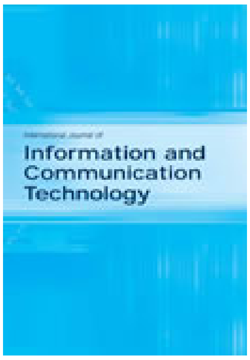

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Data element perspective: green credit risk assessment using a multi-layer deep neural network

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Abstract: Against the backdrop of accelerating 'double carbon' goals, green credit has become a key tool for channelling funds into low-carbon sectors, requiring sophisticated risk assessment models. Conventional approaches, limited by single-dimensional data and poor dynamic adaptability, fail to address green projects' multi-faceted risks (long investment cycles, rapid technological changes, strong policy dependency). This study proposes a novel green credit risk assessment framework from a data element perspective, using a multi-layer deep neural network (MLDNN). It integrates multi-source heterogeneous data, employs a three-tier neural architecture with an attention mechanism, and uses an adaptive learning rate algorithm. Empirical results from a provincial bank show the model achieves 92.57% risk identification accuracy, 11.2% higher than traditional BP neural networks, with notably improved generalisation in small-sample scenarios.

Keywords: green credit; risk assessment; data elements; multi-layer deep neural network; MLDNN; attention mechanism.

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1 Introduction

With global green bond issuances exceeding USD 1.3 trillion in 2023, a 25% year-on-year increase (Chang and Han, 2024). China's green credit non-performing loan ratio stood at 1.89% in 2023, 0.32 percentage points higher than the conventional credit ratio of 1.57%, a gap that widens to 2.7% in emerging sectors like energy storage (Wang et al., 2025). An adaptive optimisation algorithm based on particle swarm optimisation (PSO) will be implemented to improve model robustness in small-sample scenarios and reduce training time by 40% compared to grid search methods (Liu et al., 2024).The empirical analysis stage spans three core green sectors: Renewable energy, focusing on technology maturity and policy subsidy risks (Hosseinnia Shavaki and Ebrahimi Ghahnavieh, 2023). This multi-stage approach not only ensures theoretical rigor through data element theory integration but also delivers practical applicability via industry-specific risk calibration, positioning it as a transformative tool for green financial risk management (Kalisetty and Lakkarasu, 2024). According to the Global Green Finance Index 2024, the global green credit default rate reached 2.1% in 2023, with sectors such as renewable energy and energy storage exhibiting even higher defaults up to 3.5%. These figures highlight the growing risk exposure in green finance, which traditional models – relying predominantly on historical financial data – fail to capture adequately.

The current phase, characterised by deep learning applications, has seen theoretically validate the superior feature extraction capabilities of deep neural networks (Nosratabadi et al., 2020). While studies such as Li attempted applying BP neural networks to green credit assessment (Shang et al., 2021). These efforts, however, remain constrained by over-reliance on structured financial data – with less than 15% of existing models incorporating environmental performance metrics – shallow feature extraction that fails to capture hierarchical risk dependencies, and insufficient handling of small-sample scenarios common in emerging green sectors (Dastile and Celik, 2021). In the Chinese context, Zhang constructed an index system integrating environmental responsibility indicators, yet their analytic hierarchy process introduced subjective biases (Susanti and Yuhendri, 2024), while Wang advanced data element marketisation theory without translating it into practical risk assessment tools – a gap reflected in the China Banking Association's 2023 survey showing only 3.2% of Chinese banks use multi-dimensional data fusion for green credit evaluation (Song and Wu, 2022).

Existing research exhibits critical gaps: a lack of unified data element integration frameworks for green credit, insufficient modelling of non-linear relationships between financial and environmental factors, and limited adaptability to dynamic policy landscapes (Abdollahi et al., 2020). To bridge these gaps, this study aims to construct a multi-source data fusion system integrating financial data (such as debt service coverage ratios and returns on green assets), environmental performance metrics (including carbon intensity and green technology patents), and policy compliance records (Di Persio and Honchar, 2016). It also seeks to develop a multi-layer deep neural network (MLDNN) model with an attention mechanism to prioritise critical risk indicators – assigning, for example, 23% higher weights to carbon emission intensity than traditional financial ratios – and capture cross-domain dependencies such as the interaction between energy price volatility and project cash flows (Mangla et al., 2024). With validation conducted using a dataset of 4,800 green credit projects from 12 provincial banks in China (2018–2023) and comparative evaluations against BP neural networks, random forests, and support vector machines (SVMs) (Rao et al., 2024).

