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Credit Assessment Models: A Thematic Review of Traditional Statistical and Machine Learning Approaches and Scope for Future Research in the Indian Corporate Context

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ABSTRACT: Accurate corporate credit assessment is fundamental to financial system stability, influencing lending decisions, capital allocation, and regulatory risk management. This paper presents a thematic review of the literature on credit assessment models, tracing the evolution from traditional statistical approaches — including discriminant analysis, logistic regression, and structural models — to contemporary ensemble machine learning methods such as Random Forest and XGBoost. The review is organised around four themes: theoretical foundations of credit risk, traditional statistical models and their limitations, machine learning advances and comparative performance, and the Indian corporate credit landscape including regulatory interpretability considerations. A synthesis of over 20 studies confirms consistent evidence of 15–25 percent predictive accuracy gains from machine learning over traditional methods. Critical gaps persist, particularly the absence of systematic benchmarking using Indian listed corporate data, inadequate treatment of cross-sector financial ratio heterogeneity, and the unresolved tension between ensemble model performance and RBI regulatory explainability requirements. This review maps these gaps and proposes a structured agenda for future empirical research.

KEYWORDS: Credit risk, credit rating, machine learning, XGBoost, Random Forest, financial ratios, Indian corporate credit, RBI, ensemble methods, explainability, literature review.

I. INTRODUCTION

Corporate credit assessment occupies a central position in the architecture of modern financial systems. The ability of lenders, investors, and regulators to accurately evaluate the creditworthiness of corporate borrowers is a prerequisite for efficient capital allocation, prudent risk management, and systemic financial stability. When credit assessment fails — as evidenced by the role of flawed rating models in the 2008 global financial crisis — the consequences extend far beyond individual lending decisions to threaten the integrity of financial markets as a whole.

For decades, credit risk modelling has been dominated by statistical approaches derived from the foundational contributions of Altman (1968) and Merton (1974), grounded in financial ratio analysis and structural asset-liability frameworks. Their strengths — transparency, interpretability, and regulatory acceptance — have ensured their longevity despite well-documented limitations in handling the non-linear, multidimensional complexity of real-world corporate financial data. The past two decades have witnessed a paradigm shift driven by ensemble machine learning methods such as Random Forest and XGBoost, which consistently demonstrate superior predictive performance across diverse credit assessment contexts.

Despite this global trajectory, the application of machine learning to Indian corporate credit assessment remains significantly underdeveloped. India presents a uniquely rich research environment: a structured ecosystem of domestic rating agencies — CRISIL, CARE, and ICRA — mandatory financial disclosures for listed companies under SEBI regulations, and an evolving RBI regulatory framework increasingly attentive to the governance and transparency of



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credit models. This paper contributes to this emerging agenda through a structured thematic review of the literature, identifying key empirical findings, unresolved debates, and a research agenda for future empirical work in the Indian context.

II. THEORETICAL FOUNDATIONS

Three foundational theoretical frameworks underpin the evolution of credit risk modelling and situate the transition from traditional statistical to machine learning approaches within a coherent conceptual structure.

Information Asymmetry Theory (Stiglitz and Weiss, 1981) establishes that credit markets are inherently characterised by adverse selection and moral hazard, arising from lenders' inability to fully observe borrower risk profiles. Financial ratios serve as observable signals that partially resolve this informational gap, providing the foundational justification for ratio-based credit assessment models. The quality and completeness of financial disclosures is therefore a binding constraint on model performance — particularly in emerging markets where disclosure standards are uneven.

Merton's Structural Credit Risk Model (1974) treats a firm's equity as a call option on its assets, with default occurring when asset value falls below outstanding debt at maturity. This framework provides the theoretical basis for leverage-based financial ratios — particularly debt-to-equity and debt-to-EBITDA — as proxies for default probability, and has directly informed Internal Rating-Based approaches under the Basel regulatory accords.

Statistical Learning Theory (Vapnik, 1995) provides the mathematical basis for ensemble methods. The bias-variance decomposition framework explains why ensemble models achieve lower generalisation error than single complex models: bagging reduces variance by averaging across uncorrelated learners, while boosting sequentially corrects residual errors. Together, these three frameworks justify the selection of financial ratios as predictors, the use of leverage variables as core credit risk indicators, and the theoretical expectation that ensemble methods will outperform linear statistical models in capturing complex, non-linear credit risk structures.

