{4}$$

The process of solving for the partial derivatives of $\|\mathbf{W}\|_p$ matrix can be expressed as follows.

Let $k(\mathbf{w}) = h^p(\mathbf{w})$, and when $0 < p \leq 2$, the derivative is

$$\frac{\partial k(\mathbf{w})}{\partial w_j} = p|w_j|^{p-1} \cdot \text{sgn}(w_j) \tag{5}$$

$$\text{sgn}(w_j) = \frac{w_j}{|w_j|} \tag{6}$$

$$\frac{\partial k(\mathbf{w})}{\partial w_j} = p|w_j|^{p-2} \cdot w_j \tag{7}$$

After each iteration, the error between the output value and the true value becomes smaller and smaller, at which point a minimum threshold of iterative convergence is set to stop the learning process.

3.3.3. Deep Component

Deep neural networks (DNN) can extract risk features based on associations between credit risk data. The deep component uses a supervised DNN to train a credit risk assessment model for heavy polluters.

$$a^{l+1} = f\left(W^l a^l + b^l\right) \tag{8}$$

Here, l denotes the layer number, $f(\cdot)$ is an activation function, a is the activation, W is the model weights, and b is the bias at layer l. The unknown variables include $W^l b^l$, and the embedding vectors; these variables are all randomly initialized (e.g., random draws from Gaussian distribution) and will be learned to minimize the loss function during the training procedures.

3.3.4. Wide-ℓ_p *Penalty* and Deep Learning Method

Finally, the concatenated layer combines the outputs of the wide component with ℓ_p *Penalty* and the deep component. Then, it exports the final credit risk prediction by feeding the combined features to the activation function. In particular, the concatenated layer can deal with the weighted sum of these two modules together and optimize the learning parameters, simultaneously. The concatenated layer mainly consists of a fully connected layer. We denote the predicted credit risk by Y, which can be calculated as follows [56],

$$Y = f\left(W_c \cdot \mathrm{Concat}\left[Y_{\text{wide}}, Y_{\text{deep}}\right] + b_c\right) \tag{9}$$

where Concat $[\cdot]$ denotes a concatenated function to combine Y_{wide} and Y_{deep}. In the concatenated layer, the learning parameters for weight and bias are denoted by W_c and b_c, respectively.

3.3.5. Output: Credit Risk Measurement

We measured the credit risk of enterprises using Default Distance (DD) estimated from the KMV model. The greater the distance to default, the less likely it is that the firm will default. The DD formula is

$$DD = \frac{E(V_T) - DP}{E(V_T) \times \sigma_V} \tag{10}$$

where $E(V_T)$ is the expected value of the company's assets at the end of the period, σ_V represents the volatility of enterprise asset values. DP is the default point; if the value of a company's assets falls below this level, there is a possibility of default. DP assigns different weights to long- and short-term debt and lies at a point between a company's current and total liabilities.

$$DP = SD + \frac{1}{2}LD \tag{11}$$

Here, SD is the short-term debt of an enterprise and LD is the long-term debt of an enterprise.

The DD is widely used in the field of credit risk prediction, and it can effectively predict credit risk [57,58] and reflect the degree of default risk of enterprises [59]. Descriptive statistics of the DD variable are shown in Table 4.

Table 4. DD variables descriptive statistics.

Variable	N	Max	Min	Mean	Std	Median	25%	75%
DD	10,744	46.144	−67.848	0.803	3.009	1.342	0.564	1.923

4. Experimental Setup

4.1. Data Processing

The risk indicators selected in this paper have different quantity units and value ranges, and the individual indicators are often not yet comparable. To avoid the impact of different data characteristics and order of magnitude on the network hierarchy construction and indicator weight calculation, the data were normalized so that each risk label data were transformed into dimensionless indicator values on the closed interval [0, 1]. The normalization formula is

$$X' = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{12}$$

After normalization, all indicators are in the same interval range, which is suitable for putting all indicators in the model for comprehensive evaluation. At the same time, extreme value samples will delay the model training time, and data normalization can weaken the influence of some extreme values on the model, facilitate the subsequent data processing, and speed up the model training.