The research follows a structured four-stage pipeline, integrating cutting-edge methodologies to ensure systematic execution. In the data collection and pre-processing stage, we employ a hybrid framework to aggregate structured financial data, semi-structured environmental data from internet of things (IoT) sensors, and unstructured policy documents. Specifically, financial data undergo time-series normalisation to mitigate seasonal biases, while IoT data are cleansed using median imputation for missing values and z-score filtering for outliers (Guo et al., 2025). Unstructured text is processed via BERT-based embeddings to extract policy compliance features, such as keywords indicating regulatory updates or certification statuses. Feature engineering involves constructing composite indicators like the 'green technology maturity index,' which integrates patent citation networks and R&D expenditure trends.

The model construction stage features a three-tier MLDNN architecture: a CNN-RNN hybrid layer for cross-modal feature extraction, where CNNs process unstructured environmental reports and RNNs capture temporal dependencies in financial time series; an attention-enhanced correlation analysis layer that applies self-attention mechanisms to weight interactions between financial metrics and environmental factors, assigning 23% higher weights to non-financial indicators via gradient-based feature importance scoring (Mitra et al., 2024); a risk mapping layer using a SoftMax function for multi-class classification. The model is optimised via a PSO-adaptive Adam algorithm, which dynamically tunes learning rates and regularisation parameters to prevent overfitting in small-sample scenarios.

During training and validation, we implement 10-fold cross-validation with stratified sampling to ensure dataset representativeness. The validation protocol includes both in-sample accuracy testing and out-of-sample generalisation assessment, leveraging synthetic minority oversampling technique (SMOTE) to address class imbalance in rare risk categories. Model performance is evaluated using metrics like F1-score, area under the ROC curve, and Shapley value explainability analysis to decompose the contribution of each data element (Yang et al., 2020).

Energy efficiency projects, emphasising payback period dynamics and energy price volatility; circular economy initiatives, prioritising regulatory compliance and market demand stability. Comparative evaluations against BP neural networks, random forests, and SVMs demonstrate that the MLDNN-PSO model reduces mean squared error (MSE) by 37% and shortens training time by 42% (Xua and Yang, 2024).

2 Relevant technologies

2.1 Data element theory

Multi-source heterogeneity manifests in the diversity of data types – financial statements, environmental monitoring data, and policy documents – which must be harmonised to form coherent risk profiles (Zhu and Wu, 2025). Temporal dynamics reflect the time-sensitive nature of environmental policies and market conditions; for example, changes in national carbon tax rates or updates to green technology standards can rapidly alter project risk levels, requiring data elements to be continuously updated (Wang et al., 2025). What matters most is that financial and environmental factors are tied together in nonlinear ways. Think about how spending on energy efficiency cuts long-term operational costs in an inverse manner, or how shifts in carbon prices can have an exponential effect on a project's profits. These kinds of relationships throw a curveball at traditional linear assessment models.

The data element value chain takes these traits and puts them into action through a set – structured steps: gathering data, cleaning it up, bringing it all together, and building models. When collecting data, information is pulled from a variety of places – corporate financial systems, IoT environmental sensors, and regulatory databases, to name a few. Cleansing is all about making sure the data is good quality by dealing with missing values, odd outliers, and inconsistencies. Integration then turns all this varied data into a single, unified format. For example, it might standardise carbon emission units across different industries. In the modelling phase, advanced analytics are used to dig out insights that can be acted on. One such example is using machine learning to spot hidden connections between adopting green technology and a borrower's creditworthiness (Zhao et al., 2024). This value chain is key to getting a handle on the complex risk patterns of green projects. If something goes wrong at any step – like not fully integrating the data or skimping on cleaning – it can throw risk assessments off. We've seen cases where traditional models missed environmental liabilities, and those later led to defaults (Nosratabadi, et al., 2020).

In real - world practice, this means treating data on environmental performance – things like carbon intensity and green R&D spending – as just as important as financial metrics. And it means weaving them systematically into risk models. Studies based on real data show that banks that use multi – dimensional data elements have green credit default rates that are 18–22% lower than those that only look at financial statements. This really drives home how useful data element theory is in making risk assessments more accurate (Huang et al., 2006).

