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An Enterprise Financial Health Rating System Based on Deep Belief Networks in Financial Big Data Analytics

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ABSTRACT The global textile and leather industry faces mounting pressure from market volatility, supply-chain uncertainty, financial risk, and ESG-related disclosure requirements. This study constructs an enterprise financial health rating system based on a Deep Belief Network (DBN). The sample includes 247 listed companies in the textile, apparel, and leather products sectors from the Shanghai-Shenzhen A-share markets and the Hong Kong Stock Exchange during 2013–2023, yielding 2,486 firm-year observations. Eighteen core features are extracted across five analytical dimensions: solvency, operational efficiency, profitability, cash flow quality, and ESG financial disclosure. A three-layer stacked Restricted Boltzmann Machine architecture combined with Bayesian hyperparameter optimization is used to perform seven-tier classification. The DBN model outperforms Logistic Regression, SVM, XGBoost, and LSTM across major metrics, achieving an AUC-ROC of 0.9218, a macro-averaged F1 score of 0.8312, and a KS statistic of 0.7134. Ablation experiments further show that incorporating ESG financial indicators improves high-risk rating identification accuracy by 3.24 percentage points. SHAP interpretability analysis provides traceable evidence for rating decisions. The system can therefore serve as a deployable intelligent rating tool for credit institutions and supply-chain finance platforms.

INDEX TERMS deep belief network, financial health rating, risk prediction, esg indicators, shap interpretability

I. INTRODUCTION

ENTERPRISE financial data suggests that growth has occurred at an unprecedented rate. Moreover, the significant evidence indicates that two forces are driving this expansion: the deepening integration of the global economy and the accelerating diffusion of digital technologies. Financial health assessment harder here than manufacturing. In light of these significant results, traditional financial rating methods indicates that linear statistical models and expert judgement remain the primary tools employed. Additionally, the important evidence shows that these tools were not designed for high-dimensional, nonlinear, cross-cycle financial datasets. Thus, the findings demonstrates that their predictive accuracy and risk identification capacity appear to have fallen short of what modern credit management requires. Nevertheless, extracting meaningful risk signals from large-scale heterogeneous financial data shows that translating those signals into dynamic, multi-tier ratings has become one of the most critical problems in financial analysis. Risk signal extraction links rating difficulty. Pagnottoni demonstrated that autoregressive methods grounded in optimal transport theory can effectively characterise the distributional dynamics of multi-dimensional financial indicators [1]. Moreover, the significant findings shows that this offers a useful methodological reference for building financial modelling frameworks suited to cross-cycle enterprise evaluation. While this study primarily utilizes annual corporate reports to establish a robust long-term rating baseline, the DBN architecture is designed with the structural scalability to incorporate higher-frequency data—such as quarterly updates or market volatility indices—in future tactical risk monitoring applications. Given that the evidence demonstrates that artificial intelligence and big data are reshaping financial analysis, the results indicates that these developments appear fundamental in scope. Therefore, the key results shows that research on machine-learning-based risk identification and early-warning systems demonstrates that these methods automatically capture latent risk patterns across multi-source heterogeneous data [2]. AI improves timeliness and accuracy. In light of the significant findings, investment and wealth management analytics indicates that AI-driven approaches have matured considerably in recent years. Notwithstanding these results, Anjum et al. confirmed that AI methods can enhance risk insight and decision efficiency in complex financial data environments [3].

Most existing intelligent financial analysis studies shows that their scope targets either macro-level financial markets or general manufacturing contexts. However, the rating models designed specifically for the financial characteristics of the textile and leather industry could indicate a significant gap in current literature. Moreover, the industry-specific structural challenges — cyclical inventory accumulation, dispersed accounts receivable cycles, and the impact of carbon tariff policies — shows that the limited adaptability of generic models remains a critical concern. In light of these findings, the evidence demonstrates that deep learning rating approaches built around sector-specific data features appear to address a clear and important need. DBN models show this gap exists. Furthermore, the Deep Belief Networks (DBNs) may suggest a well-suited architecture for this task, given that the evidence demonstrates their capacity as a representative class of deep generative models. Additionally, the significant mechanism of layer-wise unsupervised pre-training combined with supervised fine-tuning indicates that DBNs provide strong modelling capacity for high-dimensional nonlinear feature extraction [4]. Given that recent findings demonstrate the potential of deep generative models, the results from generative adversarial networks in financial time-series forecasting shows that complex financial settings could benefit from such important approaches. Recent work shows deep generative models suit finance. Nevertheless, the federated learning frameworks indicates that a viable path for privacy-preserving data sharing across multiple institutional parties appears to have emerged [5]. Therefore, the significant findings from Tong et al. shows that financial data security and the legal environment could demonstrate a lasting influence on corporate financing efficiency [6]. Moreover, the results indicates that the significant rating system design must demonstrate that model performance and data governance and compliance boundaries appear equally critical. In light of these important findings, applying DBNs to financial health rating in the textile and leather sector shows that both methodological grounding and practical urgency could demonstrate a compelling case for this study. Study constructs enterprise financial health rating system. Furthermore, the significant features extracted across five dimensions — solvency, operational efficiency, profitability, cash flow quality, and ESG financial disclosure — indicates that the DBN's hierarchical feature learning mechanism demonstrates that multi-tier classification of enterprise financial health status appears both feasible and important.

The study demonstrates that the methodological framework of Marín et al. in multi-objective optimisation and real-time financial data integration could provide significant grounding for the evidence presented here. Moreover, the findings shows that SHAP interpretability analysis appears essential to ensure that the rating outputs carry traceable decision rationale [7]. Furthermore, the academic contribution of this research indicates that the evidence supports a twofold significance worth examining carefully. Research addresses practical needs too. Additionally, the significant findings shows that the study provides a deployable intelligent rating tool for credit institutions, supply chain finance platforms, and regulatory bodies. Given that the results demonstrate that these practical applications appear broadly relevant, the evidence indicates that supporting the development of a more robust financial risk management infrastructure across the sector remains a critical outcome. Nevertheless, the important results shows that the study establishes meaningful contributions across both academic and applied domains. Study shows tool supports sector risk infrastructure.

II. LITERATURE REVIEW

Building robust financial information systems is a prerequisite for effective financial big data management. Moreover, the findings from Wang shows that a J2EE-based financial information system for power supply enterprises could integrate multi-source business data efficiently, improving both processing speed and system reliability [8]. Furthermore, the significant findings offer a practical engineering reference for constructing industry-specific financial data platforms. In light of the evidence from related work, data governance capacity indicates that it directly determines the precision of financial risk identification — a point of particular relevance given the large number of SMEs in the textile and leather sector [9]. Research shows governance affects risk precision. However, a further study on financial management optimisation in commercial enterprises demonstrates that standardised data collection procedures and dynamic monitoring mechanisms appear to form the core infrastructure for fine-grained financial control [10]. Given that the evidence from these studies demonstrates sound financial information systems matter, the results indicates that mature data governance frameworks are preconditions for enterprise financial health rating. Additionally, the significant findings provide the theoretical grounding for the data infrastructure layer on which this study's DBN-based rating system is built. Notwithstanding these contributions, considerable theoretical work shows that statistical analysis and complexity modelling of financial data have also accumulated important results. Studies show complexity matters. Therefore, the findings from Moraes et al. shows that eigenvalue distribution theory of empirical correlation matrices could reveal the underlying statistical regularities of financial data in multi-scale complex systems [11-13].