4.2. Performance Evaluation

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Yi - \hat{Y}i)^2 \tag{13}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Yi - \hat{Y}i\right| \tag{14}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Yi - \hat{Y}i)^2} \tag{15}$$

Combined with the characteristics of the data in this paper, Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were chosen as metrics to evaluate the prediction effect of the model. Note: Yi denotes the predicted true value, $\hat{Y}i$ denotes the predicted value of the model, and n denotes the sample size.

These metrics reflect the degree of difference between the estimated quantity and the estimated quantity, and they all range from [0, +∞]. When the predicted value is the same as the true value, the metrics are equal to 0. The larger the error, the larger the metrics. Lower values of these metrics indicate that the prediction results of the prediction model are closer to the true results.

4.3. Experimental Settings

We implemented WPDL and the benchmarked methods based on programs of tensorflow-gpu-2.7.1, and keras-2.7.0. During the training of the WPDL, the MSE was used as the loss function, and the root mean square propagation (RMSProp) was used as the optimizer. In each experiment, the model was trained with a learning rate of 0.0001. A smaller batch size led to better model performance, and the best results were achieved when the batch size was set to 256. The settings of each layer parameter in WPDL are shown in Table 5.

Table 5. Settings of each layer in WPDL.

Number	Name	Settings
Wide	Logistic Regression with ℓ_p *Penalty*	activation = relu
Deep	hidden1	units = 256, activation = relu
	hidden2	units = 128, activation = relu
	hidden3	units = 64, activation = relu

Default parameters were used for the KNN, DT, RF, SVM, MLP, DNN, Gradient Boosting, and Bagging. In the MLP model, the number of units was set to 256, 128, 64, and 1 for each layer. In addition, the learning rate was set to the same value as that of the proposed model. Therefore, we applied these parameters to obtain the results of the comparison. The next subsection presents the results of the comparison.

5. Experimental Results and Analysis

5.1. Hypotheses

The experimental results prove the hypotheses that our proposed novel wide-ℓ_p *Penalty* and Deep Learning (WPDL) method will enable the accurate, interpretable, and stable assessment of credit risk based on using the real-world heavy-polluting enterprises data.

The results, summarized in Table 6, show the superiority of our WPDL method. The experimental results show that the credit risk prediction errors of the proposed WPDL method are 6.5582 (MSE), 2.3817 (RMSE), and 1.0102 (MAE). The results outperformed all the baseline models. This helps enterprises to have a higher risk prediction accuracy. Furthermore, three main experiments were conducted to evaluate the accuracy, interpretability, and stability of the WPDL method.

Table 6. Comparison of the prediction performance of different models.

Model	MSE	RMSE	MAE	Model	MSE	RMSE	MAE
KNN	8.0346	2.7949	1.225	WPDL ℓ_p *Penalty* = 0.2	6.1776	2.3329	1.0486
DT	**6.4572**	2.4891	1.1018	**WPDL $\boldsymbol{\ell_p}$ *Penalty* = 0.4**	**6.1752**	**2.3325**	**1.0482**
MLP	7.4967	2.6708	1.1499	WPDL ℓ_p *Penalty* = 0.5	6.1783	2.3332	1.0491
RF	7.7005	2.7626	1.0212	WPDL ℓ_p *Penalty* = 0.6	6.1776	2.3331	1.0489
SVM	7.6801	2.6967	1.52	WPDL ℓ_p *Penalty* = 0.8	6.1764	2.3328	1.0487
GB	6.7716	2.4564	1.0293	WPDL ℓ_p *Penalty* = 1	6.1768	2.3329	1.0487
Bagging	8.264	2.7357	1.0985	WPDL ℓ_p *Penalty* = 1.2	6.1771	2.3329	1.0488
DNN	7.1055	2.5303	1.0883	WPDL ℓ_p *Penalty* = 1.4	6.1801	2.3333	1.0491
WDL	6.5582	**2.3817**	**1.0102**	WPDL ℓ_p *Penalty* = 1.6	6.1805	2.3338	1.0494
				WPDL ℓ_p *Penalty* = 1.8	6.1806	2.3336	1.0487
				WPDL ℓ_p *Penalty* = 2	6.1814	2.3338	1.0495

The best results are highlighted in bold.

