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A Cross-Domain Analysis of Machine Learning Models for Business Forecasting and Risk Assessment

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Abstract

Accurate forecasting and effective risk assessment are critical components of modern business decision-making. With the rapid growth of data availability and computational power, machine learning (ML) has emerged as a powerful tool for improving predictive accuracy across diverse business domains. This study presents a cross-domain analysis of commonly used machine learning models for business forecasting and risk assessment, focusing on their applicability, performance, and limitations in different contexts. The research examines supervised learning models—including linear regression, decision trees, random forests, support vector machines, and neural networks—across financial forecasting, credit risk assessment, demand prediction, and operational risk management. Using secondary datasets and prior empirical findings, the study compares model performance based on prediction accuracy, interpretability, scalability, and robustness. The analysis highlights that while complex models such as neural networks and ensemble methods often achieve higher predictive accuracy, simpler models retain importance due to their transparency and ease of implementation. Furthermore, the study emphasizes that no single machine learning model is universally optimal; rather, model effectiveness depends on domain characteristics, data quality, and business objectives. The findings contribute to the growing literature on applied machine learning by offering a structured framework for selecting appropriate models across business domains. This research provides practical insights for managers, analysts, and policymakers seeking to integrate machine learning into forecasting and risk assessment processes while balancing performance and interpretability.

Keywords: Machine Learning, Business Forecasting, Risk Assessment, Predictive Analytics, Cross-Domain Analysis

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1. Introduction

Forecasting and risk assessment play a central role in business planning, financial stability, and strategic decision-making. Organizations rely on accurate forecasts to allocate resources, manage uncertainty, and maintain competitive advantage. Traditional statistical methods such as time-series analysis and econometric models have long been used for these purposes; however, their effectiveness is often constrained by assumptions of linearity, normality, and stationarity. As business environments become more complex and data-driven, these limitations have motivated the adoption of machine learning techniques.

Machine learning offers flexible, data-centric approaches capable of capturing nonlinear relationships and complex interactions among variables. In recent years, ML models have been applied extensively in areas such as sales forecasting, credit scoring, fraud detection, and operational risk management. Despite growing adoption, organizations often face challenges in selecting appropriate models due to trade-offs between accuracy, interpretability, and implementation cost.

A significant gap in the literature lies in the lack of comparative, cross-domain analysis of machine learning models applied to both business forecasting and risk assessment. Many studies focus on a single domain—such as finance or supply chain management—without evaluating how model performance varies across different business contexts. This fragmented approach limits the generalizability of findings and complicates practical decision-making.

The objective of this study is to address this gap by conducting a structured cross-domain analysis of commonly used machine learning models. The paper evaluates their performance and suitability across multiple business applications, emphasizing both predictive accuracy and managerial usability. By synthesizing evidence from prior empirical studies and applied research, this paper aims to provide a practical framework for model selection in business forecasting and risk assessment.

The remainder of the paper is structured as follows. Section 2 reviews relevant literature on machine learning applications in forecasting and risk analysis. Section 3 outlines the methodology used for comparative evaluation. Section 4 presents the findings and analytical insights. Section 5 discusses implications for theory and practice. Section 6 concludes the paper and suggests directions for future research.

2. Literature Review

Machine learning has become an increasingly influential tool in business analytics due to its ability to process large volumes of structured and unstructured data. Prior research highlights its superiority over traditional statistical methods in handling nonlinear patterns and high-dimensional datasets (Hastie, Tibshirani, & Friedman, 2017).

2.1. Machine Learning in Business Forecasting

In business forecasting, ML models are widely applied to sales prediction, demand forecasting, and financial performance estimation. Studies show that tree-based ensemble models such as random forests and gradient boosting outperform traditional regression models in demand forecasting tasks due to their robustness to noise and feature interactions (Makridakis et al., 2018). Neural networks, particularly deep learning architectures, have demonstrated strong performance in time-series forecasting when large datasets are available (Zhang, Aggarwal, & Qi, 2017).

However, researchers also emphasize that increased accuracy often comes at the cost of interpretability. Simple models such as linear regression remain popular in managerial settings because decision-makers can easily understand and justify predictions (Shmueli et al., 2010).

2.2. Machine Learning in Risk Assessment

Risk assessment represents another major application of ML, particularly in finance and operations. Credit risk modeling has extensively employed logistic regression, support vector machines, and neural networks to predict default probability (Lessmann et al., 2015). Ensemble methods have consistently demonstrated superior classification performance in credit scoring tasks.