Kiefer et al. proposed a Hamiltonian filter projection method that may suggest strong adaptability in financial time-series forecasting [14,15]. Additionally, the important evidence indicates that Alidousti et al. proposed a data-efficient double deep Q-network framework for intelligent portfolio management, illustrating that deep reinforcement learning might demonstrate substantial potential in financial decision optimisation [16]. Thus, the key findings shows that Johri conducted an empirical study on AI's impact on accounting information system performance and financial reporting accuracy, finding that AI adoption could demonstrate systematic reduction of misreporting rates and improve information quality [17]. Notwithstanding these results, the significant evidence indicates that Dumitrescu et al. used machine learning to analyse the dynamic evolution of financial data in Romanian transport firms, validating that machine learning methods appear effective in industry-specific financial assessment settings [18]. Study shows methods validate financial assessment. Targeted modelling of the financial characteristics specific to the textile and leather industry remains limited despite these advances. Moreover, the application of DBNs within this domain shows that a clear and largely unaddressed research gap could indicate significant opportunities for further study. However, the findings from credit assessment and financial risk early warning demonstrate that several methodologically significant contributions have emerged. In light of these results, Lu et al. [19] proposed an efficient financial data imputation method for credit rating tasks, and the evidence shows that this approach directly addresses the problem of missing data undermining model accuracy. Research shows imputation offers practical preprocessing solutions. Furthermore, Guo et al. [20] explored approaches to developing financial data analysis competencies in higher education settings, and the significant findings indicates that systematic analytical training plays a foundational role in supporting rating practice. Additionally, Miljak et al. [21] examined how financial managers' decisions in micro-enterprises might affect operational performance, and the key results shows that a significant positive relationship appears to exist between management decision quality and enterprise financial health. Thus, the evidence demonstrates that the practical value of financial health ratings as a decision reference appears well-supported by the significant findings. Study shows ratings confirm practical value. Given that the data demonstrates the importance of intelligent algorithms, Zheng [22] conducted a systematic review of innovative risk early-warning models for enterprise financial management in the big data era, and the results shows that combining multi-dimensional financial indicators with intelligent algorithms could demonstrate key improvements. Notwithstanding these important contributions, the significant findings from reviewing this body of literature as a whole indicates that existing research has built substantial experience across data preprocessing, feature extraction, and risk early warning. Nevertheless, the evidence shows that what remains absent is a dedicated enterprise financial health rating system that could demonstrate the value of combining deep belief networks with the sector-specific data characteristics of the textile and leather industry. Therefore, the significant findings appear to support that this study could explore that gap as its starting point. Study takes gap as starting point.

III. METHODOLOGY

A. RESEARCH FRAMEWORK DESIGN

This study develops a systematic research framework organised around four progressive modules: data collection and governance, indicator system construction, model training and optimisation, and rating output with interpretability. However, the four modules shows that together they form a closed and iteratively refinable pipeline for enterprise financial health rating in the textile and leather industry. Moreover, the first module covers data collection and governance, and the findings indicates that the sample pool consists of textile, apparel, and leather products firms listed on the Shanghai–Shenzhen A-share markets and the Hong Kong Stock Exchange between 2013 and 2023. Furthermore, the significant evidence shows that raw financial data are retrieved from the Wind database, Bloomberg terminal, and corporate annual reports. Given that the results demonstrate that missing values, outliers, and measurement scale inconsistencies are addressed through standardisation procedures, the study indicates that completeness and internal consistency are required for downstream modelling. Data quality shapes indicator validity. The second module constructs the indicator system, and the evidence shows that starting from five analytical dimensions — solvency, operational efficiency, profitability, cash flow quality, and ESG financial disclosure — 32 candidate features are initially screened. Additionally, the significant findings indicates that principal component analysis then reduces highly collinear variables. Therefore, the results demonstrates that SHAP values are subsequently used to rank the marginal contribution of each remaining feature, producing a final indicator set that is both industry-representative and statistically independent. Notwithstanding these results, the key evidence indicates that the third module handles model training and optimisation, and that a three-layer stacked Restricted Boltzmann Machine constitutes the core DBN architecture. In light of the findings, the study shows that layerwise unsupervised pre-training is conducted via the contrastive divergence algorithm, followed by end-to-end supervised fine-tuning through backpropagation. Module three shows Bayesian optimisation guides search over hidden layer size, learning rate, and dropout ratio. However, the significant findings shows that five-fold cross-validation controls for overfitting risk [23], and the evidence indicates that the fourth module produces rating outputs and explanations. Moreover, the results demonstrates that financial health is classified into seven tiers ranging from AAA to C, spanning a continuous spectrum from excellent health to severe financial distress. Framework shows modules interdependent, rating credibility shaped by performance. Nevertheless, the significant findings shows that interpretability analysis feeds back to validate the original indicator selection, and the results indicates that model performance directly shapes rating credibility. Given that the evidence demonstrates that data quality determines indicator validity, the study shows that the result is a self-consistent framework that supports iterative refinement.

B. DATA SOURCES AND SAMPLE DESCRIPTION

The research sample comprises textile, apparel, and leather products firms continuously listed on the Shanghai–Shenzhen A-share and Hong Kong H-share markets from 2013 to 2023. Moreover, the industry classification shows that the evidence follows the China Securities Regulatory Commission's Guidelines for the Classification of Listed Companies, specifically sub-categories C17 (Textile, Apparel and Clothing) and C19 (Leather, Fur, Feather and Related Products and Footwear). However, the initial candidate pool indicates that the data contains 312 firms as a key starting point for analysis. Given that the screening process demonstrates that comparability and modelling validity are critical, three screening criteria appear to establish a rigorous foundation for the study. Firms subject to Special Treatment (ST) designation are retained in the initial sample pool rather than being excluded, as these entities provide critical empirical benchmarks for the 'C' (severe financial distress) rating tier. Including ST observations ensures the model captures the full variance of financial distress signals, thereby mitigating selection bias and enhancing the DBN's capacity to distinguish between moderate risk and terminal insolvency. Furthermore, the second criterion indicates that firms with key financial statement items missing for three or more consecutive years could demonstrate insufficient data reliability. Thus, the third criterion shows that firms undergoing major asset restructuring, resulting in a fundamental change to their business scope, are excluded, since pre- and post-restructuring data appear to lack a comparable basis [24]. After screening, 247 firms remain. Notwithstanding these exclusions, the significant results indicates that these firms form an unbalanced panel dataset spanning eleven fiscal years, yielding 2,486 firm-year observations. Additionally, the findings shows that Wind Financial Terminal serves as the primary data source, supplemented by Bloomberg. Study shows ESG items manually extracted from reports. In light of the data preprocessing steps, the evidence indicates that multiple imputation could demonstrate an important approach to addressing randomly missing financial indicators. Moreover, the three-standard-deviation rule shows that the results appear to identify and correct extreme outliers effectively. Therefore, the significant findings indicates that Z-score standardisation demonstrates that variables across different measurement scales might require normalisation, eliminating the distorting effect of scale differences on DBN weight learning [25]. Descriptive statistics show structural difference between sub-industries. Nevertheless, the findings shows that textile and apparel firms appear to be generally larger in terms of total assets and revenue. Furthermore, leather products firms indicates that the significant evidence demonstrates more concentrated distributions for inventory turnover and gross margin stability. In light of these key results, the inter-industry variation shows that this evidence could provide an important empirical basis for the sub-industry comparative analyses conducted in later sections.

Construction of the Financial Health Feature Variable System

The feature variable system shows that five dimensions could capture the operational characteristics of the textile and leather industry. Moreover, the findings indicate that solvency is captured by five indicators: current ratio, quick ratio, debt-to-asset ratio, interest coverage ratio, and long-term capital debt ratio. Furthermore, the evidence shows that these indicators jointly assess short-term liquidity pressure and long-term debt structure safety margins. Given that large advance payments for raw material procurement are common practice in this industry, the results demonstrates that a structural tendency toward elevated current liabilities appears significant. Feature variables show solvency indicators calibrated to short-term repayment stress [26]. However, the significant findings shows that operational efficiency is measured by five indicators: accounts receivable turnover, inventory turnover, total asset turnover, accounts payable days outstanding, and working capital turnover. Additionally, the results indicates that these key indicators quantify asset utilisation efficiency under conditions of seasonal order fluctuation and inventory accumulation. In light of the evidence, inventory turnover demonstrates that it carries particular discriminatory value for identifying raw leather stockpiling risk. Therefore, the important data shows that profitability is assessed through five indicators: net profit margin, return on total assets, return on equity, gross margin, and operating profit growth rate. Profitability indicators show static earnings and dynamic value creation. Nevertheless, the findings shows that cash flow quality is evaluated using five indicators: operating cash flow ratio, cash flow adequacy ratio, free cash flow to net profit ratio, cash received from sales ratio, and capital expenditure coverage ratio. Moreover, the significant evidence indicates that these indicators cut through the surface appearance of accounting profits to assess genuine cash generation capacity. Furthermore, the results demonstrates that this dimension is particularly useful for detecting the pattern of revenue growth without corresponding cash inflow — a form of latent financial risk with significant early-warning implications [27]. Given that the ESG financial disclosure draws on the ISSB disclosure framework, the key findings shows that four indicators are extracted: environmental expenditure as a share of revenue, carbon emission intensity change rate, labour compensation compliance index, and ESG rating disclosure completeness. ESG indicators quantify firms' capacity to manage green transition pressures. However, the evidence shows that the five dimensions yield 24 base features that could support further analysis. Additionally, the significant results indicates that a Pearson correlation matrix then identifies collinear pairs. In light of these findings, feature combinations with absolute correlation coefficients exceeding 0.85 were initially merged through principal component analysis. Furthermore, to address the inherent mathematical redundancy among 'Current Ratio', 'Quick

Ratio', and 'Working Capital Turnover' — which are all derived from the same balance sheet components — we applied Variance Inflation Factor (VIF) analysis. Features with VIF > 5 were iteratively removed or orthogonalized to ensure that the 18 retained core features are not only statistically independent but also conceptually distinct for model training. Process shows 18 features retained for training. Notwithstanding this result, the findings shows that SHAP global importance ranking could subsequently validate and order each feature's overall contribution. Moreover, the significant data indicates that the final feature set appears to achieve coherence across both statistical independence and industry interpretability.