5.2. Accuracy Observation: Model Comparisons

The WPDL method was applied to the credit risk data of heavily polluting enterprises. The credit risk data of heavily polluting enterprises contain 181 characteristics per enterprise sample, with a total of 10,744 samples, corresponding to different credit risk levels.

We applied ten-fold cross-validation to conduct the experiments, that is, we randomly divided the dataset into ten folds, using the first (second, third, fourth . . . to tenth) fold as the test set and the remaining folds as the training set. The average result was reported as the performance indicator of each method used in our experiments. The test set was used to check whether the learning results of the model on the training set were applied to the new data in the test set, and if the model passed the test with a good fitting effect and high accuracy, it could continue to be used for risk warning.

As shown in Table 6, experimental results are presented and analyzed in more detail from two perspectives: a comparison of different models and a comparison of different ℓ_p *Penalty*.

5.2.1. Comparison of Different Models

In this section, the eight algorithms compared are KNN, DT, MLP, RF, SVM, Gradient Boosting, Bagging, and DNN. In this experiment, the smaller the regression error, the better the model performance. As can be seen in Figure 2, WPDL has smaller MSE, MAE, and RMSE in credit risk assessment, indicating that the model has the smallest prediction error. Therefore, our proposed WPDL framework can provide a highly accurate risk warning, which is better than the traditional model.

5.2.2. Comparison of Different ℓ_p *Penalty*

Figures 3–5 show that for the minimum regression error, the regularization order p is not 1 or 2 but a non-integer value of 0.4. The ℓ_p *Penalty* regularization outperforms other linear regularizations, and a mandatory use of the traditional integer parameterization does not necessarily lead to better models. The use of a rational paradigm tends to give better results than an integer paradigm, and the exact value of the rational should be determined with the algorithm depending on the data. At ℓ_p *Penalty* = 1.4 to 2, the prediction error rate is higher, mainly because the multidimensional indicators contained in the dataset contain noise or some of the dimensions are not related to the credit risk. In this case, the selection of variables that contained noise or were not related to the degree of credit risk led to inaccurate models and thus reduced the prediction accuracy.

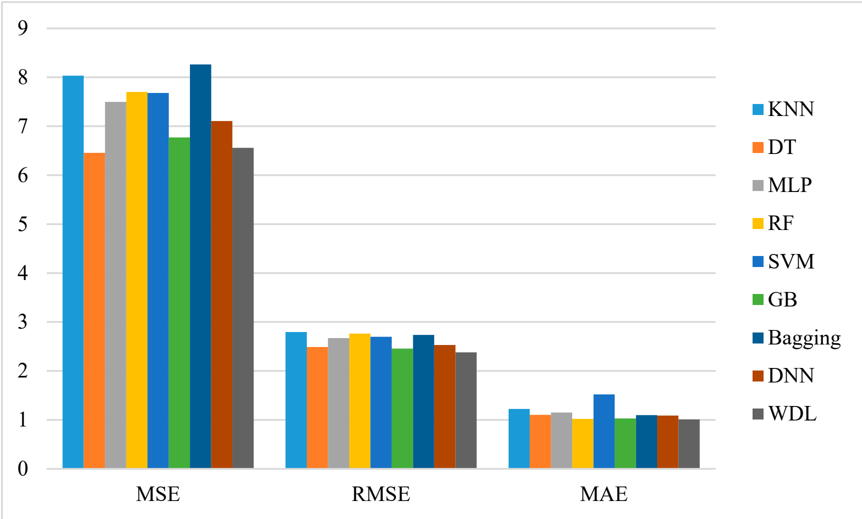

Figure 2. Comparison of the different models measured with MSE, RMSE, and MAE.