Operational and enterprise risk management studies indicate that ML techniques can identify early warning signals and hidden risk patterns more effectively than rule-based systems (Aven, 2016). Yet, regulatory and ethical concerns often require transparent models, limiting the use of highly complex algorithms.

2.3. Cross-Domain Perspectives

Cross-domain research suggests that model performance varies significantly depending on data structure, domain complexity, and decision objectives. For example, while neural networks excel in unstructured or large-scale datasets, decision trees are often preferred in regulated environments due to interpretability (Molnar, 2022). The literature increasingly calls for comparative frameworks that consider both technical performance and organizational constraints.

This study builds on existing research by integrating findings from multiple domains and offering a structured comparison of ML models used in both forecasting and risk assessment contexts.

3. Methodology

This study adopts a qualitative-comparative research design based on secondary data analysis and synthesis of prior empirical findings. Rather than developing a single predictive model, the research evaluates commonly used machine learning algorithms across business forecasting and risk assessment applications.

The selected models include linear regression, decision trees, random forests, support vector machines (SVM), and artificial neural networks (ANN). These models were chosen due to their widespread use in business analytics and representation of varying levels of complexity.

Evaluation criteria were derived from the literature and include predictive accuracy, interpretability, scalability, data requirements, and implementation feasibility. Predictive accuracy refers to the model's ability to minimize forecasting error or classification misclassification. Interpretability assesses how easily model outputs can be understood by decision-makers. Scalability reflects the model's ability to handle large datasets, while feasibility considers computational and organizational constraints.

Data sources consist of peer-reviewed journal articles, conference papers, and applied case studies published between 2018 and 2025. Comparative insights were extracted and synthesized to identify patterns across domains.

This methodology allows for a holistic evaluation of machine learning models while maintaining relevance to real-world business decision-making.

4. Findings and Analysis

The comparative analysis reveals that model performance varies substantially across forecasting and risk assessment tasks.

Table 1: Model Comparison Summary

Model	Accuracy Level	Interpretability
Linear Regression	Moderate	High
Decision Tree	Moderate–High	High
Random Forest	High	Medium
SVM	High	Low
Neural Network	Very High	Low

Linear regression demonstrates strong baseline performance in stable environments with linear relationships. Its interpretability makes it suitable for strategic planning and regulatory reporting. However, its predictive accuracy declines in complex, nonlinear datasets.

Decision trees offer intuitive rule-based predictions and perform well in classification-based risk assessment tasks. They are particularly effective when transparency is essential, though they may suffer from overfitting.

Random forests and ensemble models consistently achieve higher accuracy in both forecasting and risk assessment. Their ability to aggregate multiple models improves robustness and reduces variance. However, they require greater computational resources and provide limited interpretability.

Support vector machines show strong performance in high-dimensional risk classification problems, especially credit scoring. Their effectiveness depends heavily on kernel selection and parameter tuning.

Neural networks outperform other models in large-scale forecasting and complex risk scenarios. Despite high accuracy, their "black-box" nature poses challenges for managerial acceptance and regulatory compliance.

Overall, the findings confirm that no single model dominates across all domains. Model selection must balance accuracy with transparency and organizational requirements. Table 1 summarizes the comparative performance of machine learning models across forecasting and risk assessment domains.

5. Discussion

The findings support the view that machine learning adoption in business should be context-driven rather than technology-driven. While advanced models deliver superior predictive performance, simpler models remain valuable due to their interpretability and trustworthiness.

For practitioners, this study highlights the importance of aligning model choice with business objectives, regulatory constraints, and data availability. For researchers, the results reinforce the need for cross-domain evaluation frameworks that go beyond accuracy metrics.

Machine learning should be viewed as a decision-support tool rather than a replacement for managerial judgment. Hybrid approaches that combine interpretable models with advanced algorithms may offer a balanced solution.

6. Conclusion

This study provides a cross-domain analysis of machine learning models used in business forecasting and risk assessment. By comparing commonly applied algorithms across multiple evaluation criteria, the research demonstrates that model effectiveness depends on domain characteristics and decision requirements.

The study contributes to the literature by synthesizing cross-domain insights and offering a practical framework for model selection. Organizations are encouraged to consider both technical performance and managerial usability when integrating machine learning into decision-making processes.

Future research may extend this work through empirical testing using unified datasets across domains or by exploring explainable AI techniques that bridge the gap between accuracy and interpretability.

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