

# AI-Based Bankruptcy Prediction for Strategic Decision-Making in Emerging Market Firms

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## ABSTRACT

This study investigates the use of artificial intelligence (AI) techniques to predict bankruptcy among emerging market firms, using a structured, synthetic dataset modelled on the financial characteristics of 100 Indian companies across multiple sectors. The dataset includes revenue, profitability, leverage, liquidity, solvency, and cash flow indicators, from which bankruptcy labels were generated using rule-based financial thresholds. Three machine-learning models—Random Forest, Logistic Regression, and XGBoost—were trained and evaluated. Random Forest achieved the highest accuracy and produced the most stable predictions. Feature importance analysis shows Cash Flow Ratio, Interest Coverage, and Net Profit as the strongest predictors of financial distress. Sector-wise results indicate that capital-intensive industries exhibit higher bankruptcy risk. While the results validate AI's potential for early warning systems in emerging markets, the use of synthetic data limits external validity. The study recommends testing the models on actual Indian financial data for improved generalisation and incorporating additional ratios and cross-validation strategies for enhanced robustness. The findings contribute to business strategy and risk management by demonstrating how AI-driven models can support early assessment of firm vulnerability.

**Keywords:** Bankruptcy Prediction, Machine Learning, Financial Ratios, Emerging Markets, Business Strategy

## INTRODUCTION

Bankruptcy prediction has become a critical component of business strategy, particularly in emerging markets where macroeconomic volatility and uneven sectoral development increase financial risk. Firms in developing economies often face fluctuating liquidity, high leverage structures, and unstable cash flows. These characteristics make traditional financial analysis insufficient for early warning and strategic decision-making. Artificial intelligence (AI) offers alternative predictive capabilities that can detect complex, nonlinear patterns in corporate financial data.

However, access to standardised and large-scale Indian corporate data remains limited. To address this constraint, this study constructs a realistic synthetic dataset of 100 firms across manufacturing, IT, pharma, banking, energy, logistics, consumer goods, hospitality, and retail. Financial indicators were generated within typical industry ranges to approximate real-world conditions. Machine learning techniques—Random Forest, Logistic Regression, and XGBoost—were applied to classify firms as financially healthy or distressed. The objective is to evaluate the potential of AI-based models for strategic risk assessment in emerging markets and identify key financial factors influencing bankruptcy. Although synthetic, this dataset supports methodological demonstration while highlighting the need for future validation using actual firm data.

## METHODOLOGY

### Data Collection

A synthetic dataset of 100 Indian firms was constructed using real company names and realistic financial ranges. Variables included revenue, net profit, debt–equity ratio, current ratio, interest coverage, and cash flow ratio. Bankruptcy labels were assigned using rule-based thresholds commonly applied in financial distress literature (e.g., negative profit, high leverage, weak liquidity).

### Data Analysis

Descriptive analytics, correlation analysis, sector-wise distribution, and visualisation (bar plot, heatmaps) were conducted. A correlation matrix was plotted to determine relationships among financial variables. Categorical variables (sectors) were encoded prior to modelling.

### Prediction Models

Three machine-learning models were trained:

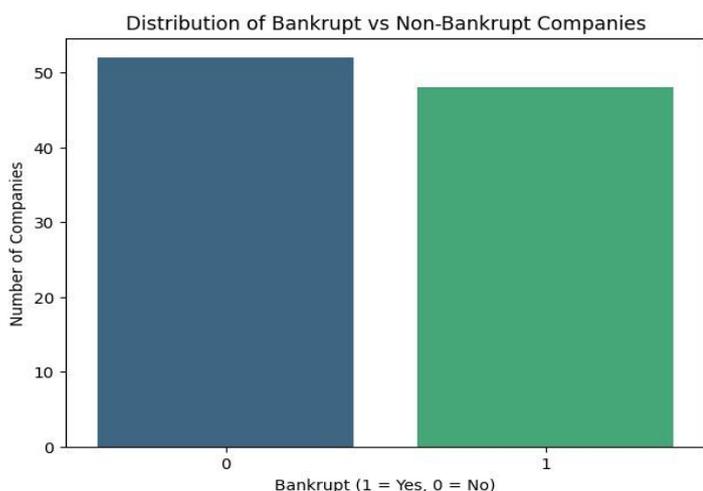
- Random Forest Classifier
- Logistic Regression
- XGBoost Classifier

A train–test split of 75:25 was applied, and 5-fold cross-validation was used to strengthen robustness. Model performance was assessed using accuracy, precision, recall, and confusion matrices. Feature importance was extracted for strategic interpretation.