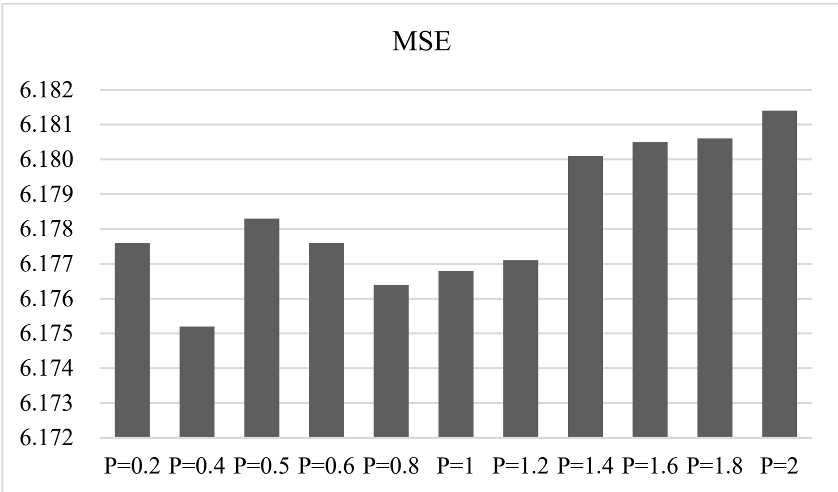

Figure 3. Comparison of the different ℓ_p *Penalty* measured with MSE.

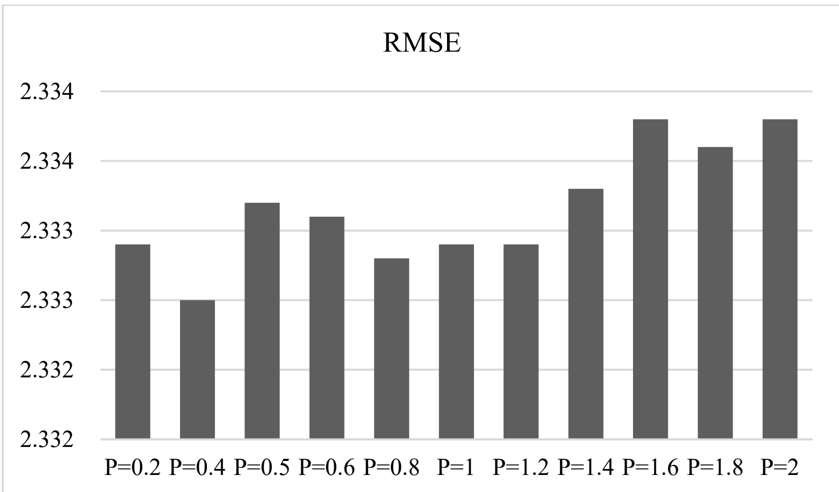

Figure 4. Performance of the different ℓ_p *Penalty* measured with RMSE.

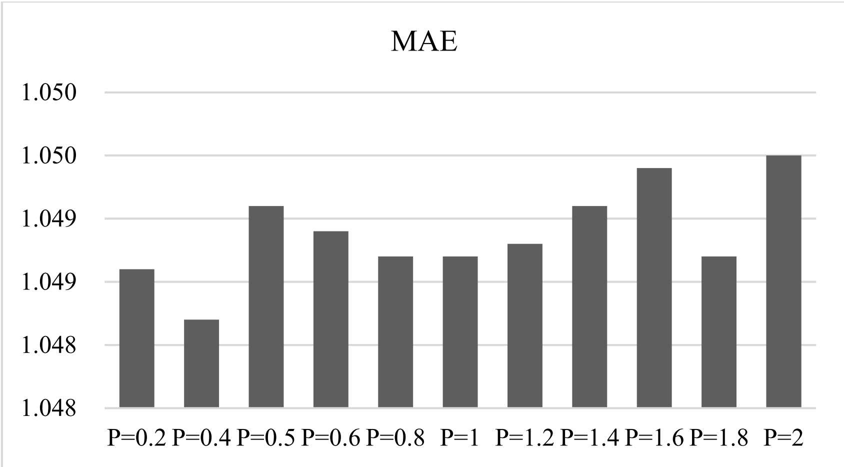

Figure 5. Performance of the different ℓ_p *Penalty* measured with MAE.

The experimental results show that WPDL has the smallest regression error when comparing other machine learning models. When comparing the different ℓ_p *Penalty*, the regression error is less than the traditional integer value of 1 or 2 when ℓ_p *Penalty* takes a rational number value.

5.3. Interpretability Observation: Feature Selection Results

In this section, we analyze the top 50 important risk characteristics generated using the WPDL method to provide guidelines for the credit risk management of heavy polluters. The ranking of the top 50 feature weights is shown in Figure 6. A higher ranked feature is more valuable for risk assessment than a lower ranked feature. Moreover, ignoring features that have a rank lower than a specific threshold can also increase model speed.