III. REVIEW OF LITERATURE

A. Traditional Statistical Models

Altman (1968) pioneered quantitative credit assessment with the Z-score model, applying Multiple Discriminant Analysis to five financial ratios spanning liquidity, profitability, leverage, solvency, and activity dimensions, achieving bankruptcy classification accuracy of 72–80 percent. This study formalised financial ratios as statistically validated credit risk predictors and established the empirical foundation upon which all subsequent structured credit scoring systems have been built. Thomas et al. (2002) comprehensively reviewed logistic regression and discriminant analysis in credit markets, documenting accuracy of 65–75 percent while identifying their fundamental limitations: assumptions of linearity, predictor independence, and normally distributed residuals mean these models systematically underperform when confronted with the non-linear, interaction-rich structure of real-world corporate financial data.

Despite these limitations, linear statistical models retain significant practical relevance. Their full coefficient interpretability — each parameter carrying a direct meaning in terms of the marginal effect of a financial ratio change on default probability — makes them the natural benchmark for regulatory credit frameworks and the standard against which machine learning methods are evaluated. The transparency and audit-friendliness of logistic regression continues to underpin credit scoring practices across many Indian banks, making a clear empirical understanding of their performance boundaries directly actionable for practitioners. Importantly, the regulatory acceptance of linear models under Basel-aligned frameworks means that any transition toward ensemble methods must demonstrate not only superior predictive accuracy but also sufficient transparency to satisfy supervisory expectations — a constraint that shapes the entire machine learning credit research agenda.

B. Machine Learning in Credit Risk

The emergence of ensemble machine learning methods has fundamentally transformed credit risk modelling capabilities. Madaan et al. (2015) demonstrated that Random Forest consistently outperformed logistic regression on peer-to-peer lending data, exploiting the variance-reduction advantages of aggregating predictions across multiple uncorrelated decision trees. Li and Chen (2018) extended this comparison to XGBoost, LightGBM, and stacking



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architectures, finding that gradient boosting methods systematically surpassed logistic regression across AUC and F1-score metrics. Fuster et al. (2019) provided macroeconomic-scale evidence that gradient boosting outperformed logistic regression in mortgage default prediction by approximately 15 percent while also improving processing efficiency. Jagtiani and Lemieux (2018) demonstrated that fintech lenders deploying machine learning-based scoring systems were able to extend credit access to previously underserved borrowers without materially increasing default rates, indicating that ensemble methods offer superior discriminatory efficiency in risk segmentation relative to traditional approaches. Chang et al. (2024) confirmed XGBoost's superiority in credit card risk modelling, particularly under class imbalance conditions where investment-grade or non-default observations dominate — a condition characteristic of corporate rating datasets.

More recent studies have reinforced and extended these findings. Emmanuel et al. (2024) demonstrated that stacked ensemble architectures combining Random Forest, Gradient Boosting, and XGBoost produced superior F1-scores compared to any single classifier. Hussain et al. (2024) emphasised that deliberate feature engineering — including ratio transformation and sector-aware normalisation — can substantially amplify ensemble model predictive power, establishing that the quality of feature construction is at least as important as the choice of algorithm. Gafsi et al. (2025) found that firm-specific financial indicators, particularly leverage and profitability, are more powerful predictors under gradient boosting, while logistic regression retains an advantage in regulatory interpretability. Van den Berg et al. (2025) confirmed that Random Forest significantly outperformed linear discriminant analysis in commercial banking distress prediction, with SHAP-based explainability tools enabling feature-level transparency without sacrificing predictive performance.

C. The Indian Corporate Credit Context

India's corporate credit landscape presents a uniquely structured environment for empirical credit research. CRISIL, CARE, and ICRA employ standardised rating methodologies combining quantitative financial ratio analysis with qualitative assessments of management quality, competitive positioning, and regulatory environment. Mandatory SEBI disclosure requirements for listed companies ensure consistent availability of audited financial data across BSE and NSE-listed entities. India's capital market has witnessed significant expansion over the past decade, with the number of rated entities growing substantially as domestic rating agencies have deepened coverage across manufacturing, infrastructure, and financial services sectors. The RBI's implementation of Basel III capital adequacy norms has simultaneously raised standards for internal credit model validation, risk governance, and stress-testing, creating strong institutional incentives for financial institutions to invest in more sophisticated and empirically validated credit assessment capabilities. These dual forces — expanding data availability and heightened regulatory expectations — create both the opportunity and the necessity for more rigorous, evidence-based credit assessment research in the Indian context.