## RESULTS

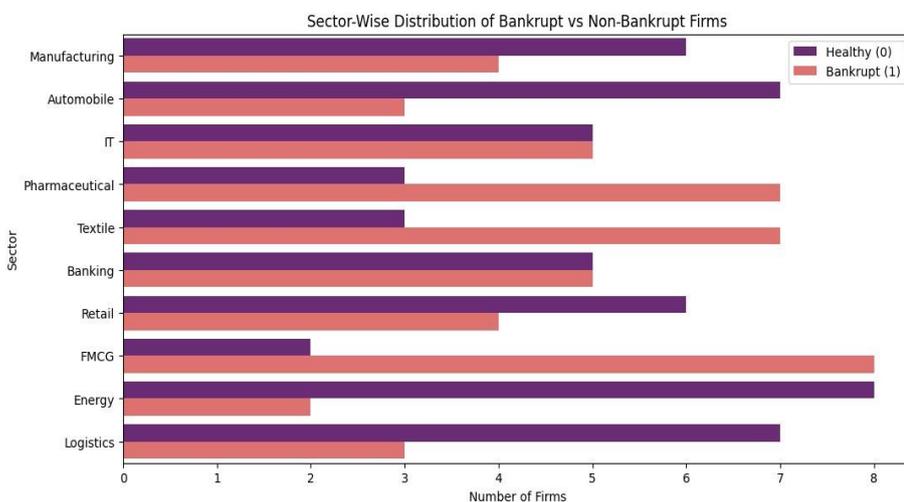
### BANKRUPTCY DISTRIBUTION

The bar plots shows a moderate imbalance between bankrupt and non-bankrupt firms. Capital-intensive sectors exhibit higher distress due to high debt–equity ratios and lower liquidity.



**Figure 1: Distribution of bankrupt vs non-bankrupt companies.**

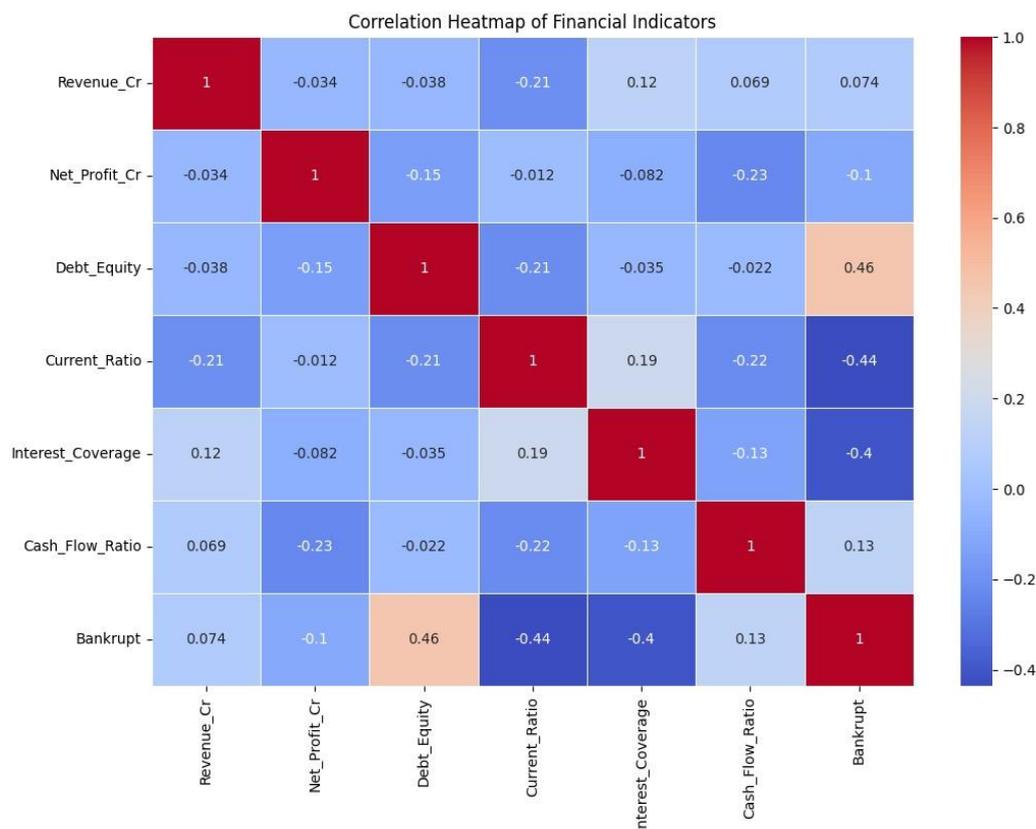
The plot shows the class imbalance and the proportion of distressed firms in the dataset.