First, we analyzed which characteristics significantly affected credit risk from the carbon elements perspective. Carbon performance indicators—such as wastewater discharge, CO_2 emissions from paraffin, SO_2 emissions, soot and dust emissions, COD emissions, CO_2 emissions from fuel oil, and clean production implementation—are positively correlated with corporate performance. The better the carbon emission reduction performance, the lower the credit risk. Higher carbon emissions jeopardize the sustainability of heavy polluters. Lower carbon emissions will improve the resource efficiency of heavy polluters, thereby improving their financial performance.

Secondly, from a financial perspective, the impact mechanism of the indicators on credit risk is analyzed. According to signaling theory, carbon disclosure indicators such as Environmental Education and Training, Environmental Protection Philosophy, Social Responsibility Report, and Environmental Incident Response Mechanism reduce information asymmetry to increase firm value. In particular, companies' active responses to climate change and disclosure of carbon information can promote sustainable management, environmental management and social responsibility disclosure, and reduce the asymmetry of environmental and social responsibility information. As a result, rating agencies tend to give higher credit ratings to companies with good social performance, thereby reducing their credit risk. In the long run, therefore, companies that disclose carbon information will benefit.

EBITDA, Gross Operating Margin, Return on Assets, etc. are profitability indicators. NC Liabilities Ratio, LT Capital Indebtedness Ratio, etc. are solvency indicators. Corporate Free Cash Flow (FCF) is a cash flow level indicator. These indicators affect credit risk by influencing short-term repayment ability and company performance.

The Shareholders' Equity Turnover Operating Index is an example of an operating capacity indicator, and Income Tax Rate is an operating management indicator. GR of net profit attributable, GR of administrative expenses, GR of owners' equity, GR of total assets, etc. are growth capacity indicators. Companies with better growth prospects are more likely to receive more favourable loan agreements, as banks take the sustainability of the business into account when deciding on loan agreements, thereby reducing the risk of default.