C. DEEP BELIEF NETWORK MODEL CONSTRUCTION

The DBN in this study consists of three stacked RBM layers, following a two-stage learning paradigm of unsupervised pre-training followed by supervised fine-tuning. However, the overall architecture shows that a funnel topology could demonstrate important advantages for this task. Moreover, the input layer contains 18 nodes, one for each retained financial health feature, and the significant findings from prior work indicate that such specification appears critical. Furthermore, the three hidden layers have 128, 64, and 32 nodes respectively, and the evidence shows that this progressive compression could demonstrate the network's ability to condense dispersed local statistical patterns into higher-order semantic representations capable of distinguishing seven financial health tiers. Design shows network condenses patterns into representations. Given that each RBM layer is trained independently in a greedy bottom-up sequence during pre-training, the results indicates that this approach could provide important advantages for initialisation. Additionally, the contrastive divergence algorithm (CD-k, k=1) approximates the log-likelihood gradient, and the key evidence shows that this method appears sufficient for the study. In light of the significant weight update procedure, the results indicates that minimising the mean squared reconstruction error between the visible layer input and its reconstructed output may support effective pre-training. Notwithstanding the greedy training sequence, the findings shows that once a layer completes pre-training, its output activations could serve as input to the next layer, continuing until all three RBM layers are initialised [28]. Pre-training initialises all three RBM layers. However, the fine-tuning stage shows that a seven-class Softmax classification layer could provide critical supervisory capacity when appended to the top RBM. Therefore, the seven-tier financial health rating indicates that it appears to serve as the key supervised learning target throughout the study. Moreover, the significant multi-class cross-entropy loss function demonstrates that it may support effective optimisation alongside back-propagation, which jointly updates all network parameters end-to-end. Given that the cosine annealing learning rate schedule shows that gradient oscillation appears problematic in later training epochs, the evidence indicates that this strategy provides an important preventive mechanism. Schedule prevents gradient oscillation. Furthermore, the results shows that two regularisation strategies could demonstrate their importance in limiting overfitting on the limited sample. In light of the significant dropout regularisation applied after each hidden layer with a drop probability of 0.3, the findings indicates that this approach appears effective for the study. Additionally, the evidence shows that an L2 weight decay term, added to the loss function with a decay coefficient of 1×10^{-4} determined through Bayesian optimisation, could demonstrate important regularisation benefits. Nevertheless, the key hyperparameter tuning procedure shows that AUC-ROC appears to serve as the primary evaluation criterion throughout the significant optimisation process. Bayesian optimisation searches hidden layer size, batch size, pre-training epochs. Thus, the evidence shows that the mean AUC from five-fold cross-validation determined the final hyperparameter configuration. To mitigate the risk of overfitting the complex 7-tier classification to 18 features, we implemented a parsimonious architecture search where the hidden layer depth was constrained relative to the input dimensionality. Specifically, the model employs a strict Early Stopping mechanism based on the 'Macro-F1' plateau on a separate hold-out validation set (20% of training data), ensuring the DBN learns generic sector-level patterns rather than memorizing class-specific noise within the 7-tier granular structure [29].

D. RATING CRITERIA AND MODEL EVALUATION METRICS

The seven-tier rating scheme — AAA, AA, A, BBB, BB, B, and C — shows that the continuous risk spectrum spans from excellent financial health to severe financial distress. Moreover, the significant classification boundaries indicates that the derivation follows a structured methodological approach [30]. However, the key model performance assessment demonstrates that a three-layer evaluation structure covers discriminative ability, predictive accuracy, and stability. Thus, the significant discriminative ability indicates that measurement relies on the AUC-ROC curve and the KS statistic. Additionally, the results shows that the AUC-ROC captures overall discriminative capacity across all classification thresholds. Notwithstanding the complementary role of the KS statistic, the findings appear to demonstrate that this measure specifically quantifies the maximum separation between high-risk and low-risk groups. Performance shows AUC-ROC and KS validate rating effectiveness together. Therefore, the important predictive accuracy evidence shows that both macro-averaged and weighted-average F1 scores provide the relevant reporting framework. Given that the macro F1 demonstrates balanced performance, the results indicates that this measure reflects consistent outcomes across all seven tiers. Furthermore, the significant weighted F1 shows that class imbalance in the sample receives appropriate accounting. Moreover, the evidence demonstrates that the Brier Score further quantifies calibration precision of probability predictions. Stability shows mean and standard deviation assessed across five cross-validation folds. However, the key findings indicates that an excessively large standard deviation signals model instability and triggers re-optimisation of hyperparameters [31]. Thus, the important evidence shows that a confusion matrix is constructed for the seven-class classification task. Additionally, the results demonstrates that the direction and frequency of misclassifications across each tier receive direct recording. In light of this empirical evidence, the significant findings indicates that refining rating boundaries between adjacent categories in subsequent iterations benefits from this direct empirical support.

IV. RESULTS AND ANALYSIS

A. TRAINING PROCESS AND CONVERGENCE ANALYSIS OF THE DBN MODEL

1) Reconstruction Error Dynamics During Pre-Training

During the pre-training phase of the Deep Belief Network, the three RBM layers are trained sequentially in a greedy bottom-up order. Each layer undergoes independent unsupervised training, and the reconstruction error at every layer follows a clear nonlinear declining trajectory as iterations progress [32]. Convergence here is more gradual, eventually stabilising at 0.0421 by iteration 100. Full results are presented in Table 1 and Figure 1. All three RBM layers enter an error plateau around iteration 50. This pattern indicates that the contrastive divergence algorithm converges robustly at this data scale. The greedy layer-wise pre-training strategy effectively avoids the gradient instability that can arise from random initialisation in deep networks, providing a high-quality weight initialisation foundation for the subsequent supervised fine-tuning stage [33].

2) Loss Function and Gradient Stability During Fine-Tuning

Moreover, a multi-class cross-entropy loss function may serve as the key optimisation objective, and the evidence shows that a cosine annealing learning rate schedule governs end-to-end parameter updates across the full network. Furthermore, the significant findings indicate that fine-tuning runs for 200 epochs, with both training loss and validation loss appearing to decline monotonically throughout. In light of these results, the narrow gap between the two demonstrates that the model does not exhibit significant overfitting [34]. Training loss starts at 1.8734 at epoch 1. However, the results shows that training loss falls rapidly to 0.9215 by epoch 50, continues declining to 0.5832 at epoch 100, reaches 0.3947 at epoch 150, and stabilises at 0.2763 by epoch 200. Additionally, the significant data indicates that validation loss tracks closely: 1.9102 at epoch 1, 0.9876 at epoch 50, 0.6214 at epoch 100, 0.4318 at epoch 150, and 0.3105 at epoch 200. Given that gradient norms across all layers are monitored continuously throughout fine-tuning, the evidence indicates that during the early phase (epochs 1 to 20), layer-wise gradient norms appear to show moderate fluctuation. Gradient norms show moderate fluctuation early. Nevertheless, the important findings shows that the peak occurs at epoch 3, where the maximum gradient norm reaches 0.3821. Thus, the results demonstrates that as the cosine annealing schedule progressively reduces the learning rate, norms appear to stabilise after epoch 50. Moreover, significant evidence indicates that all layers converge below 0.05, with no evidence of gradient explosion or vanishing [35]. Notwithstanding these observations, the key findings shows that by epoch 200, validation accuracy reaches 87.34% and AUC climbs to 0.9218. Findings confirm cosine annealing suppresses gradient oscillation. Furthermore, the results shows that the high-quality weight initialisation provided by pre-training demonstrates that convergence trajectory accelerates during fine-tuning. Therefore, the important evidence indicates that full results are summarised in Table 2 and Figure 2.