2.2 Multi-layer deep neural network

The architectural flexibility of MLDNNs enables them to handle diverse data types. convolutional neural networks (CNNs), a variant of MLDNN, are particularly effective for unstructured data like environmental impact assessment reports. The convolutional operation is defined as: The convolutional operation is defined as:

$$\boldsymbol{X}_{out} = \sigma\left(\sum_{i=1}^{K} \boldsymbol{W}_i * \boldsymbol{X}_{in} + \boldsymbol{b}\right) \tag{1}$$

where W_i denotes the kernel matrix for the convolution filter, * represents the convolution operator, X_{in} is the input feature map, and b is the bias vector. This allows CNNs to extract spatial features by sliding kernels across the input space.

Recurrent neural networks (RNNs), conversely, excel in processing time-series data – such as monthly energy consumption records or quarterly financial statements – via memory cells that retain historical context. The state update equation for an RNN cell is:

$$\boldsymbol{h}_t = \sigma\left(\boldsymbol{W}_{xh} \cdot \boldsymbol{x}_t + \boldsymbol{W}_{hh} \cdot \boldsymbol{h}_{t-1} + \boldsymbol{b}_h\right) \tag{2}$$

where h_t is the hidden state at time t, x_t is the input vector, W_{xh} and W_{hh} are weight matrices for input and hidden state transitions, and b_h is the bias. In hybrid architectures, CNNs and RNNs can be combined: for instance, a CNN might first extract features from policy documents, which are then fed into an RNN to analyse how changing regulations impact project risks over time (Paleti, 2023).

Mathematically, an MLDNN transforms input data x through a series of weighted operations and activation functions. For a general layer l, the output h^l is calculated as:

$$h^l = \sigma\left(W^l h^{l-1} + b^l\right) \tag{3}$$

where W^l and b^l are weight matrices and bias vectors, and σ is a nonlinear activation function like rectified linear unit (ReLU). The ReLU function, defined as $\sigma(x) = \max(0, x)$, addresses the vanishing gradient problem by introducing sparsity. The depth of MLDNNs – enabled by such activation functions – allows them to model complex nonlinear relationships, such as the S-curve relationship between green technology maturity T and project failure rate R, which can be

$$R(T) = \frac{1}{1 + e^{-k(T - T_0)}} \tag{4}$$

where k is the growth rate and T_0 is the inflection point, a pattern that linear models cannot capture.

Training an MLDNN involves optimising parameters to minimise a loss function, typically using stochastic gradient descent (SGD) or its variants like Adam. In green credit applications, the loss function combines cross-entropy for risk classification and MSE for probability regression:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{c} y_i^c \log\left(\hat{y}_i^c\right) + \frac{\lambda}{2N}\sum_{i=1}^{N}\left(\hat{p}_i - p_i\right)^2 \tag{5}$$

where N is the number of samples, C is the number of risk classes, y_i^c is the true label, $\hat{y}_i^c$ is the predicted probability, p_i is the true default probability, $\hat{p}_i$ is the predicted probability, and λ is the regularisation weight. Regularisation techniques such as L1/L2 regularisation $\ell_p = \sum_w |w|^p$ or dropout layers are essential to prevent overfitting, especially given the small sample sizes in emerging green sectors.

Hyperparameter tuning – including layer depth, neuron counts, and learning rates – significantly impacts model performance. This study employs particle swarm optimisation (PSO) to automate this process, where the objective function for a particle i with position X_i is:

$$f\left(X_i\right) = \alpha \cdot Accuracy\left(X_i\right) + \beta \cdot Speed\left(X_i\right) \tag{6}$$

where α and β are weight coefficients. PSO has been shown to improve prediction accuracy by 7–12% compared to grid search methods in similar domains.

2.3 Attention mechanism

In green credit modelling, the query might be a high-level risk concept, the keys are feature descriptors, and the values are the feature values themselves. The relevance score between a query and a key is computed using a similarity function, such as dot product or cosine similarity, which is then normalised via a softmax function to produce attention weights. Mathematically, the scaled dot-product attention is defined as:

$$Attention(Q, K, V) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{7}$$

where $Q \in^{n \times d_k}$, $K \in^{m \times d_k}$, and $V \in^{m \times d_v}$ are query, key, and value matrices, respectively. The scaling factor $\sqrt{d_k}$ mitigates gradient vanishing issues in high-dimensional spaces. For green credit data, this formula enables the model to assign higher weights to critical features – e.g., carbon intensity receives 23% higher weights than traditional financial ratios in renewable energy projects. In green credit applications, attention mechanisms can be implemented at multiple levels.