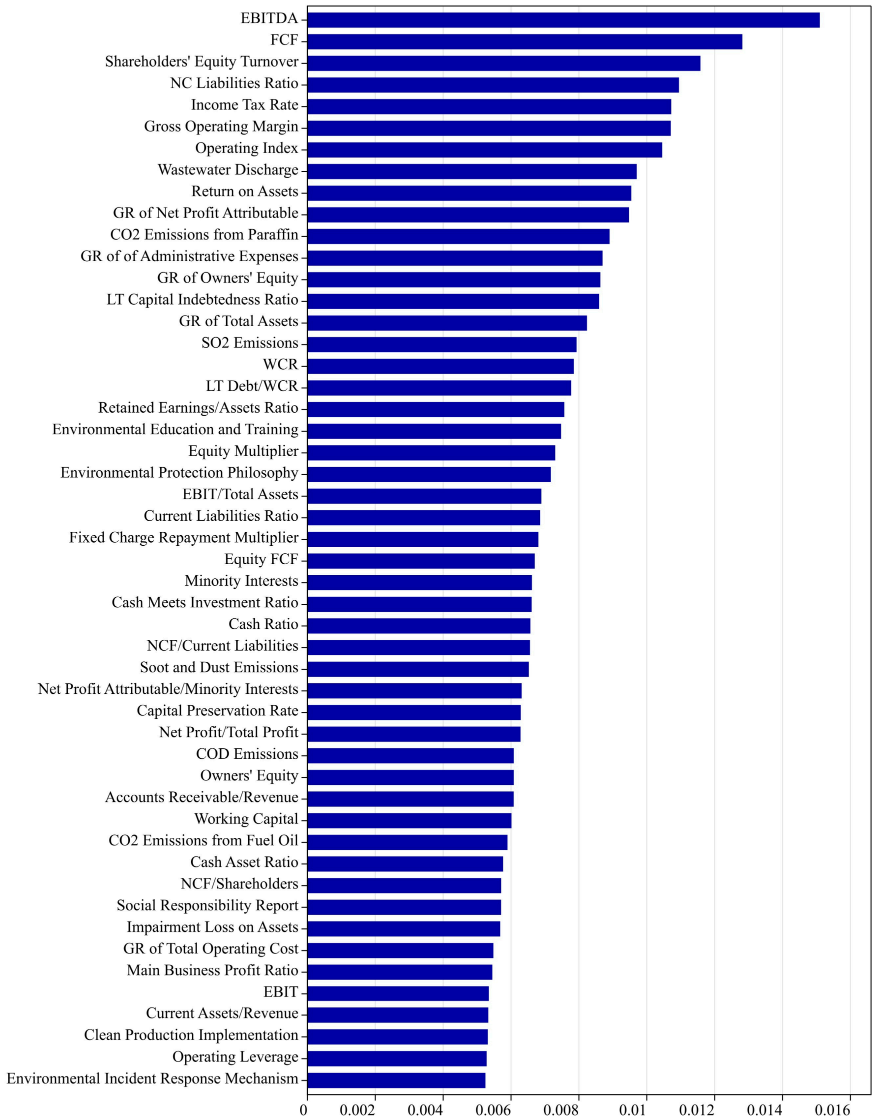

Figure 6. Ranking of top 50 feature weights.

5.4. Stability Observation: Convergence Rate

The convergence speed capability of the algorithm reflects to some extent the efficiency and stability of the algorithm. To keep the experiments comparable, different ℓ_p *Penalty* values were set, and other model parameters were kept consistent.

The convergence of the model was compared for 500 epochs with ℓ_p *Penalty* = 0.4, 1, 1.4, and 2 as examples. The MSE was used to evaluate the convergence rate. The experimental results are shown in Figure 7. The X-axis records the number of epochs, the Y-axis records the loss score, the blue line corresponds to $p = 0.4$, the yellow line corresponds to $p = 1$, the red line corresponds to $p = 1.4$, and the black line corresponds to $p = 2$. It is evident that ℓ_p *Penalty* = 0.4 has the fastest convergence rate and is the most stable on credit risk assessment.

In a word, the WPDL method can effectively select features that contribute more to the credit risk assessment of heavy polluters and outperform the other algorithms overall. The results show that the performance of the WPDL is better and more robust than that of other models, indicating that the heavy-polluting enterprises credit risk assessment with ℓ_p *Penalty* is more effective, validating the superiority of the new method. This provides methodological support to help heavy-polluting enterprises prevent and control debt maturity risk.

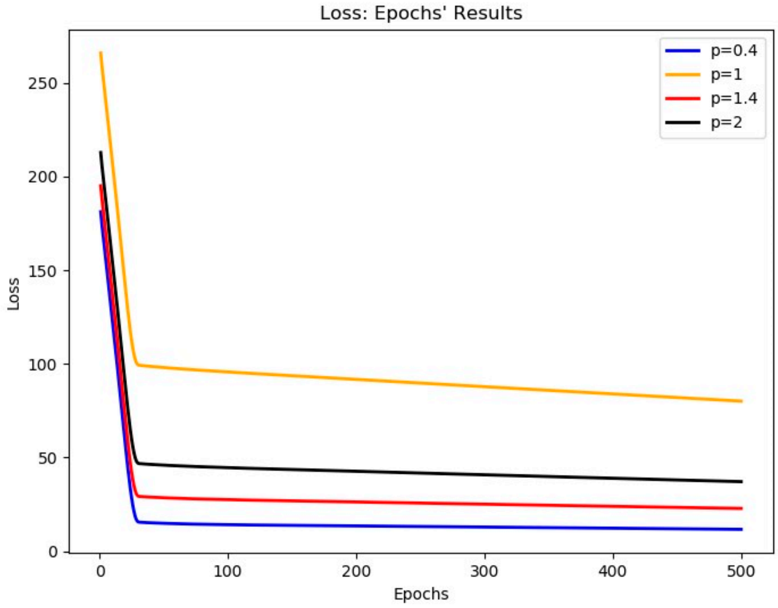

Figure 7. Convergence rate of WPDL with different ℓ_p *Penalty*.

6. Conclusions

How to accurately assess the credit risk of heavy-polluting corporations has important senses for themselves, investors, even national economy. In the real world, there are many factors that affect a company's credit risk, and given the characteristics of heavy polluters, credit risk assessment needs to consider the carbon elements. We have developed a credit risk indicator system that includes carbon elements. However, the numerous risk indicators are also accompanied by data noise, which affects the accuracy of risk assessment. In this paper, we put forth a Wide-ℓ_p *Penalty* and Deep Learning model (WPDL) for credit risk assessment based on highly noisy data.