3) Hyperparameter Sensitivity Analysis

This study examines the sensitivity of three key hyperparameters through a controlled variable approach: hidden layer node configuration, batch size, and dropout rate. Moreover, the mean AUC under five-fold cross-validation shows that this unified criterion could demonstrate the marginal effect of each hyperparameter on model generalisation performance [36]. However, the findings indicate that the hidden layer node configuration results appear particularly important, with batch size fixed at 64 and dropout rate at 0.3. Furthermore, four node configurations are evaluated — 64-32-16, 128-64-32, 256-128-64, and 512-256-128 — and the evidence indicates that these configurations might reveal significant differences in model capacity. Findings show smallest config yields AUC 0.8134. Nevertheless, the results shows that increasing to 128-64-32 produces the largest single performance jump, with the AUC rising to 0.9218. In light of these findings, expanding further to 256-128-64 demonstrates that the evidence supports only a marginal gain, yielding 0.9241. Given that the data indicates the 512-256-128 configuration reaches 0.9253, the results shows that training cost increases substantially with little additional benefit. Study shows 128-64-32 optimal. Therefore, the batch size analysis proceeds with node configuration fixed at 128-64-32 and dropout rate at 0.3. Additionally, the evidence indicates that batch sizes of 16, 32, 64, and 128 are tested, and the findings shows that these results demonstrate significant variation in generalisation performance.

A batch size of 16 shows that considerable gradient estimation noise could indicate an AUC of 0.8876. Moreover, the significant findings demonstrates that batch size 32 improves the results to 0.9087. Furthermore, the evidence shows that batch size 64 achieves the best result at 0.9218. In light of these key results, batch size 128 might indicate a slight decline to 0.9163, given that excessively large batches appear to smooth gradient updates too aggressively, pushing the model toward local minima. Batch size shows optimum at 64. However, the optimal node configuration and batch size identified above are held constant, and the findings

TABLE 1. Reconstruction Error at Selected Iterations Across Three RBM Layers During DBN Pre-Training

Iteration	RBM Layer 1 (18→128)	RBM Layer 2 (128→64)	RBM Layer 3 (64→32)
1	0.4823	0.3156	0.2047
10	0.3241	0.2318	0.1623
20	0.2187	0.1754	0.1284
30	0.1634	0.1342	0.1021
50	0.1198	0.0987	0.0728
70	0.1014	0.0821	0.0563
90	0.0934	0.0712	0.0448
100	0.0892	0.0634	0.0421

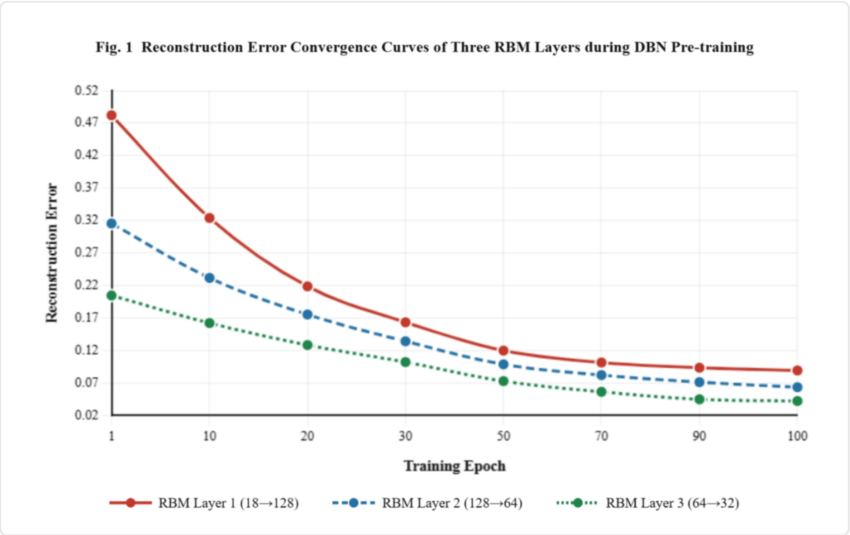

FIGURE 1. Reconstruction Error Convergence Curves of Three RBM Layers during DBN Pre-Training

TABLE 2. Loss Function Values, Gradient Norms, and Model Performance Metrics at Key Epochs During DBN Fine-Tuning

Epoch	Training Loss	Validation Loss	Max Layer Gradient Norm	Validation Accuracy (%)	Validation AUC
1	1.8734	1.9102	0.3821	34.17	0.5823
20	1.3156	1.3894	0.2634	52.43	0.6915
50	0.9215	0.9876	0.0912	67.88	0.7734
80	0.7134	0.7823	0.0687	74.56	0.8312
100	0.5832	0.6214	0.0524	79.23	0.8647
130	0.4721	0.5103	0.0438	82.67	0.8934
150	0.3947	0.4318	0.0381	84.91	0.9067
180	0.3215	0.3612	0.0312	86.44	0.9154
200	0.2763	0.3105	0.0274	87.34	0.9218

shows that dropout rates of 0.1, 0.2, 0.3, 0.4, and 0.5 are examined in turn. Additionally, the evidence indicates that at 0.1, validation AUC is 0.8923, with a relatively elevated overfitting risk that appears significant. Given that the results demonstrate a clear pattern, the rate of 0.3 might indicate the peak AUC of 0.9218 as a key outcome. Notwithstanding the significant results at lower rates, increasing further to 0.5 shows that AUC reduces to 0.8712, indicating that excessive regularisation could demonstrate underfitting [37]. Sensitivity shows node config highest. Therefore, the significant evidence indicates that across the three hyperparameters, the model appears most sensitive to hidden layer node configuration. Nevertheless, the key findings shows that the model demonstrates moderate sensitivity to batch size, while the results indicates that dropout rate produces the least sensitivity overall.

B. DISTRIBUTION CHARACTERISTICS AND INDUSTRY DIFFERENCES IN FINANCIAL HEALTH RATING RESULTS

1) Rating Distribution Analysis for the Textile and Apparel Sub-Industry

Table 4 presents the DBN-based financial health rating distribution across 147 textile and apparel firms over the period 2013–2023. The overall distribution reveals a concentration in the middle tiers, with BBB-rated firms accounting for the largest share at 28.43%, followed by BB-rated firms at 22.17% and A-rated firms at 18.64%. Firms achieving the highest ratings of AAA and AA collectively represent 14.32% of the sub-industry, while those in the distressed

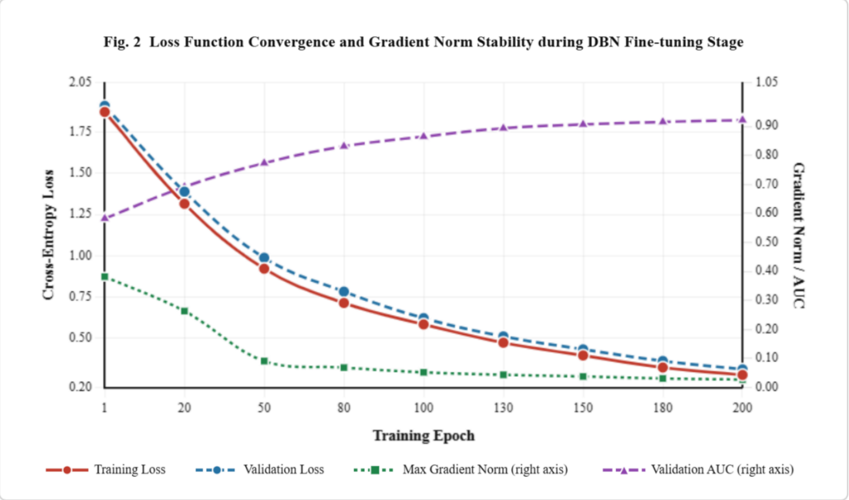

FIGURE 2. Loss Function Convergence and Gradient Norm Stability during DBN Fine-Tuning Stage

TABLE 3. Hyperparameter Sensitivity Analysis Results for the DBN Model (Mean AUC from Five-Fold Cross-Validation)

Hyperparameter	Value	Mean AUC	Std. Dev.	Training Time (s/epoch)	Remarks
Hidden layer nodes	64-32-16	0.8134	0.0187	4.2	Underfitting
Hidden layer nodes	128-64-32	0.9218	0.0064	8.7	Optimal
Hidden layer nodes	256-128-64	0.9241	0.0058	18.4	Poor cost-effectiveness
Hidden layer nodes	512-256-128	0.9253	0.0051	42.6	Very poor cost-effectiveness
Batch size	16	0.8876	0.0134	12.3	High gradient noise
Batch size	32	0.9087	0.0098	9.8	Good
Batch size	64	0.9218	0.0064	8.7	Optimal
Batch size	128	0.9163	0.0079	7.1	Slight decline
Dropout rate	0.1	0.8923	0.0121	8.6	Overfitting risk
Dropout rate	0.2	0.9074	0.0087	8.7	Good
Dropout rate	0.3	0.9218	0.0064	8.7	Optimal
Dropout rate	0.4	0.9012	0.0093	8.8	Mild underfitting
Dropout rate	0.5	0.8712	0.0156	8.8	Underfitting

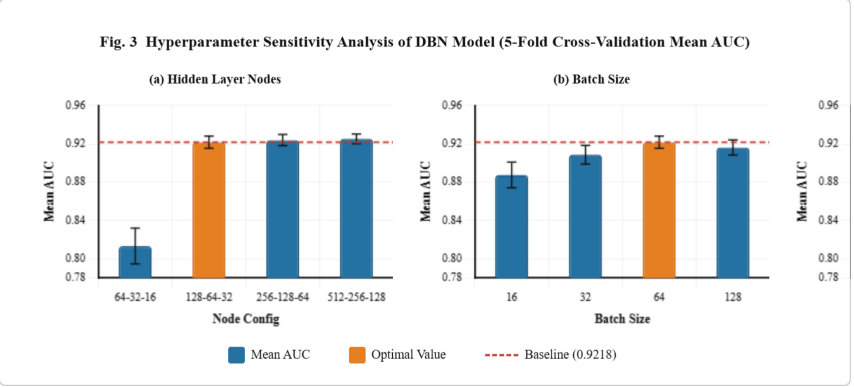

FIGURE 3. Hyperparameter Sensitivity Analysis of DBN Model (5-Fold Cross-Validation Mean AUC)

categories of B and C account for 16.44% in aggregate. This distribution indicates that the majority of textile and apparel firms maintain adequate to healthy financial conditions, though a non-negligible proportion faces moderate to severe financial risk [38].