Despite this, the academic literature on machine learning applications in Indian corporate credit assessment remains underdeveloped. Johri (2024) provides the most directly relevant contribution, benchmarking machine learning against traditional statistical methods in the Indian banking sector and finding 10–15 percent superior predictive performance for machine learning while cautioning that RBI explainability requirements create governance challenges for ensemble model deployment. The majority of existing Indian credit risk studies focus on retail and consumer lending rather than the corporate rated universe, leaving a significant gap in the literature that empirical research using CRISIL, CARE, and ICRA corporate rating data is well-positioned to address.

A distinctive structural feature of the Indian rated universe that has received insufficient attention is sector heterogeneity. Manufacturing, infrastructure, and financial services firms exhibit fundamentally different financial ratio profiles: infrastructure companies carry high leverage ratios that would signal distress in other sectors yet receive investment-grade ratings by virtue of government backing and contracted long-term revenues; financial services companies operate under distinct capital adequacy frameworks that give their leverage and coverage ratios a structurally different interpretive meaning. A credit model that applies uniform financial ratio benchmarks across sectors may produce systematically biased predictions, yet this cross-sector variation in credit risk drivers has not been adequately addressed in the India-specific literature.

D. Regulatory and Interpretability Considerations

The predictive advantages of ensemble machine learning are accompanied by significant model interpretability concerns with direct regulatory implications. Dil (2025) identified that black-box ensemble algorithms introduce



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substantial validation complexity and may conflict with supervisory expectations requiring credit models to be transparent, auditable, and contestable. The Basel Committee on Banking Supervision (2024–2025) has acknowledged that traditional model risk management frameworks require significant adaptation to address the opacity of ensemble methods, calling for enhanced documentation, stress-testing, and ongoing monitoring.

In India specifically, the RBI's Digital Lending Directions (2025) have formalised expectations around transparency and accountability in automated credit decisioning, positioning explainability as a compliance requirement rather than an optional enhancement. Post-hoc explainability tools, particularly SHAP (SHapley Additive exPlanations) values, have emerged as a practical resolution to this challenge. Kakkar (2025) demonstrated that SHAP analysis can decompose XGBoost predictions into per-decision feature attributions compatible with regulatory transparency requirements without sacrificing predictive performance. Van den Berg et al. (2025) confirmed this finding in a commercial banking context, suggesting that the perceived trade-off between machine learning performance and regulatory compliance is increasingly resolvable in practice — but this resolution has not yet been demonstrated empirically for Indian corporate credit models.

IV. SYNTHESIS OF KEY LITERATURE

The literature reviewed above collectively establishes a clear and consistent empirical trajectory in favour of ensemble machine learning for credit risk prediction. Table 1 synthesises the principal contributions reviewed, including methodology, context, key findings, and their specific relevance to the Indian corporate credit context.

Table 1: Synthesis of Key Literature on Credit Assessment Models

Author(s)	Method(s)	Context	Key Finding	Relevance to India
Altman (1968)	MDA / Z-score	US Corporates	Financial ratios predict bankruptcy with 72–80% accuracy	Foundational ratio framework used by Indian rating agencies
Merton (1974)	Structural Model	Theoretical	Default probability linked to asset-debt ratio	Basis for leverage ratio use in RBI and Basel frameworks
Thomas et al. (2002)	Logistic Regression	Consumer/Corporate	LR achieves 65–75% accuracy; constrained by linearity	Most common model still in use at Indian banks
Madaan et al. (2015)	RF vs. LR	P2P Lending	Random Forest consistently outperforms logistic regression	Supports ensemble adoption for Indian NBFC lending
Li & Chen (2018)	XGBoost, LightGBM	Corporate Credit	Ensemble methods systematically surpass LR on AUC, F1	Benchmark for gradient boosting on structured financial data
Fuster et al. (2019)	Gradient Boosting	Mortgage Default	ML outperforms LR by ~15%; improves processing efficiency	Scale evidence applicable to Indian corporate lending
Doko et al. (2021)	Tree Models vs. LR	Credit Registry	Tree models outperform LR; data quality is binding constraint	Audited listed-company data mitigates this risk in India
Johri (2024)	ML vs. Statistical	Indian Banking	10–15% ML superiority; RBI explainability governance needed	Most directly relevant India-specific study
Chang et al.	XGBoost vs. LR	Credit Card Risk	XGBoost superior under	Directly applicable to India's