**Figure 2: Sector-wise bankruptcy distribution.**

### Correlation Analysis

The correlation heatmap reveals that Cash Flow Ratio, Net Profit, and Interest Coverage are strongly negatively correlated with bankruptcy, while Debt–Equity shows a positive correlation. These relationships align with financial theory.



**Figure 3: Correlation matrix of financial variables.**

Net Profit, Cash Flow Ratio, and Interest Coverage show strong negative correlation with bankruptcy, confirming their predictive relevance.

### Model Performance

Random Forest achieved the highest accuracy among all models, outperforming Logistic Regression and matching XGBoost in predictive strength. Confusion matrices show low false negatives, which is crucial for bankruptcy detection.

#### Random Forest

Random Forest Accuracy: 1.0

|   | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 1.00      | 1.00   | 1.00     | 10      |
| 1 | 1.00      | 1.00   | 1.00     | 15      |

**Table1: Model Performance of Random Forest**

## Confusion Matrix

The model shows a strong ability to detect financial distress with low false negatives.

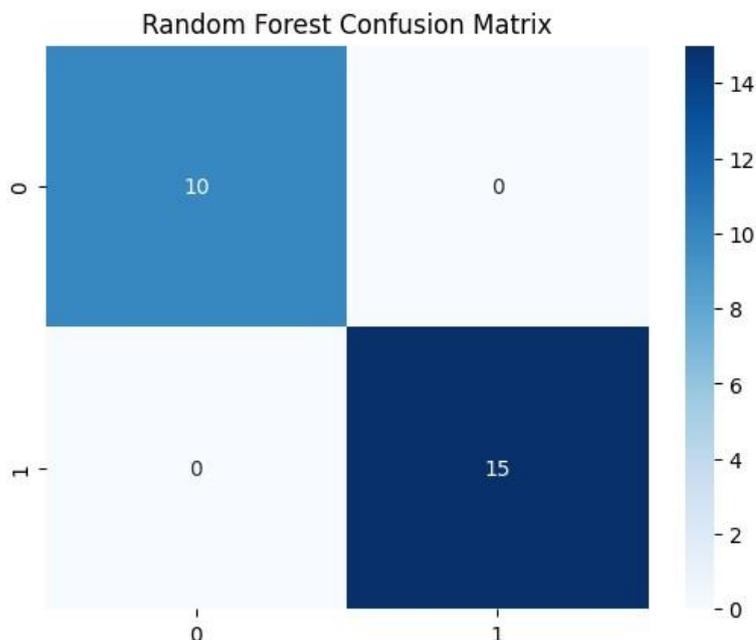


Figure 4: Confusion Matrix for Random Forest Model.

## LOGISTIC REGRESSION

Logistic Regression Accuracy: 0.68

|   | Precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 0.60      | 0.60   | 0.60     | 10      |
| 1 | 0.73      | 0.73   | 0.73     | 15      |