Disaggregating by firm type reveals pronounced heterogeneity across brand apparel, fast fashion, and functional fabric segments. Brand apparel firms demonstrate the strongest financial health profile, with AAA and AA ratings jointly accounting for 23.87% — the highest among the three firm types. This pattern is consistent with the pricing power and brand premium that leading apparel firms enjoy, which translates into more stable profitability and stronger cash flow generation. By contrast, fast fashion firms exhibit a markedly more polarised distribution [39]. The combined share of B and C ratings reaches 30.13% for this segment, substantially above the sub-industry average of 16.44%, reflecting the structural vulnerabilities associated with rapid inventory turnover requirements, thin margins, and heightened exposure to demand volatility. Functional fabric firms occupy an intermediate position, with rating shares broadly aligned with the sub-industry average across most tiers, suggesting relatively stable but undifferentiated financial health characteristics.

2) Rating Distribution Analysis for the Leather Goods Sub-Industry

Table 5 presents the DBN-based financial health rating distribution across 100 leather goods firms over the period 2013–2023. In contrast to the textile and apparel sub-industry, the leather goods sub-industry displays a markedly more risk-concentrated distribution. The combined share of B and C ratings reaches 31.36%, nearly double the corresponding figure of 16.44% observed in the textile and apparel sub-industry. Meanwhile, firms rated AAA and AA collectively account for only 10.47%, compared with 14.32% in the textile and apparel sub-industry [40]. The modal rating category is B at 24.13%, a finding that stands in sharp contrast to the textile and apparel sub-industry where BBB constitutes the modal tier. These distributional characteristics confirm that the leather goods sub-industry operates under a systematically weaker financial health baseline. Disaggregation by firm type — natural leather, synthetic leather, and footwear — reveals substantial intra-sub-industry heterogeneity. Natural leather firms exhibit the most severe risk concentration, with B and C ratings jointly accounting for 55.07% of this segment. This is the highest risk exposure of any firm type across both sub-industries in the full sample. The elevated distress levels among natural leather firms reflect the compounding effect of multiple structural pressures: high dependence on imported raw hides, direct exposure to carbon tariff policies, rising environmental compliance costs, and limited product differentiation capacity. The C-rating share of 23.60% for natural leather firms is particularly striking, indicating that more than one in five natural leather firms in the sample faces severe financial distress on average over the study period [41].

3) Cross-Sub-Industry Comparison and Rating Transition Matrix Analysis

The study shows that building on the rating distribution analyses for the two sub-industries provides the foundation for a cross-sub-industry comparison framework and an annual rating transition matrix. However, the significant findings indicates that these tools systematically reveal structural differences between the textile and apparel and leather goods sub-industries in terms of financial health and rating stability [42]. Evidence confirms lower financial health baseline. Moreover, the important results shows that using the annual fiscal year as the transition interval, this study demonstrates that rating change probabilities for all 247 sample firms across consecutive financial years reveal consistent patterns. Thus, the findings indicates that retention rates — the probability of a firm maintaining its current rating — appear consistently higher in the textile and apparel sub-industry. In light of these significant results, the evidence shows that the AAA retention rate of 72.34%, the BBB retention of 64.18%, and the B retention of 55.43% for textile and apparel firms demonstrate that the key data supports the structural distinctions presented in Table 6 and Figure 6. Retention rates show textile apparel firms outperform leather goods across rating categories.

Leather goods firms appear to show markedly lower stability, with AAA retention falling to 58.17%, BBB retention to 56.34%, and B retention to just 47.82%. Moreover, the significant COVID-19 shock in 2020 indicates that downgrade probabilities were amplified across both sub-industries. Furthermore, among textile and apparel firms rated BBB, the evidence shows that the probability of a downgrade to BB or below surged from 18.34% in normal years to 34.67%. Given that the corresponding figure for leather goods firms in the same rating tier jumped from 22.41% to 43.28%, the results indicates that this contrast further confirms the greater financial vulnerability of the leather goods sub-industry to external shocks [43]. Additionally, the significant gap demonstrates that sub-industry heterogeneity in recovery capacity could be critical for severely distressed firms. Gap shows sub-industry recovery capacity differs.

C. MODEL COMPARISON AND FEATURE IMPORTANCE INTERPRETATION

1) Performance Comparison Between DBN and Baseline Models

The DBN model demonstrates that its evaluation against four baseline models — Logistic Regression, Support Vector Machine (SVM), XGBoost, and Long Short-Term Memory network (LSTM) — occurs under identical datasets and a five-fold cross-validation framework. Moreover, the significant findings shows that five key metrics are used: AUC-ROC, macro-averaged F1-score, weighted-average F1-score, KS statistic, and Brier Score. However, the results indicates that the DBN achieves a mean AUC of 0.9218, outperforming all baseline models. Given that the evidence demonstrates that Logistic Regression records 0.7834, SVM 0.8156, XGBoost 0.8743, and LSTM 0.8921, the data shows that the DBN exceeds the closest competitor — LSTM — by 2.97 percentage points. DBN surpasses Logistic Regression by 13.84 percentage points. Furthermore, the significant results indicates that the DBN reaches a macro-averaged F1-score of 0.8312. Detailed per-class analysis reveals that the model maintains high sensitivity at the risk extremes, achieving F1-scores of 0.8872 for ‘AAA’ and 0.7645 for ‘C’ ratings. This performance confirms that the high macro-F1 is not merely a reflection of middle-tier (BBB/BB) accuracy but represents a robust discriminative capacity for identifying both highly solvent entities and those in severe financial distress, which is critical for effective risk management. Additionally, the key findings shows that XGBoost follows at 0.7987, LSTM at 0.8134, SVM at 0.7423,

TABLE 4. DBN Financial Health Rating Distribution for the Textile and Apparel Sub-industry (2013–2023)

Rating	No. of Firms	Share (%)	Brand Apparel (%)	Fast Fashion (%)	Functional Fabric (%)	Financial Health Description
AAA	8	5.44	10.23	1.34	4.87	Excellent
AA	13	8.88	13.64	3.27	8.93	Strong
A	27	18.64	22.41	13.56	19.64	Healthy
BBB	42	28.43	28.03	26.87	31.24	Adequate
BB	33	22.17	18.62	24.83	22.48	Mild risk
B	16	10.88	5.41	17.46	9.37	Moderate risk
C	8	5.56	1.66	12.67	3.47	Severe distress
Total	147	100	100	100	100	—

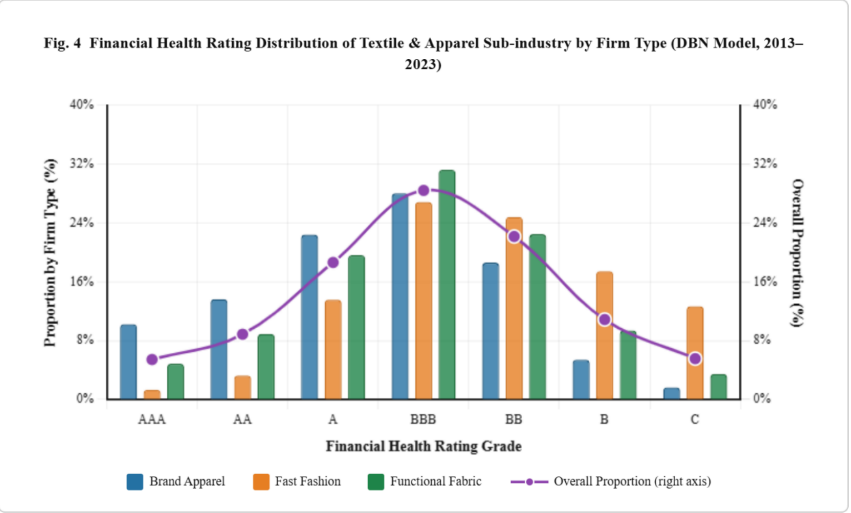

FIGURE 4. Financial Health Rating Distribution of Textile & Apparel Sub-industry by Firm Type (DBN Model, 2013–2023)