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Author(s)	Method(s)	Context	Key Finding	Relevance to India
(2024)			class imbalance conditions	investment-grade dominated universe
Kakkar (2025)	XGBoost + SHAP	Corporate Credit	SHAP provides regulatory-grade per-decision transparency	Addresses RBI Digital Lending Directions explainability requirement
Gafsi et al. (2025)	RF, GB, Neural Nets	Corporate Credit	Gradient boosting achieves highest AUC; LR retains compliance edge	Informs model selection for RBI-regulated institutions
Van den Berg et al. (2025)	RF + SHAP	Commercial Banking	RF outperforms LDA; SHAP resolves interpretability–accuracy tradeoff	Model for Indian bank credit governance framework

Source: Compiled by authors from reviewed literature.

Across the reviewed studies, four consistent patterns emerge. First, ensemble machine learning models outperform traditional statistical approaches robustly across geographies, data types, and modelling tasks, with reported R^2 improvements of 20–35 percent and accuracy gains of 15–25 percent over logistic regression well-documented. Second, the architecture of the ensemble model matters: gradient boosting methods such as XGBoost consistently outperform bagging-based methods such as Random Forest, particularly on structured, lower-dimensional financial ratio datasets where sequential error-correction is most effective. Third, class imbalance — where investment-grade or non-default observations dominate — is a pervasive methodological challenge affecting both model training and performance evaluation in corporate credit datasets, and is inadequately addressed in much of the existing literature. Fourth, SHAP-based explainability tools offer a practical resolution to the interpretability challenge, enabling per-decision feature attribution without sacrificing predictive performance.

A fifth pattern, less frequently discussed but of particular relevance to Indian corporate credit research, concerns the role of sector classification as a predictor variable. Several studies have found that sector or industry membership encodes substantial credit quality information that transcends individual financial ratio performance, suggesting that models which treat sector as an explicit feature — rather than applying uniform ratio benchmarks across industries — achieve materially superior discriminatory performance. This finding has direct implications for credit model design in the Indian context, where the financial ratio profiles of manufacturing, infrastructure, and financial services companies are structurally distinct in ways that a sector-blind model cannot adequately accommodate. The absence of sector-aware modelling in existing India-specific credit research represents both a methodological gap and a practical limitation for financial institutions seeking to deploy credit models across diverse borrower segments.

V. RESEARCH GAPS AND SCOPE FOR FUTURE RESEARCH

A. Identified Gaps

The review reveals five significant and interrelated gaps in the existing literature, each representing a priority area for future empirical research.

Gap 1 — Absence of India-specific corporate credit benchmarking. Despite over 20 published studies documenting machine learning superiority in credit risk modelling, no study has systematically compared traditional statistical and ensemble models using standardised financial ratio data for listed Indian corporate entities across multiple sectors. Most existing studies are conducted in Western consumer lending contexts or on proprietary datasets. India's combination of publicly available audited financial data from Screener.in and verifiable agency ratings from CRISIL, CARE, and ICRA creates a unique opportunity for reproducible empirical research that has not yet been exploited.

Gap 2 — Inadequate treatment of sector heterogeneity. Existing literature predominantly applies uniform financial ratio benchmarks across sectors, failing to account for the fundamentally different financial structures of manufacturing, infrastructure, and financial services companies. Few studies have explicitly modelled sector



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classification as a feature in credit prediction models or examined whether ensemble architectures can learn sector-specific financial benchmarks, a gap with direct practical consequences for credit assessment in the Indian rated universe.

Gap 3 — Dominance of binary classification frameworks. The majority of machine learning credit studies adopt binary default versus non-default frameworks, failing to reflect the ordinal, multi-class structure of agency credit ratings. Rating distinctions within the investment-grade range carry material implications for borrowing costs and regulatory capital treatment, yet research evaluating model performance in terms of rating notch prediction error — a directly practitioner-interpretable unit — remains scarce.

Gap 4 — Unresolved explainability challenge in the Indian regulatory context. While SHAP-based explainability tools have demonstrated promise globally, no published study has applied them to an ensemble credit model trained on Indian corporate financial data. The RBI's Digital Lending Directions (2025) have elevated explainability to a compliance requirement, yet the practical demonstration of RBI-compatible transparent machine learning credit models in the Indian corporate context remains absent from the literature.