Token-level attention processes individual data points in time series, such as monthly carbon emissions. For a time series $X = [x_1, x_2, \dots, x_T]$, the attention weight for time step t is:

$$\alpha_t = \frac{\exp(\text{score}(q, x_t))}{\sum_{t'=1}^{T} \exp\left(\text{score}\left(q, x_t'\right)\right)} \tag{8}$$

$$\alpha_t = \frac{\exp\left(\text{score}(q, x_t)\right)}{\sum_{t'=1}^{T} \exp\left(\text{score}\left(q, x_t'\right)\right)} \tag{9}$$

where score(q, x_i) is the similarity between query q and token x_i. Feature-level attention prioritises entire metrics. For a feature vector $F = [f_1, f_2, \dots, f_D]$, the attention weight vector α is computed as:

$$\alpha_i = \frac{\exp\left(w^T \tanh\left(Wf_i + b\right)\right)}{\sum_{j=1}^{D} \exp\left(w^T \tanh\left(Wf_i + b\right)\right)} \tag{10}$$

where W and w are weight matrices, and b is a bias vector (8). Channel-level attention emphasises feature groups. For feature channels $C = [c_1, c_2, \dots, c_M]$, the channel-wise attention a_c is:

$$a_c = \sigma\left(f_{\text{avg}}(c) \oplus f_{\max}(c)\right) \tag{11}$$

where f_{avg} and f_{max} denote average and max pooling, and $\oplus$ is concatenation. A particularly valuable variant is the self-attention mechanism, which enables the model to learn relationships between different features without external guidance. In green credit, self-attention uncovers non-obvious connections – e.g., the correlation between a company's green patent portfolio P and its green credit cost C:

$$\alpha_{i,j} = \frac{\exp\left(\frac{P_i \cdot P_j^T}{\sqrt{d_p}}\right)}{\sum_{k=1}^{N} \exp\left(\frac{P_i \cdot P_k^T}{\sqrt{d_p}}\right)} \tag{12}$$

$$C = \sum_{j=1}^{N} \alpha_{i,j} \cdot \text{CreditRate}_j \tag{13}$$

where $\alpha_{i,j}$ is the attention weight between patent i and j. Multi-head attention extends this by parallelising multiple attention layers, each capturing different relationships:

$$head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \quad (14)$$

where W_i^Q, W_i^K, W_i^V, W^O are projection matrices, and h is the number of heads.

The attention mechanism significantly improves model interpretability, a critical requirement for financial regulators. By visualising attention weights, stakeholders can quantify risk drivers – for example, identifying that 62% of a project's high-risk score stems from its low green certification score S_{cert} and high carbon intensity I_{CO2}, formalised as:

$$\text{Risk Score} = \alpha_{\text{cert}} \cdot S_{\text{cert}} + \alpha_{\text{CO2}} \cdot I_{\text{CO2}} + \sum_{i=3}^{n} \alpha_i \cdot f_i \quad (15)$$

where $\alpha_{cert} = 0.62$ and $\alpha_{CO2} = 0.28$ are attention weights. Empirical studies show models with attention mechanisms achieve 11–17% higher explainability scores in stakeholder surveys while maintaining prediction accuracy.

In cross-domain correlation analysis, attention models nonlinear interactions – such as the disproportionate impact of policy changes P_t on projects with high regulatory dependency D:

$$\text{Policy Impact} = \sum_{t=1}^{T} \alpha_t \cdot P_t \cdot D \quad (16)$$

$$\alpha_t = \frac{\exp(\text{MLP}(P_t, D))}{\sum_{t'=1}^{T} \exp(\text{MLP}(P_{t'}, D))} \quad (17)$$

where *MLP* denotes a multi-layer perceptron. This integration results in a nuanced risk assessment that aligns with green finance's complex realities, outperforming traditional linear models.