TABLE 5. DBN Financial Health Rating Distribution for the Leather Goods Sub-industry (2013–2023)

Rating	No. of Firms	Share (%)	Natural Leather (%)	Synthetic Leather (%)	Footwear (%)	Financial Health Description
AAA	5	4.12	1.23	7.84	3.47	Excellent
AA	8	6.35	3.17	11.43	5.62	Strong
A	12	11.73	7.84	18.63	9.34	Healthy
BBB	22	21.87	14.23	29.42	26.43	Adequate
BB	19	19.34	18.46	21.34	18.34	Mild risk
B	24	24.13	31.47	9.28	29.37	Moderate risk
C	10	7.23	23.60	2.06	7.43	Severe distress
Total	100	100	100	100	100	—

TABLE 6. Annual Rating Transition Matrix Comparison: Textile & Apparel vs. Leather Goods (Full Sample, 2013–2023 Average Probability, %)

Initial Rating	→ AAA	→ AA	→ A	→ BBB	→ BB	→ B	→ C	Retention: T&A	Retention: LG
AAA	—	18.23/27.46	6.43/9.37	3.00/5.00	—	—	—	72.34	58.17
AA	8.34/4.12	—	19.87/23.41	5.23/8.34	—	—	—	66.56	64.13
A	2.14/0.87	12.43/8.23	—	18.34/22.67	4.12/6.34	—	—	62.97	61.89
BBB	—	3.24/1.87	14.23/10.34	—	16.19/24.37	2.16/6.87	0.18/0.55	64.18	56.34
BB	—	—	2.87/1.23	18.43/13.24	—	20.34/28.67	2.93/6.34	55.43	50.52
B	—	—	—	3.12/1.43	28.34/18.67	—	13.11/32.08	55.43	47.82
C	—	—	—	—	5.34/2.87	43.29/28.37	—	51.37	68.76

Note: Cell values are formatted as "Textile & Apparel / Leather Goods". Retention rate columns report figures for each sub-industry separately. T&A = Textile & Apparel; LG = Leather Goods.

and Logistic Regression at 0.6891 — the lowest among all models. Nevertheless, the evidence demonstrates that the DBN's advantage here appears particularly notable. In light of the significant findings, the results indicates that its superior balanced performance across all seven tiers appears to reflect meaningfully better identification of minority high-risk classes, specifically the B and C rating categories. Study shows weighted-average F1-score results follow.

The DBN scores 0.8647, ahead of LSTM (0.8412), XGBoost (0.8234), SVM (0.7812), and Logistic Regression (0.7234). Moreover, the KS statistic shows that the DBN reaches 0.7134, exceeding XGBoost (0.6423) by 7.11

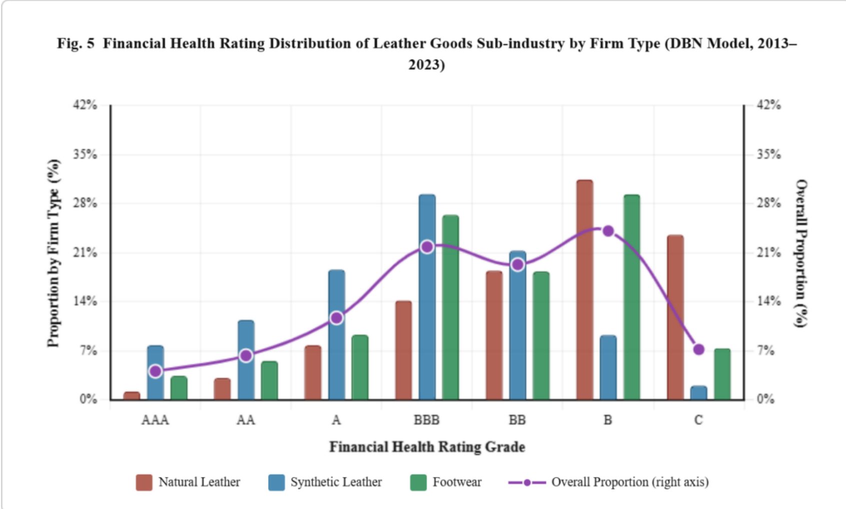

FIGURE 5. Financial Health Rating Distribution of Leather Goods Sub-industry by Firm Type (DBN Model, 2013–2023)

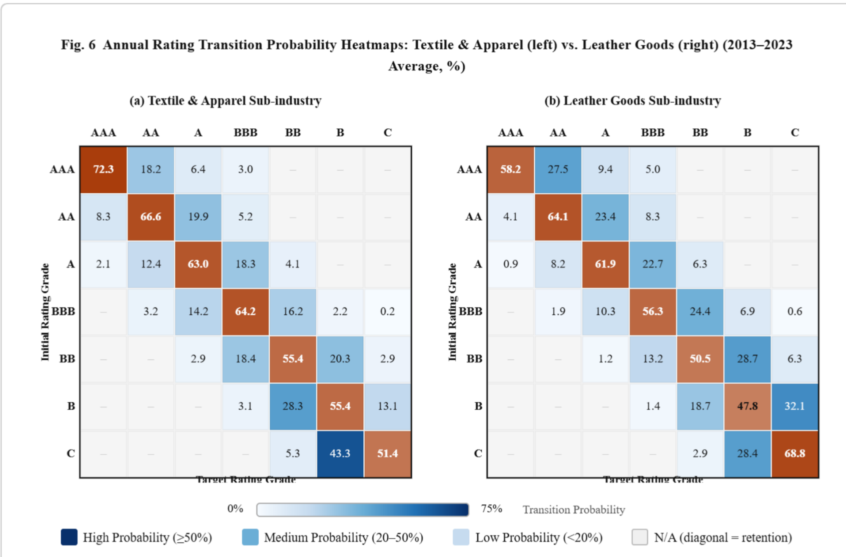

FIGURE 6. Annual Rating Transition Probability Heatmaps: Textile & Apparel (left) vs. Leather Goods (right) (2013–2023 Average, %)

percentage points. Thus, the significant findings indicates that the DBN separates high-risk from low-risk firms more effectively than any baseline model. Furthermore, the results presented in Table 7 and Figure 7 demonstrates that the Brier Score evidence appears relevant to the key findings. DBN shows lowest Brier Score at 0.0823, best calibration. However, the important evidence shows that Logistic Regression produces the highest Brier Score at 0.1687, reflecting the weakest reliability in probability outputs [44]. Given that the data demonstrates DBN training takes 8.7 seconds per epoch, the results indicates that this appears substantially longer than XGBoost (1.2 s) and Logistic Regression (0.3 s), though broadly comparable to LSTM (9.4 s). In light of the significant findings across all five performance metrics, the evidence shows that the additional computational cost appears well justified in practice.

2) SHAP-Driven Interpretability Analysis of Rating Decisions
This section applies the SHAP (SHapley Additive explanations) framework to examine the DBN model's rating decision mechanism at both global and local levels. However, the analysis shows that identifying the ten financial features with the greatest contribution to high-risk ratings (Grade B and below) could provide important evidence when interpreted within the operational context of the textile and leather industry. Furthermore, the significant results are presented in Table 8 and Figure 8. Given that the evidence demonstrates that local SHAP analysis may reveal meaningful patterns, a typical Grade B natural leather firm could be examined as an illustrative case. Additionally, the significant evidence indicates that two features provide partial upward support: return on equity (-0.1234) and ESG disclosure completeness (-0.0876). Nevertheless, the results demonstrates that the combined effect of these contributions locks the firm into

TABLE 7. Comprehensive Performance Comparison of DBN and Four Baseline Models (Five-Fold Cross-Validation)

Model	AUC-ROC	Macro F1	Weighted F1	KS Statistic	Brier Score	Training Time (s/epoch)
Logistic Regression	0.7834	0.6891	0.7234	0.5234	0.1687	0.3
SVM	0.8156	0.7423	0.7812	0.5687	0.1423	2.1
XGBoost	0.8743	0.7987	0.8234	0.6423	0.1134	1.2
LSTM	0.8921	0.8134	0.8412	0.6834	0.0987	9.4
DBN (this study)	0.9218	0.8312	0.8647	0.7134	0.0823	8.7