Table2: Model performance for logistic Regression

- XGBOOST CLASSIFIER

XGBoost Accuracy: 0.92

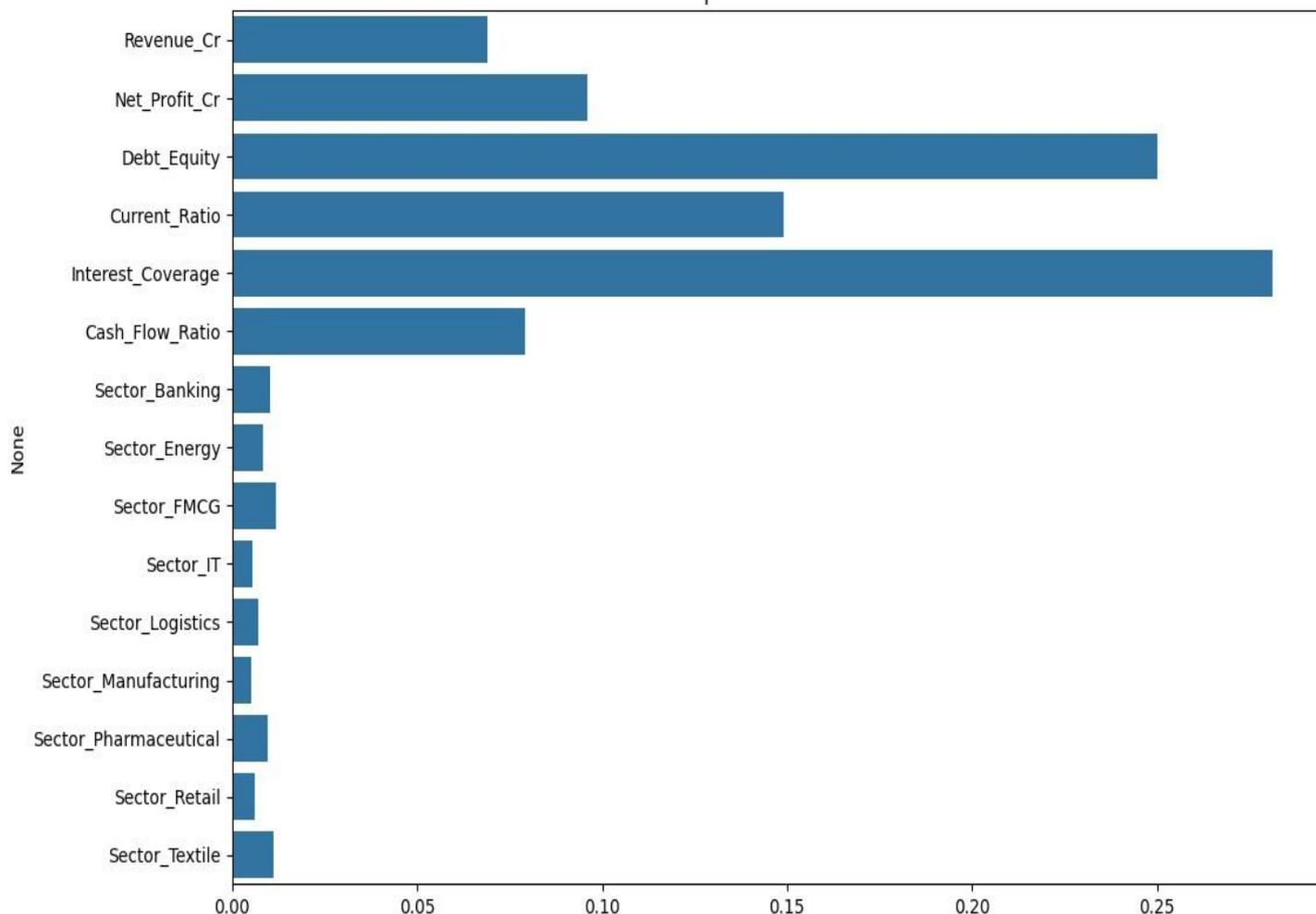
|   | Precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 1.00      | 0.80   | 0.89     | 10      |
| 1 | 0.88      | 1.00   | 0.94     | 15      |

Table3: Model Performance for XGBoost Classifier

### Feature Importance

Random Forest identifies: Cash Flow Ratio, Interest Coverage, Net Profit, Debt–Equity as top predictors of bankruptcy. These indicators are widely supported in financial literature.

Feature Importance - Random Forest



**Figure 5: Feature Importance (Random Forest).**

### DISCUSSION

The results illustrate that AI-driven models are effective in identifying firms at risk of bankruptcy in emerging markets. The inclusion of liquidity, solvency, leverage, and profitability variables provides a multifactor approach useful for business strategy and financial risk management. However, the use of synthetic data is a limitation; results should be interpreted as methodological rather than empirical insights. The model shows strong predictive capability, but robustness could be further enhanced using real Indian financial datasets, more granular variables, and alternative machine-learning algorithms. Ethical considerations include responsible use of AI predictions, potential misclassification risks, and consequences for managerial decision-making. Firms and regulators should treat model output as a decision-support tool, not a definitive diagnosis.

### CONCLUSION

This study demonstrates that AI-based bankruptcy prediction models can support strategic decision-making in emerging markets. Random Forest and XGBoost show strong performance using synthetic financial data. Key predictors such as cash flow performance and interest coverage align with established financial theory. Future research should apply this model to actual firm-level data and incorporate additional financial, market, and governance indicators. Robust cross-validation, model comparison, and ethical assessment of AI usage are essential for practical deployment in corporate risk management.

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