To be specific, our WPDL is composed of a Wide-ℓ_p *Penalty* component and a deep component. The Wide-ℓ_p *Penalty* component can extract the feature through a linear model with an ℓ_p-regularized mechanism. The deep component consists of DNN, which can generalize indicator features from the credit risk data. In this paper, we proposed a p-parametric regularization, which allows the algorithm to choose the order p ($0 < p \leq 2$) of the regularization parametrization. The experimental results show that the regularization order p is not 0, 1, or 2 but some non-integer value at the minimum regression error. Moreover, we evaluated WPDL by conducting a performance comparison with the other eight existing ML and DL models via extensive experiments. Our experimental results reveal that WPDL outperforms traditional ML and DL approaches.

Theoretically, we proposed ℓ_p *Penalty*-based feature selection using the framework of the neural network. On the one hand, the neurons of the neural network solve the objective function; on the other hand, the ℓ_p *Penalty* is used to guide the learning process of the neural network so that the objective function converges while the weight matrices between the input and hidden layers are sufficiently sparse to allow feature selection.

It can conclude three practical usefulness from the results of comparative analysis.

First, in terms of accurate credit risk assessment. We proposed the Wide-ℓ_p *Penalty* and Deep Learning method, which can choose the ℓ_p *Penalty* of the regularization paradigm such that $0 < p \leq 2$. We applied this model to the real data of credit risk assessment of heavily polluting enterprises. The experimental results show that when designing the risk assessment model, the evaluation effect is not necessarily good when the integer paradigm is used compulsorily. The evaluation effect is often better than that of the integer model by adopting the rational number model, and the specific value of the rational number is determined by the actual problem.

Second, in terms of decision-making interpretability. The rational ℓ_p *Penalty* removes noise from the data via feature selection and selects the optimal subset of features. It filters out redundant or irrelevant features that do not contribute to the learning process. At the same time, the model provides interpretable risk indicator weights to derive the key indicators affecting the credit risk of heavy-polluting enterprises. It can provide decision support for corporate credit risk management.

Third, in terms of stable credit risk assessment. We compared the convergence rate of the WPDL method with a different ℓ_p *Penalty*. It was found that the fastest convergence rate was achieved when ℓ_p *Penalty* took non-integer values. This experiment, together with the model accuracy comparison experiment, demonstrated the superior performance of our WPDL with the non-integer ℓ_p *Penalty*.

Future work about WPDL for enterprises' credit risk assessments will need to further optimize the structure of the deep component. We hope that better deep learning models (such as residual and fractal networks) can be introduced and examined to improve accuracy to a greater extent.

Author Contributions: Conceptualization, W.S. and J.M.; methodology, W.S.; software, W.S.; validation, W.S. and J.Y.; formal analysis, J.M.; investigation, W.S.; resources, J.Y.; data curation, W.S.; writing—original draft preparation, W.S.; writing—review and editing, W.S. and J.M.; visualization, W.S.; supervision, J.Y.; project administration, J.M.; funding acquisition, J.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by project 17BGL023 supported by the National Social Science Funds of China.

Data Availability Statement: Publicly available datasets were analyzed in this study. This data can be found here: WIND (https://www.wind.com.cn/) and CSMAR (https://www.gtarsc.com/).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Credit risk assessment indicator system.

Dimension		Indicator
Carbon Information Dimension	Carbon Investment	environmental input
	Carbon Emissions	CO_2 emissions from coal, CO_2 emissions from coke, CO_2 emissions from crude oil, CO_2 emissions from gasoline, CO_2 emissions from paraffin, CO_2 emissions from diesel, CO_2 emissions from fuel oil, CO_2 emissions from natural gas, total CO_2 emissions, wastewater emissions, COD emissions, SO_2 emissions, soot and dust emissions, and industrial solid waste generation
	Carbon Performance	green invention patent authorization, green utility model patent authorization, waste gas emission reduction and treatment, wastewater emission reduction and treatment, dust and smoke treatment, solid waste utilization and disposal, noise and light pollution and radiation treatment, and clean production implementation
	Carbon Disclosure	environmental protection philosophy, environmental protection objectives, environmental protection management system, environmental education and training, environmental protection special operations, environmental incident response mechanism, environmental protection honors or awards, "three simultaneous" system, disclosure of annual reports of listed companies, disclosure of social responsibility reports, and disclosure of environmental reports
	Carbon Regulation	whether it is a key pollution monitoring unit, whether the pollutant emissions meet the standards, sudden environmental accidents, environmental violations, environmental petition cases, whether it has passed ISO14001 certification, and whether it has passed ISO9001 certification