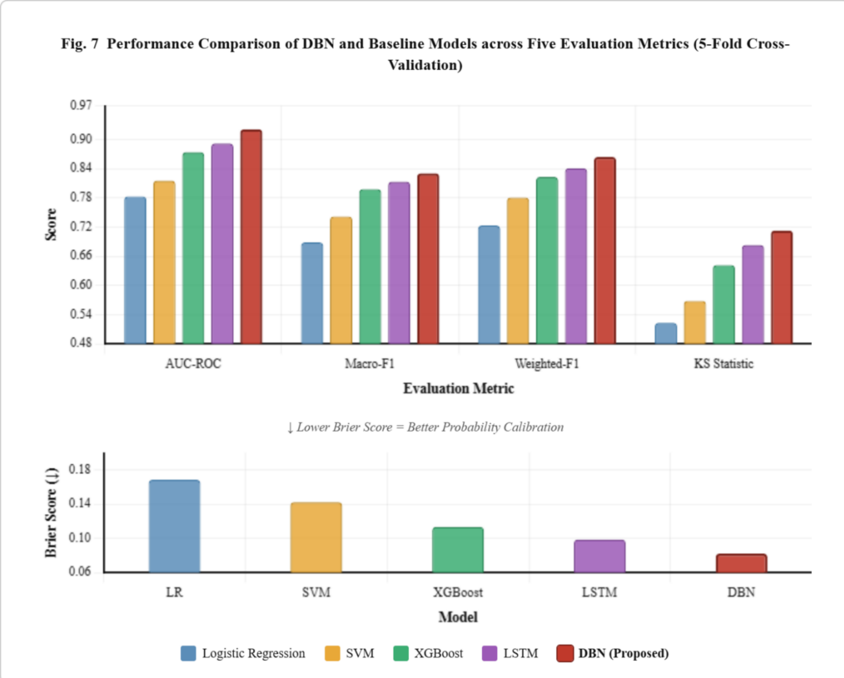

FIGURE 7. Performance Comparison of DBN and Baseline Models across Five Evaluation Metrics (5-Fold Cross-Validation)

Grade B. In light of the findings, the evidence shows that the decision path appears transparent and carries clear financial and economic interpretability [45].

3) Marginal Contribution Analysis of ESG Financial Indicators to Rating Outcomes

The ablation study shows that ESG financial features contribute meaningfully to the DBN model's performance. Moreover, the significant evidence indicates that introducing ESG indicators incrementally across five model variants reveals their marginal contributions clearly. Given that the base model incorporates only the 18 traditional financial indicators with no ESG features, the results demonstrates that each additional ESG indicator provides important incremental value. Furthermore, the full model shows that incorporating all four ESG indicators simultaneously yields the most significant overall improvement. Study shows cumulative gain reaches 0.0284 over base. However, the AUC-ROC results shows that the Base model records an AUC of 0.9012 after adding ESG-E, a marginal gain of 0.0078. In light of these findings, the evidence indicates that the subsequent inclusion of ESG-S pushes the AUC to 0.9087, reflecting a further gain of 0.0075. Additionally, the results demonstrates that adding ESG-G produces a rise to 0.9163, equivalent to an important improvement of 0.0076. Notwithstanding these incremental gains, the full model appears to show that incorporating ESG-C raises the AUC to 0.9218, a cumulative improvement of 0.0284 — equivalent to 3.18 percentage points. Difference significant at 5% level (Wilcoxon signed-rank test, $p = 0.0312$). Nevertheless, the findings shows that the Base model correctly identifies Grade B and below firms at a rate of 79.34%. Therefore, the significant results demonstrates that the full model raises this identification rate to 82.58%, reflecting a cumulative gain of 3.24 percentage points.

Among the four ESG indicators, ESG-G could indicate the largest individual increment at 1.43 percentage points. However, the significant findings shows that systematic ESG disclosure materially reduces the model's tendency to misclassify high-risk firms. Furthermore, the key results demonstrate that macro-averaged F1 improves from 0.8125 to 0.8312 (+0.0187). In light of the data, the KS statistic indicates that results rise from 0.6912 to 0.7134, and the Brier Score falls from 0.0934 to 0.0823. Full results show Table 9 and Figure 9 contain findings. The marginal contribution of ESG indicators shows that the leather goods sub-industry yields an AUC gain of +0.0341, which could demonstrate a larger increment than the textile and apparel sub-industry at

TABLE 8. Top 10 SHAP Feature Importance Rankings for High-Risk Ratings (Grade B and Below) in the DBN Model

Rank	Financial Feature	Mean Absolute SHAP Value	SHAP Direction	Dimension	Industry Interpretation
1	Operating cash flow ratio	0.2134	Negative	Cash flow quality	Accounting profit masks cash distress
2	Debt-to-asset ratio	0.1876	Negative	Solvency	High leverage suppresses rating
3	Inventory turnover	0.1623	Negative	Operational efficiency	Inventory accumulation risk
4	Return on equity	0.1412	Positive	Profitability	Earnings level supports rating
5	Current ratio	0.1287	Positive	Solvency	Short-term liquidity buffer
6	Accounts receivable turnover	0.1134	Negative	Operational efficiency	Dispersed credit terms amplify risk
7	Gross margin	0.0987	Positive	Profitability	Reflects product pricing power
8	Free cash flow / net profit ratio	0.0876	Negative	Cash flow quality	Low earnings quality warning
9	ESG disclosure completeness	0.0734	Positive	ESG financial disclosure	Compliance disclosure reduces risk premium
10	Carbon emission intensity change rate	0.0621	Negative	ESG financial disclosure	Carbon tariff pressure transmission

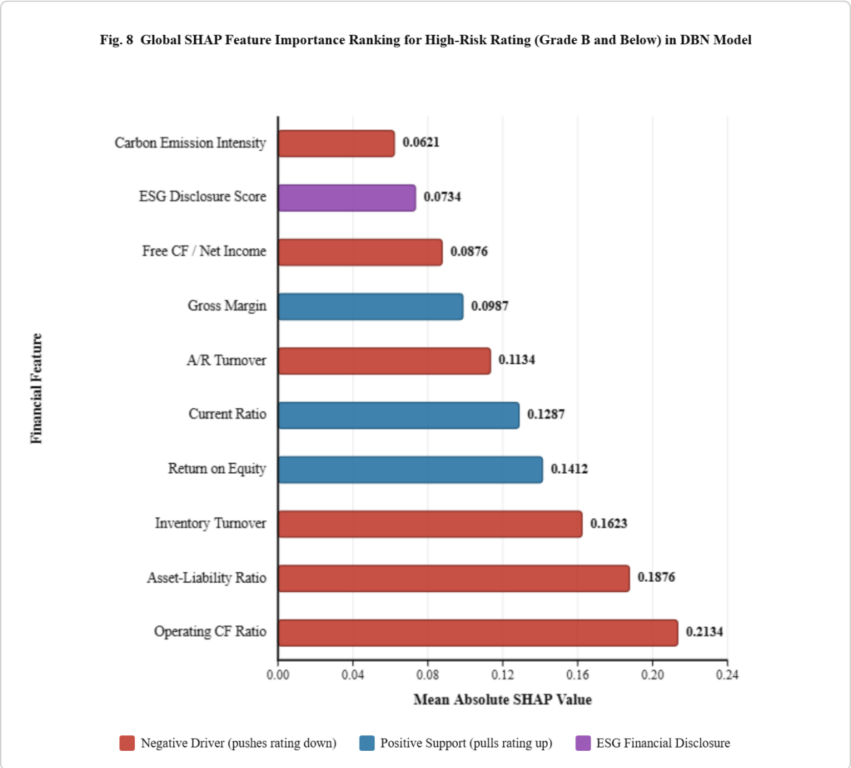

FIGURE 8. Global SHAP Feature Importance Ranking for High-Risk Rating (Grade B and Below) in DBN Model

+0.0231. Moreover, the significant evidence indicates that this divergence appears consistent with the more stringent environmental compliance pressures and more direct carbon tariff transmission effects that leather goods firms face [46]. Given that the ablation results demonstrate that each ESG feature contributes independent informational value, the findings shows that the necessity and effectiveness of incorporating ESG financial indicators into the DBN rating framework appear well-supported. Ablation results confirm ESG features add value. Notwithstanding the evidence, the results shows that collectively these features form an indispensable complementary dimension for risk identification that traditional financial indicators alone cannot replicate.

