Research Paper

Can AI Predict Start-up Failure? A Data-Driven Study on Early Financial Indicators

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Abstract

This study investigates if machine learning models can predict start-up failure within three years of inception by analyzing early financial, operational, and macroeconomic variables. I train and assess logistic regression, random forest, and gradient boosting models using a dataset of 1,842 technological start-ups created between 2014 and 2020, obtained from Crunchbase and Orbis. The best-performing model (XGBoost) achieves 83% accuracy with an AUC of 0.88. Key predictors include cash runway under six months, customer acquisition cost exceeding lifetime value, and operating in a sector with declining venture capital inflows. Profitability metrics show negligible predictive power in early stages. Results suggest that AI-based early warning systems, when grounded in sound financial logic, can offer practical value to founders and investors.

Introduction

Start-up failure is common but not random. While popular narratives often attribute collapse to “bad timing” or “weak teams,” financial data tells a more precise story. Many ventures fail not because their ideas lack merit, but because they run out of cash before achieving sustainable unit economics.

The rise of predictive analytics raises a practical question: can artificial intelligence identify warning signs of failure before they become irreversible? Existing models like Altman’s Z-score work well for established firms but falter with early-stage companies that lack earnings or stable revenue. This paper tests whether a combination of liquidity ratios, cost structure indicators, business model traits, and macroeconomic context can improve prediction accuracy for young start-ups.

I approach this not as a theoretical exercise but as a practical inquiry. Working with early-stage founders and reviewing financial statements, I noticed recurring patterns: high growth masked by negative cash flow, unsustainable customer acquisition costs, and misalignment between burn rate and funding cycles. This study formalizes those observations using data and machine learning.

Literature Review

Financial distress prediction has a long history. Altman (1968) demonstrated that accounting ratios could forecast bankruptcy in public firms with over 70% accuracy. However, start-ups operate under different assumptions. They prioritize growth over profit, often carry minimal debt, and may not generate revenue for months or years.

Recent work adapts these ideas to venture contexts. Puri and Rocholl (2021) found that start-ups with high cash balances relative to monthly expenses survive longer, even after controlling for funding. Similarly, Bapna et al. (2022) showed that unit economics, particularly the ratio of customer lifetime value (LTV) to customer acquisition cost (CAC), strongly correlate with long-term viability.

On the AI side, Li et al. (2020) used natural language processing on pitch decks to predict funding success, while Wang and Wang (2023) applied deep learning to founder social networks. Few studies, however, integrate granular financial metrics with external economic signals in a predictive framework for failure not just funding outcomes.

This paper fills that gap by focusing on *operational and financial fundamentals* as inputs to machine learning models, treating AI as a tool to amplify, not replace, financial insight.

Data and Methods

Data Sources

The dataset combines three sources:

- Crunchbase: Founding date, funding rounds, business model (B2B/B2C), sector, and closure status (n = 1,210).
- Orbis (Bureau van Dijk): Financial statements for start-ups that filed with local registries, providing cash, revenue, operating expenses, and employee counts (n = 987).
- PitchBook & World Bank: Quarterly venture capital funding by sector and annual GDP growth by country.

Start-ups were labeled “failed” if they ceased operations, filed for insolvency, or showed no activity after three years with no acquisition or IPO. The final sample includes 1,842 start-ups, of which 764 (41.5%) failed within three years.

Feature Engineering

Key variables were derived as follows:

- Cash runway = (Cash and equivalents) / (Monthly operating expenses)
- CAC = (Sales and marketing expenses) / (New customers acquired)
- LTV/CAC ratio = Estimated lifetime revenue per customer / CAC
- Burn multiple = Net cash outflow / Net new annual recurring revenue (adapted from SaaS benchmarks)
- Sector VC trend = 12-month moving average of sector funding, normalized by total VC activity

Traditional ratios (current ratio, debt-to-equity) were included but expected to have low signal in early stages.

Model Specification

Three models were trained on 80% of the data and tested on 20%:

1. Logistic regression (baseline)
2. Random forest (handles interactions)
3. XGBoost (optimized for structured data)

Accuracy, precision, recall, and the area under the ROC curve were all used to assess performance. To ensure interpretability, feature importance was calculated using SHAP (SHapley Additive exPlanations) values.

All analysis was conducted in Python (scikit-learn, XGBoost, SHAP). Code and data dictionary are available upon request.

Results

Model Performance

Model	Accuracy	Precision	Recall	AUC
Logistic regression	75%	0.72	0.69	0.77
Random forest	80%	0.78	0.74	0.84
XGBoost	83%	0.82	0.77	0.88

The XGBoost model significantly outperformed the baseline, particularly in identifying true failures (higher recall).

Key Predictors (SHAP Analysis)

The top five features by mean absolute SHAP value were:

1. Cash runway < 6 months (strongest negative signal)
2. LTV/CAC ratio < 2.0
3. Burn multiple > 2.5
4. Operating in a sector with declining VC funding (e.g., crypto in 2022, edtech post-2021)
5. Monthly revenue growth volatility (standard deviation > 30%)

Notably, net profit margin and return on assets showed near-zero contribution, confirming that profitability is irrelevant in early-stage prediction.

A start-up with fewer than six months of capital runway and an LTV/CAC ratio of less than 1.5 was 92% certain to fail within three years, regardless of team background or market size.

Discussion

Practical Implications

These data reflect a simple but significant observation: liquidity and unit economics are more important than growth indicators alone. Many failing start-ups in the sample reported substantial month-over-month user growth while ignoring cash burn and client profitability. AI algorithms that detect these mismatches early on could assist entrepreneurs in correcting course by lowering CAC, increasing runway, or shifting price before cash runs out.

For investors, the model serves as a quantitative complement to due diligence. A high risk score may prompt more financial modeling or milestone-based funding.

Limitations

The dataset favors funded, tech focused start-ups with public filings. Bootstrapped enterprises and those operating in informal markets are significantly underrepresented. In addition, the model forecasts the likelihood of failure rather than the cause. It is unable to discern between market failure, execution errors, and fraud.

Future work could include founder background, product usage data, or emotion from earnings calls, but data availability remains a challenge for student researchers.

Conclusion

Artificial intelligence can predict start-up failure but only when it starts with the right questions and the right data. This study shows that simple financial indicators, long taught in accounting and finance courses, remain the strongest signals of distress. Machine learning does not replace financial literacy; it scales it.

The message to founders is clear: track cash runway and unit economics as closely as you track user growth. For academics, it confirms that feature relevance founded in economic reality, rather than algorithmic complexity, determines predictive power.

As I continue my studies in data science and economics, I hope to refine these models with real-time banking data and behavioral variables. But the core principle holds: numbers tell stories. The best predictions begin not with code, but with understanding what the numbers mean.

References

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Note: All data processing and modeling were conducted independently by the author using publicly available or licensed academic datasets. No proprietary company data was used.