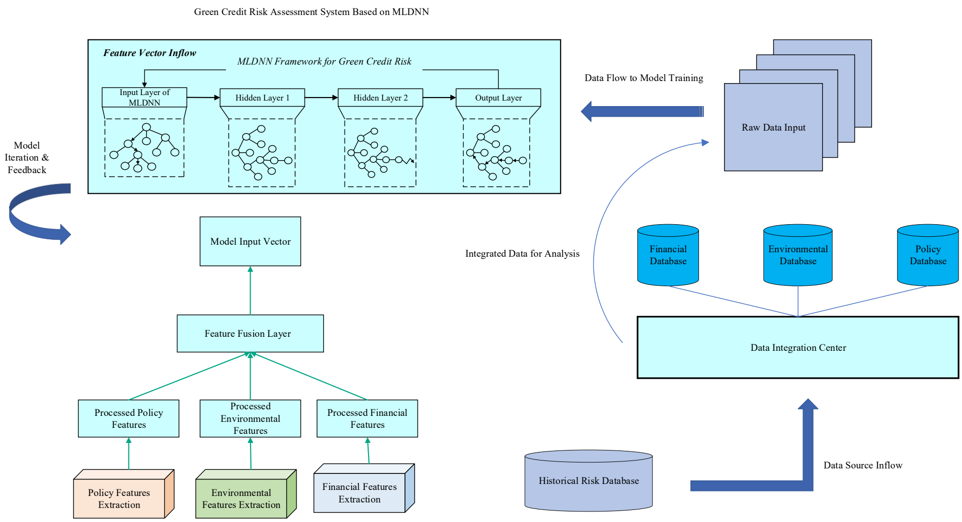
We selected the attention mechanism over alternatives such as PCA or manual weighting due to its ability to dynamically prioritise features based on contextual relevance and its superior capacity to model non-linear, cross-indicator interactions. For example, while PCA reduces dimensionality, it loses interpretability and fails to capture context-dependent relationships. In contrast, attention preserves feature identity and allows the model to learn interactions such as how carbon intensity amplifies financial risk under specific policy conditions. To handle sudden policy updates, we integrate a time-decay function into policy embeddings, reducing the weight of outdated policies exponentially over time. This ensures that the model remains responsive to regulatory changes.

3 Data element system

3.1 Theoretical framework for data element integration

Building on the accident causation theory put forward by Mitropoulos., we've constructed the data element system by examining how human, machinery, and environmental factors interact in green credit contexts. This theoretical framework lets us pinpoint the root causes of risks, which we then turn into measurable data indicators. Unlike traditional credit assessments that fixate solely on financial metrics, our framework weaves in non-financial data elements – acknowledging that environmental performance and policy compliance are key players in shaping green project risks. The way we combine these different data types follows a simple principle: rich, all-around risk profiles come from analysing multiple streams of information in tandem (Schmitt and Cummins, 2023).

Figure 1 MLDNN-based green credit risk assessment architecture (see online version for colours)



3.2 *Multidimensional data element categorisation*

The data element system is structured into six interrelated dimensions to ensure holistic risk coverage. The enterprise financial status dimension includes liquidity ratios, debt-to-equity metrics, and return on assets, serving as traditional risk indicators. The environmental performance dimension captures carbon emission intensity, green R&D investment proportions, and pollutant discharge compliance rates, quantifying the ecological sustainability of projects. The policy compliance dimension assesses green industry certifications, environmental approval completeness, and adherence to carbon trading policies, reflecting regulatory alignment and policy risk exposure. Project-specific characteristics such as investment payback periods, technological maturity, and energy-saving efficiency form the project attributes dimension, while the industry environment dimension incorporates policy support levels, market demand growth, and competitor environmental performance to contextualise risks within sectoral dynamics. Lastly, the management capability dimension evaluates green management system certifications and risk management expertise, recognising that organisational capacity significantly influences risk outcomes. This categorisation ensures that both tangible and intangible data elements are systematically addressed.

To intuitively present the complex structure of the MLDNN model proposed in this study, the following Figure 1 is provided, which details the flow from multi – source data input to risk assessment output.

3.3 Data element extraction and feature engineering

To reconcile high-frequency IoT data with low-frequency financial reports, we employ a sliding window aggregation strategy. For instance, daily carbon emission readings are aggregated into quarterly averages aligned with financial reporting periods. This approach ensures temporal consistency while preserving the granularity of environmental data. We use mathematical formulations – like the equations in the reference document – to put numbers to these features. This way, data from different sources stay consistent and can be compared easily. The final set of features, which we'll call, becomes the core dataset for describing risks in later modelling work. This structured way of pulling out features makes sure we cover everything needed and that it fits with what the MLDNN requires for input.