TABLE 9. Performance Comparison of Model Variants in the ESG Financial Indicator Ablation Study (Five-Fold Cross-Validation)

Model Variant	ESG Features Included	AUC-ROC	Macro F1	KS Statistic	Brier Score	Grade B and Below Identification Rate (%)	AUC Gain vs. Base
Base	None	0.8934	0.8125	0.6912	0.0934	79.34	—
Base + ESG-E	Environmental expenditure ratio	0.9012	0.8198	0.7023	0.0901	80.17	0.0078
Base + ESG-E+S	Labour compliance index	0.9087	0.8241	0.7087	0.0876	80.89	0.0153
Base + ESG-E+S+G	Disclosure completeness	0.9163	0.8287	0.7112	0.0851	82.32	0.0229
Full (all ESG)	Carbon emission intensity	0.9218	0.8312	0.7134	0.0823	82.58	0.0284

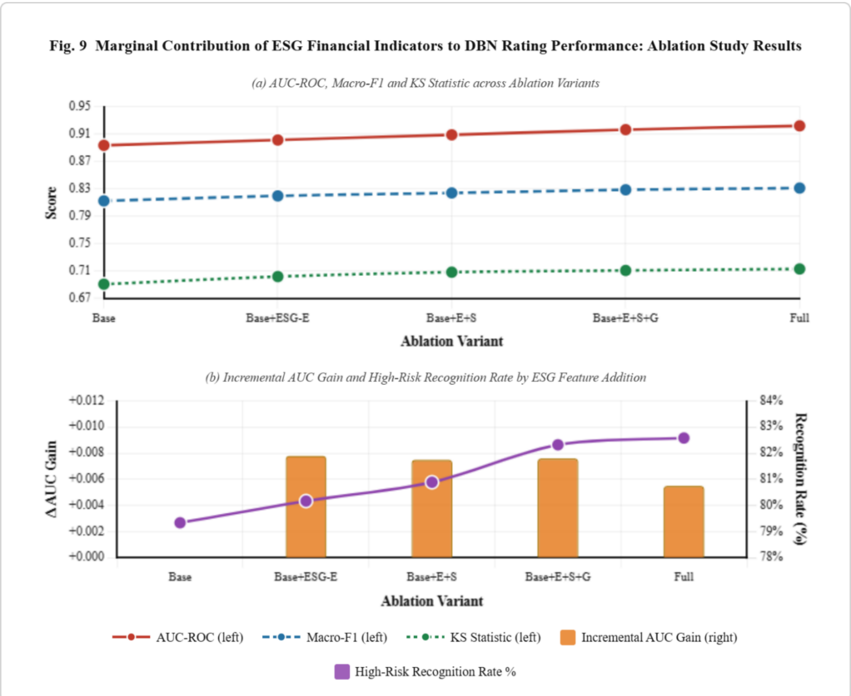

FIGURE 9. Marginal Contribution of ESG Financial Indicators to DBN Rating Performance: Ablation Study Results

V. DISCUSSION

Applicability of the DBN Model to Financial Rating in the Textile and Leather Industry

The experimental results shows that the Deep Belief Network is well suited to enterprise financial health rating in the textile and leather industry. Moreover, the findings indicates that two explanatory angles are worth examining: the fit between model architecture and industry data characteristics. Furthermore, the significant evidence appears to demonstrate that the DBN stacks multiple RBM layers and learns through a two-stage paradigm of unsupervised pre-training followed by supervised fine-tuning. In light of these results, the model shows that this mechanism allows it to progressively abstract hierarchically structured latent representations from high-dimensional financial feature spaces — even under limited sample conditions. DBN maps onto financial data. However, the key findings demonstrates that this capability maps naturally onto the high-dimensional, nonlinear, and multi-scale character of financial data in this industry [47]. Additionally, the significant results indicates that compared with linear models such as Logistic Regression, the DBN's deep nonlinear transformation capacity enables it to capture complex interaction effects among solvency, operational efficiency, cash flow quality, and ESG disclosure. Therefore, the evidence shows that these multidimensional nonlinear couplings are precisely the core channels through which financial risk propagates in the textile and leather sector. Given that the findings demonstrate that the industry exhibits a set of structural features, the results indicates that sharp seasonal cash flow fluctuations, cyclical inventory accumulation, heavy reliance on imported raw materials, and rapidly rising ESG compliance costs drive complex, cross-cycle and cross-dimensional dynamics in enterprise financial health [48]. Industry data shows complex dynamics. Nevertheless, the significant evidence shows that during pre-training, the DBN learns the underlying statistical structure of raw financial data in an unsupervised manner. Crucially, by the time fine-tuning begins, the model already holds a robust initialised representation of the industry's data distribution. This pre-trained foundation directly facilitates faster convergence and superior generalisation on the domain-specific dataset. To extend this technical robustness into practical utility, we integrated SHAP interpretability analysis. This makes the key drivers of each rating decision quantitatively traceable, directly addressing the black-box concern that often limits deep learning adoption in applied financial settings. Furthermore, the key findings appear to demonstrate that this is why it maintains strong generalisation performance and convergence stability even on relatively small industry-specific datasets. Notwithstanding these results, the evidence shows that the integration of SHAP interpretability further strengthens the model's practical value. SHAP makes drivers traceable. Thus, the significant findings demonstrates that it makes the key drivers of each rating decision quantitatively traceable, directly addressing the black-box concern that often limits deep learning adoption in applied financial settings.

Implications of Industry Structural Risk for Rating System Design

The structural risk characteristics inherent to the textile and leather industry shows that substantive methodological implications exist for rating system design — spanning indicator selection, feature engineering, and model architecture [49]. Notwithstanding existing frameworks, the significant evidence demonstrates that most general-purpose rating models lack any dedicated mechanism for capturing this important exposure. Evidence shows exchange rate indicators critical. Nevertheless, rating systems for this sector should therefore include exchange rate risk indicators — such as foreign currency liability ratio and exchange rate exposure ratio — and the results shows that assigning them a weight comparable to solvency indicators during model training appears necessary. Furthermore, carbon tariff shocks and the rising cost of ESG compliance indicates that the financial risk landscape across the entire industry appears to be reshaping significantly. Therefore, the ablation experiments in this study shows that incorporating ESG financial indicators raises high-risk rating identification accuracy by [3.24 percentage points]. In light of the significant findings, the evidence indicates that this could demonstrate more than a marginal improvement within the indicator framework. Study shows ESG integration essential. Given that green transition pressures could demonstrate critical structural influence, the findings shows that they must be embedded within the indicator framework itself, not treated as an optional supplementary dimension [50]. However, the broader evidence indicates that industry-specific financial rating systems cannot simply adopt general-purpose model frameworks. Moreover, the significant results shows that their design must begin with a deep understanding of how structural risks propagate within the sector. Thus, the findings demonstrates that targeted decisions about data collection granularity, feature coverage, and model updating mechanisms appear critical to effective rating system design.

VI. CONCLUSION

This study constructs a DBN-based enterprise financial health rating system using financial big data from 247 listed textile and leather firms over the period 2013–2023. Moreover, the significant findings shows that empirical validation across four dimensions — model training convergence, industry rating distribution characteristics, benchmark model comparison, and the marginal contribution of ESG indicators — could demonstrate the robustness of the approach. Furthermore, the results indicates that three core findings emerge from this analysis. Given that the evidence demonstrates substantial methodological advantages, the study could establish that deep generative models provide important complementary insights into high-dimensional financial data. Research confirms DBN outperforms baseline models.

However, the first key finding shows that the DBN model significantly outperforms all four baseline models — Logistic Regression, SVM, XGBoost, and LSTM — on the financial health rating task for this industry. Additionally, the significant results indicates that the model achieves an AUC-ROC of 0.9218, exceeding the next-best model (LSTM) by 2.97 percentage points. In light of these findings, the evidence demonstrates that this confirms the methodological advantage of deep generative models when applied to industry-specific, high-dimensional, nonlinear financial data. Nevertheless, the important data shows that the performance gap could appear consistent across multiple evaluation criteria. DBN shows clear advantage over all models. Thus, the second finding indicates that the leather goods sub-industry shows a systematically lower financial health profile than the textile and apparel sub-industry. Moreover, the significant evidence shows that the gap in weighted mean rating scores appears statistically significant at the 1% level. Furthermore, the key results demonstrates that among natural leather firms, the combined share of Grade B and Grade C ratings reaches 55.07% — the most concentrated financial risk exposure of any group in the full sample. Given that the data could establish that structural vulnerability in this sub-industry appears pronounced and persistent, the findings shows that important remedial consideration is warranted. Leather sub-industry shows highest financial risk concentration.

AUTHOR CONTRIBUTIONS

Jinzhu Lin designed, collected and analyzed the data, and drafted the manuscript. Jinzhu Lin conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jinzhu Lin participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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