Table A1. *Cont.*

Dimension		Indicator
Compliance Dimension	Solvency	current ratio, quick ratio, cash ratio, working capital to borrowings, working capital, net cash flows (NCF)/current liabilities, gearing ratio, long-term (LT) borrowings to total assets, tangible assets to liabilities ratio, tangible assets to interest-bearing debt, equity multiplier, equity ratio, equity to debt ratio, LT capital indebtedness ratio, LT debt to equity ratio, LT debt to WCR, EBITDA/total liabilities, net cash flow from operating activities/total liabilities, net cash flow from operating activities/interest-bearing debt, debt to equity market value ratio, tangible net worth debt ratio, and fixed charge repayment multiplier
	Profitability	return on assets, net profit margin on total assets, net profit margin on current assets, net profit margin on fixed assets, return on net assets (ROE), earnings before interest and taxes (EBIT), earnings before interest, taxes, depreciation and amortization (EBITDA), net profit to total profit, total profit to EBIT, EBIT to total assets, return on invested capital (ROIC), return on LT capital, gross operating margin, operating cost margin, operating profit margin, net operating margin, total operating cost margin, cost of sales margin, administrative expense margin, finance cost margin, selling period expense margin, cost margin, impairment loss on assets, EBITDA margin, EBITDA operating margin, cash to total profit ratio, return on net assets attributable to parent company (ROE), and return on assets attributable to parent company's consolidated earnings ratio
	Operating capacity	accounts receivable to revenue, accounts receivable turnover, accounts receivable turnover days, inventory to revenue, inventory turnover, inventory turnover days, operating cycle, accounts payable turnover, cash and cash equivalents turnover, current assets to revenue, current assets turnover, fixed assets to revenue, fixed assets turnover, non-current (NC) assets turnover, capital intensity, total assets turnover, and shareholders' equity turnover
	Growth capacity	capital preservation rate, capital preservation rate of parent company, capital accumulation rate, capital accumulation rate of parent company, growth rate (GR) of fixed assets, GR of total assets, GR of net profit attributable, GR of operating revenue, GR of total operating revenue, GR of total operating cost, GR of selling expenses, GR of administrative expenses, accruals, GR of sustainable, GR of owners' equity, and GR of net assets per share
	Cash flow levels	net cash content of net profit, cash content of operating income, net cash content of operating income, net cash flow to creditors from financing activities, NCF to shareholders, depreciation and amortization, corporate cash flow, equity cash flow, corporate free cash flow, equity free cash flow (FCF), operating index, capital expenditure to depreciation and amortization ratio, cash fit ratio, cash reinvestment ratio, cash meets investment ratio, and corporate free cash flow
	Operations Management	interest cover multiple, cash asset ratio, asset receivables ratio, working capital to current assets ratio, WCR, working capital, working capital to net assets ratio, NC assets ratio, fixed assets ratio, intangible assets ratio, tangible assets ratio, owner's equity ratio, retained earnings to assets ratio, LT assets to assets ratio, shareholders' equity to fixed assets ratio, current liabilities ratio, operating liabilities ratio, financial liabilities ratio, NC liabilities ratio (NC liabilities ratio), owner's equity of parent company, minority interests, main business profit ratio, profit from financial activities ratio, operating profit ratio, non-operating income ratio, turnover tax rate, comprehensive tax rate, income tax rate, net profit attributable to parent company, net profit attributable to minority interests, consolidated income from net profit, other comprehensive income, consolidated income attributable to parent company, consolidated income attributable to minority interests, owner's equity to invested capital ratio of parent company, financial leverage, operating leverage, and consolidated leverage

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