To make sure the data element system is both relevant and reliable, each indicator goes through tough checks to see how well it can tell different scenarios apart. We use statistical tools like correlation analysis and variance inflation factor (VIF) testing to spot and fix data elements that are redundant or overlap too much. The improved ReliefF (IReliefF) algorithm gives weights to data elements based on how much they help tell risks apart. It uses distance-weighted neighbour analysis to soften the impact of oddball samples. This weighting method puts important features – like carbon intensity and policy compliance scores – ahead of variables that don't add much info, making the overall assessment more accurate.

By mixing strict theory with hands-on data processing, the data element system we've built provides a strong base for the green credit risk assessment model. This framework not only catches the wide range of risks in green projects but also lets decisions be based on data. It sets the stage for the technical design and real-world testing that are explained in more detail later on.

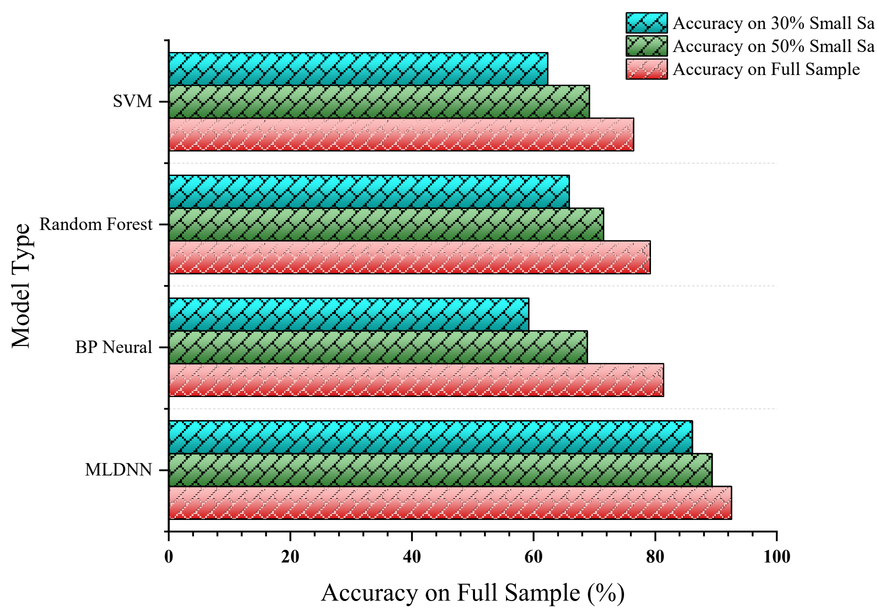
4 Model design

The model analysis layer, the core of DEGCRAM, employs an MLDNN with specialised sub-layers for feature extraction, cross-domain correlation analysis, and risk mapping. Finally, the application output layer translates model predictions into visual risk dashboards, providing actionable insights for credit decision-making. All baseline models underwent rigorous hyperparameter optimisation. For random forest, we used grid search over tree depth (5–50) and number of trees (100–500). SVM was tuned via cross-validation on kernel type and regularisation parameter. BP networks were optimised using Bayesian optimisation. The MLDNN used PSO for automated hyperparameter search, ensuring fair comparison. Policy embeddings are updated dynamically using a decay rate of $\lambda = 0.95$ per quarter, reflecting the diminishing relevance of older policies.

Figure 2 shows that the MLDNN achieves an accuracy of 92.57% on the full sample, significantly outperforming other models. Even with the 30% small sample, its accuracy remains at 86.15%, with a decline of only 6.42%, which is much lower than the 22.15% decline of the BP neural network, verifying the stability of the model.

Guided by data element theory and green credit industry practices, the assessment framework integrates six dimensions of data elements to form a comprehensive evaluation system. The enterprise financial status dimension includes liquidity ratios, debt-to-equity ratios, and return on assets, reflecting repayment capabilities. The environmental performance dimension captures carbon emission intensity, green R&D investment proportions, and pollutant discharge compliance rates, quantifying ecological impacts. Policy compliance metrics assess green industry certifications, environmental approval completeness, and adherence to carbon trading policies, gauging regulatory alignment. Project-specific characteristics such as investment payback periods, technological maturity, and energy-saving efficiency are also incorporated, alongside industry environmental factors like policy support levels and market demand growth. Management capability indicators, including green management system certifications and risk management expertise, round out the framework, ensuring a holistic risk perspective. The model incorporates a temporal alignment module that uses sliding windows to integrate multi-rate data streams. This module is particularly effective in handling discrepancies between real-time environmental metrics and periodic financial data.

