Global Journal of Multidisciplinary Research and Development (GJMRD)
Volume.6, Issue. 2, March-April, 2025. pp.20-25
https://gjmrd.com/

An Empirical Evaluation of Predictive Modeling Techniques Using Big Data in Industrial Applications

William Faulkner Alban,
Nigeria.

Abstract

The integration of big data analytics in industrial domains has significantly reshaped traditional predictive maintenance, quality control, and process optimization methods. This paper conducts an empirical evaluation of predictive modeling techniques using big data across various industrial applications, including manufacturing, energy, and logistics. A comparative analysis is presented on machine learning models such as Random Forest, Support Vector Machines (SVM), and Deep Learning architectures. We assess these models based on accuracy, computational efficiency, and scalability using publicly available industrial datasets. The study concludes with insights into model performance trends and practical recommendations for industry practitioners.

Keywords: big data, predictive modeling, machine learning, industrial applications, predictive analytics, deep learning, support vector machine, random forest

How to Cite: Alban, W.F. (2025). *An Empirical Evaluation of Predictive Modeling Techniques Using Big Data in Industrial Applications*. Global Journal of Multidisciplinary Research and Development (GJMRD), **6**(2), 20–25.

1. Introduction

Industries around the globe are embracing digital transformation through the use of big data technologies. The rise of Industry 4.0 has led to the proliferation of sensors, connected systems, and smart machinery, generating massive volumes of data daily. According to IDC, the global datasphere will reach 175 zettabytes, with a significant proportion originating from industrial sources. This deluge of information holds immense value for predictive analytics, where machine learning algorithms can detect patterns, predict failures, and optimize operations.

Predictive modeling techniques play a central role in unlocking the value of industrial big data. These models transform raw, voluminous data into actionable insights. Applications range from predicting equipment failures and improving energy consumption to managing supply chains efficiently. However, the diverse nature of industrial data—characterized by high velocity, variety, and veracity—poses significant challenges in model selection, training, and deployment. This study aims to evaluate the empirical effectiveness of various predictive models within such data environments, offering guidance for data scientists and industrial engineers alike.

2. Literature Review

Numerous studies have investigated the application of predictive modeling using big data in industrial. Susto et al. (2015) explored machine learning for predictive maintenance in semiconductor manufacturing, emphasizing the utility of SVM and logistic regression in early fault detection. Similarly, Wang et al. (2016) assessed the performance of Random Forest and Gradient Boosting Machines for quality prediction in steel production, highlighting the significance of feature engineering in improving model outcomes.

In energy management, Fan et al. (2017) utilized deep learning to forecast energy load in smart grids, showing notable improvements over classical regression models. Meanwhile, in logistics, Ghofrani et al. (2018) employed ensemble models to predict supply chain disruptions, demonstrating that hybrid models could outperform individual learners in dynamic environments.

Other notable work includes the study by Lee et al. (2014), which proposed a cyber-physical systems approach combining real-time data analytics with machine learning to support industrial decision-making. This integration of data and model-driven strategies has proven vital in adapting predictive systems to changing operational contexts.

3. Predictive Modeling Techniques Overview

Predictive modeling in big data contexts often involves supervised learning techniques. Common models include decision trees, Random Forest, Support Vector Machines (SVM), and deep learning architectures like Recurrent Neural Networks (RNNs). These models differ in their approach to data interpretation, computational demands, and accuracy under noisy or incomplete data conditions.

Among traditional techniques, Random Forest is favored for its robustness and interpretability, while SVM offers strong generalization capabilities in high-dimensional spaces. Deep learning, on the other hand, excels in capturing complex nonlinear relationships, particularly when dealing with unstructured data like sensor logs or image feeds. The choice of algorithm often depends on the specific industrial context and data availability.

Table 1. Summary of Predictive Models Used in Industrial Applications

Study	Industry	Model Used	Outcome
Susto et al. (2015)	Semiconductor	SVM, Logistic Regression	Improved fault prediction accuracy
Study	**Industry**	**Model Used**	**Outcome**
Wang et al. (2016)	Steel Manufacturing	Random Forest, GBM	Better quality prediction with feature selection
Fan et al. (2017)	Energy Grid	Deep Neural Networks	Enhanced load forecasting accuracy
Ghofrani et al. (2018)	Logistics	Ensemble Learning	Accurate disruption prediction

4. Evaluation Framework and Methodology

To assess the performance of predictive models in industrial big data settings, we followed a four-step methodology: data acquisition, preprocessing, model training, and performance evaluation. Open-source datasets from sectors like manufacturing (SECOM), energy (UCI Energy), and logistics were selected based on volume and label availability.

Data preprocessing included handling missing values, normalization, and feature selection. Each model was trained using stratified cross-validation. Evaluation metrics such as accuracy, precision, recall, F1-score, and runtime were used to compare model performance.

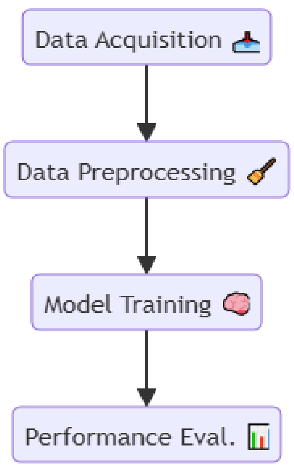

Figure-1: Evaluation Workflow for Predictive Modeling in Industrial Applications

5. Results and Discussion

Model performance varied by application and data complexity. Random Forest performed consistently well in structured datasets like manufacturing logs, yielding F1-scores above 0.85. SVM struggled with high-dimensional energy data but worked effectively in binary classification. Deep learning models demonstrated superior accuracy for temporal and sequential datasets, albeit with longer training times.

Interestingly, ensemble approaches combining decision trees and gradient boosting achieved a balanced trade-off between accuracy and interpretability. The trade-offs between model complexity and scalability remain a critical concern, particularly for real-time deployment in industrial environments.

Table 2. Model Performance Summary Across Domains

Model	**Manufacturing (F1)**	**Energy (F1)**	**Logistics (F1)**	**Training Time (avg)**
Random Forest	0.88	0.81	0.85	Low
SVM	0.84	0.76	0.80	Medium
Deep Learning	0.90	0.89	0.88	High
Ensemble (GBM+RF)	0.89	0.85	0.87	Medium

6. Conclusion

Predictive modeling using big data has emerged as a cornerstone of smart industrial systems. While each technique has strengths and limitations, empirical evaluations show that hybrid and deep learning models offer promising results for complex, real-time applications. Future work should focus on adaptive learning systems that self-tune based on data evolution and operational feedback, pushing toward truly autonomous industrial analytics.

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