Gap 5 — Insufficient documentation of small-sample and class-imbalance effects: India-focused credit research has generally used small, non-representative samples without adequately documenting the methodological consequences of class imbalance and cross-validation degradation. In corporate credit datasets where investment-grade ratings predominate, standard cross-validation can produce misleading performance estimates, yet few studies report these effects transparently, limiting the credibility and replicability of published findings.

B. Proposed Future Research Agenda

Based on the identified gaps, five research priorities are proposed for future empirical work in Indian corporate credit assessment.

Priority 1 — Systematic empirical benchmarking on Indian corporate data: Future research should conduct a rigorous comparative evaluation of traditional statistical models and ensemble machine learning models using standardised financial ratio data for listed Indian companies, sourced from platforms such as Screener.in and cross-verified against audited annual reports. Such a study should span multiple sectors, report results using R^2 , MAE, and RMSE in rating notch units, and document cross-validation performance and its degradation under small-sample and class-imbalance conditions with full methodological transparency.

Priority 2 — Sector-aware modelling: Future studies should explicitly model sector classification as a feature and evaluate whether ensemble architectures learn sector-specific financial ratio benchmarks from the data. Research should additionally examine whether sector-specific model training — fitting separate models for manufacturing, infrastructure, and financial services companies — outperforms a single cross-sector model, directly informing the practical design of credit assessment frameworks for Indian financial institutions.

Priority 3 — Ordinal rating prediction frameworks: Future research should move beyond binary default classification and adopt ordinal regression or ordinal classification frameworks that preserve the rank-ordering information in multi-class agency rating scales. Evaluation in terms of rating notch prediction error would enable direct comparison of model outputs against the practical credit differentiation thresholds used by Indian financial institutions and rating agencies, delivering findings of immediate practical relevance.

Priority 4 — SHAP-based explainability in the Indian regulatory context: Future studies should systematically apply SHAP analysis to ensemble credit models trained on Indian corporate financial data, demonstrating that per-decision feature attribution is achievable and interpretable for credit practitioners and regulators. Such research would directly inform the governance frameworks required for RBI-compliant deployment of machine learning credit models and bridge the gap between the predictive superiority documented in the academic literature and the transparency requirements of Indian regulatory practice.

Priority 5 — Longitudinal and expanded sample studies: Future research should extend from cross-sectional designs to longitudinal panel data frameworks, enabling dynamic modelling of credit quality migration across economic cycles. Sample sizes should be expanded substantially — targeting 200 or more companies with multiple



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years of financial data — to improve cross-validation reliability and extend the analysis to speculative-grade issuers currently underrepresented in the rated universe. Incorporating qualitative variables such as management quality scores, ESG ratings, and governance indices alongside financial ratios would further improve model completeness and bring empirical credit models closer to full agency rating methodologies.

VI. CONCLUSION

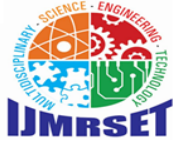
This paper has presented a structured thematic review of the literature on corporate credit assessment models, tracing the evolution from the foundational statistical contributions of Altman (1968) and Merton (1974) through the machine learning advances of the past two decades, and situating this trajectory within the specific context of the Indian corporate credit market.

The review establishes four principal conclusions. First, ensemble machine learning models — particularly gradient boosting architectures such as XGBoost — consistently outperform traditional statistical approaches in credit risk prediction across a wide range of contexts, with accuracy improvements of 15–25 percent well-documented. Second, the Indian corporate credit context offers a uniquely suitable environment for empirical machine learning research, combining publicly available audited financial data and standardised agency rating methodologies, but this potential remains systematically unexploited in the academic literature. Third, sector heterogeneity — the fundamentally different financial ratio profiles of manufacturing, infrastructure, and financial services companies — is a structural feature of the Indian rated universe that existing credit models inadequately address. Fourth, the tension between machine learning's predictive superiority and RBI regulatory transparency requirements is increasingly resolvable through SHAP-based explainability tools, but has not yet been demonstrated empirically in the Indian corporate credit context.

Together, these conclusions point to a significant and actionable research agenda. The five gaps identified — systematic Indian corporate benchmarking, sector-aware modelling, ordinal rating frameworks, RBI-compliant explainability, and transparent small-sample methodology — and the corresponding five research priorities proposed in Section V define the empirical programme that future work must pursue to advance both the academic understanding and the practical application of credit assessment models in India's evolving financial landscape.

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