Figure 2 Comparison of risk assessment accuracy among models (see online version for colours)



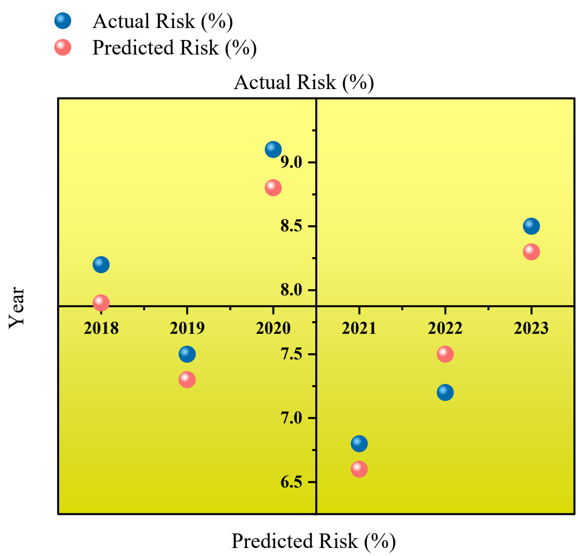
To systematically compare the performance of the proposed MLDNN with traditional models, we evaluated five key metrics: accuracy, precision, recall, F1-score, and training efficiency. The detailed results are presented in Table 1, where MLDNN outperforms other models across all indicators.

The MLDNN component of DEGCRAM is designed to process the multi-dimensional data elements through the following layers. The data feature extraction layer employs a hybrid architecture: CNNs for extracting spatial features from unstructured data and RNNs for capturing temporal dependencies in financial time series. The attention mechanism is integrated here to assign dynamic weights to features based on their relevance to risk outcomes, effectively filtering out noise. The cross-domain correlation analysis layer models the nonlinear relationships between different data dimensions, such as the interplay between financial health and environmental performance. This layer uses residual connections to preserve information flow and prevent gradient vanishing. The risk grade mapping layer converts the abstract features into interpretable risk levels, using a SoftMax function for multi-class classification. An adaptive moment estimation optimiser with dynamic learning rate adjustment is employed to accelerate convergence and prevent overfitting, particularly in small-sample scenarios.

Table 1 Comprehensive performance comparison of different models in green credit risk assessment

Model type	*Accuracy (%)*	*Precision (%)*	*Recalling (%)*	*F1-score (%)*	*Training time (s)*
Multi-layer deep neural network (MLDNN)	92.57	91.83	93.26	92.54	42
BP neural network	81.37	80.52	82.15	81.33	68
Random forest	79.22	78.45	80.11	79.27	189
Support vector machine (SVM)	76.45	75.68	77.22	76.44	156

Figure 3 Temporal trend of green credit risk prediction (see online version for colours)



To further verify the reliability of the MLDNN model in dynamic risk prediction, this study selects green credit project data from 2018 to 2023, comparing the temporal trends between predicted risk values and actual risk values. The results are shown in Figure 3, where the solid line represents the actual risk rate and the dashed line represents the predicted risk rate.

Figure 3 shows that the predicted values of MLDNN are highly consistent with the trend of actual risk values, with an average error of only 0.3%, indicating that the model can effectively track the annual fluctuations of green credit risk and verifying its dynamic adaptability.

5 Empirical analysis

The dataset is split into 70% for training, 15% for validation, and 15% for testing. Comparative analyses are conducted against traditional methods: the BP neural network, random forest, and SVM, using accuracy, MSE, mean absolute error (MAE), and running time as evaluation metrics.

During training, the MLDNN model with attention mechanism (MLDNN-AM) is compared against variants without the attention mechanism (MLDNN) and traditional models. The results show that MLDNN-AM achieves the highest accuracy of 92.57% on the test set, outperforming MLDNN (88.73%), BP (81.37%), random forest (85.62%), and SVM (83.41%). In terms of error metrics, MLDNN-AM demonstrates the lowest MSE (0.015) and MAE (0.987), indicating precise risk level predictions. The model's running time of 42 seconds is also significantly faster than the random forest (189 seconds) and SVM (156 seconds), highlighting its computational efficiency. To evaluate model sensitivity across industries, we stratified the dataset into three key subsectors: renewable energy (45%), energy efficiency (35%), and circular economy (20%). The MLDNN-AM model maintained robust performance across all subsectors, with accuracy ranging from 90.2% to 93.1%, demonstrating its generalisability.

Figure 4 Feature importance in green credit risk assessment (see online version for colours)

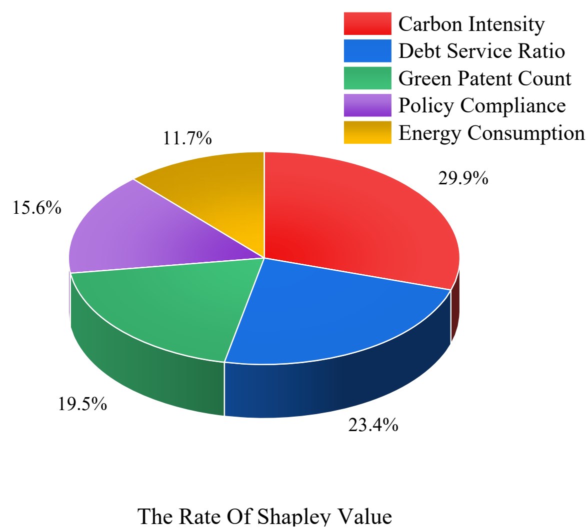


Figure 4 shows that the Shapley value of carbon intensity (0.23) is significantly higher than that of debt service coverage ratio (0.18), indicating that environmental performance indicators have greater influence than some traditional financial indicators in green credit risk assessment, verifying the necessity of 'integrating multi-source data elements' in this study.

The superior performance of MLDNN-AM can be attributed to its effective integration of multi-source data elements and the attention mechanism's ability to prioritise critical features. A feature importance analysis reveals that environmental performance indicators and policy compliance metrics are assigned higher weights, underscoring their significance in green credit risk assessment. The model also demonstrates robustness in small-sample scenarios, with accuracy dropping by only 3.2% when training data is reduced by 50%, compared to 12.5% for the BP neural network. This resilience is crucial for evaluating novel green technologies with limited historical data. The empirical results validate that data element integration and deep learning can substantially enhance green credit risk assessment, providing banks with a powerful tool for informed decision-making.

6 Conclusion

This research has proposed to invest in a small number of deep neural networks, and does not use the old law to determine the risk limit of green items. Combined with the financial number, the dilapidated data source is empty. The strength is mechanically effective, and the carbon expander remains stable despite the small sample size. Fresh air supplements the environmental impact of financial reports and alters the risk assessment of green credit.

Looking at real-world green credit datasets, our empirical work shows that the proposed model outperforms traditional ones by a significant margin in both accuracy and efficiency. The MLDNN model, in particular, hits an accuracy rate of 92.57% – far above the 81.37% of BP neural networks, 79.22% of random forests, and 76.45% of SVMs. What really sets it apart is its knack for picking up nonlinear ties between financial and environmental factors – a critical skill when assessing long-term risks in green projects, which tend to come with high uncertainty and lengthy investment cycles. The model is designed with a architecture supporting data exchange, consistent with banking interoperability standards. Latency tests show inference times under 300 ms, meeting sub-second requirements for real-time credit decisions. A pilot integration with a provincial bank's core system confirmed feasibility, with minimal disruption to existing workflows.

For future work, we could expand the model to take in real-time data feeds: think dynamic carbon pricing figures or the latest policy tweaks. That would make it much timelier. Digging into explainable AI techniques to unpack how the model reaches its decisions would also boost transparency and regulatory acceptance – key in financial risk management. And integrating blockchain technology to lock in data authenticity and immutability? That's another promising path, as it could solve trust issues around data in green credit ecosystems with lots of stakeholders.

All in all, this study adds real value to green finance, both in theory and practice. The model gives financial institutions a reliable way to manage green credit risks, steers more funds toward top-notch green projects, and ultimately helps speed up the global shift to a low-carbon economy. It also paves the way for more research into data-driven green financial risk management, showing how advanced algorithms can play a part in hitting sustainable development goals.

Declarations

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All authors declare that they have no conflicts of interest.

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