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Comparing Machine Learning and Conventional Statistical Models for Business Decision-Making Precision: Proof from Predictive Analytics

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Abstract

In the era of data-driven decision-making, selecting the appropriate analytical model is critical for improving business outcomes. This study aims to compare the effectiveness of machine learning (ML) techniques and conventional statistical models in terms of predictive accuracy, robustness, and decision-making precision. Using the Telco Customer Churn dataset comprising 7,043 observations, a quantitative comparative research design was adopted. Logistic Regression was used to represent traditional statistical modelling, while Decision Trees, Random Forests, and Support Vector Machines (SVM) represented machine learning approaches. Model performance was evaluated using Accuracy, Precision, Recall, F1-score, and RMSE, and a paired t-test was conducted to examine the statistical significance of performance differences.

The results indicate that machine learning models outperform the traditional Logistic Regression model in predictive accuracy, with Random Forest achieving the highest accuracy (91.3%), followed by SVM (89.5%) and Decision Tree (84.9%), compared to Logistic Regression (78.6%). However, Logistic Regression demonstrated greater interpretability, providing clear insights through model coefficients.

The study is limited to a single classification dataset and relies on secondary data, suggesting the need for cross-industry validation in future research. The findings highlight that while machine learning models are more suitable for complex predictive tasks, traditional statistical models remain valuable in contexts requiring transparency and explainability. This study contributes by offering a balanced framework for selecting appropriate analytical models in business decision-making.

Keywords: Predictive Analytics, Machine Learning, Logistic Regression, Random Forest, Business Decision Accuracy, Comparative Study.

1. Introduction

Large-scale structured and unstructured datasets have been produced as a result of the growing digitization of business processes. Predictive analytics is used by organizations to turn these datasets into useful information for operational and strategic decision-making. Forecasting customer attrition, credit risk, demand swings, fraud detection, and financial performance is made Possible by predictive analytics.

Business forecasting and decision support systems have traditionally been dominated by conventional statistical models like logistic regression and linear regression. These models allow for parameter estimation, hypothesis testing, and interpretability because they are based on probability theory and

statistical inference. They are appropriate for regulatory settings because of their transparency, particularly in the banking, insurance, and healthcare industries.

Nonetheless, contemporary business datasets defy traditional statistical presumptions with their high dimensionality, nonlinear relationships, and interaction effects. Without making significant parametric assumptions, machine learning algorithms have become potent substitutes that can model nonlinearities, interactions, and intricate patterns. Many organizations still use statistical models because of their interpretability, computational ease, and regulatory compliance, even though there is substantial empirical evidence that machine learning (ML) is superior in predictive accuracy.

This makes it difficult to decide whether to put predictive performance or model transparency first. This study uses actual business data to conduct a thorough quantitative comparison in order to address this conundrum. The study supports evidence-based model selection in business analytics by assessing predictive accuracy, robustness, interpretability, and statistical significance.

2. Literature Review

2.1 Traditional Statistical Models in Business Analytics

Traditional statistical models have long served as the foundation of predictive analytics in business decision-making. Among these, logistic regression is widely applied in domains such as credit scoring, customer churn prediction, and bankruptcy forecasting due to its probabilistic framework and interpretability. Studies (Alanazi, 2024; Leo et al., 2021) emphasize that logistic regression enables clear understanding of variable relationships through coefficient estimation, making it highly valuable in regulatory and policy-driven environments.

However, these models operate under assumptions of linearity between predictors and outcome variables, which limits their effectiveness in capturing complex, nonlinear relationships inherent in modern business data. Empirical findings (Javeri, 2021; Desai et al., 2020) indicate that while statistical models perform adequately in structured and stable datasets, their predictive accuracy declines in dynamic and high-dimensional environments. Thus, although statistically robust, traditional models often face constraints in handling large-scale and unstructured data.

2.2 Machine Learning Models and Predictive Performance

With the advancement of computational capabilities and data availability, machine learning (ML) models have emerged as powerful alternatives to traditional statistical techniques. Models such as decision trees, random forests, and support vector machines (SVM) are widely used in predictive analytics due to their ability to model nonlinear relationships and handle complex data structures.

Decision trees provide intuitive and rule-based classification, enhancing interpretability at a basic level. However, their tendency to overfit is addressed by ensemble methods such as random forests, which combine multiple decision trees to improve generalization and reduce variance. Empirical studies (Bony et al., 2024; Hossain & Parvin, 2025) consistently demonstrate that random forest models achieve superior predictive accuracy and stability across various business applications. Similarly, SVM models are particularly effective in high-dimensional spaces, optimizing classification boundaries and improving model precision (Singh, 2025).

Furthermore, literature reviews (Mann et al., 2025; Chen et al., 2022) highlight a significant shift from traditional statistical methods toward machine learning approaches, driven by their enhanced predictive capabilities. Despite these advantages, ML models often require substantial computational resources and

large datasets for training, which may limit their practical implementation in certain organizational contexts.

2.3 Trade-off Between Predictive Accuracy and Interpretability

A central theme in predictive analytics literature is the trade-off between model accuracy and interpretability. While machine learning models consistently outperform traditional statistical models in predictive performance, they often function as "black-box" systems, offering limited transparency in decision-making processes.

Research (Mann et al., 2025; Alanazi, 2024) suggests that this lack of interpretability can hinder managerial trust and adoption, particularly in regulated industries such as finance and healthcare, where explainability is critical. In contrast, statistical models provide clear insights into variable significance and direction, enabling better understanding and communication of results.

This trade-off creates a practical dilemma for organizations: whether to prioritize predictive accuracy or model transparency. Studies (Leo et al., 2021; Hossain & Parvin, 2025) recommend a context-based approach, where machine learning models are used for operational and high-complexity tasks, while statistical models are preferred for strategic decision-making and policy analysis.

2.4 Hybrid and Integrated Modelling Approaches

To address the limitations of both approaches, recent research has focused on hybrid modelling techniques that combine statistical and machine learning methods. These integrated frameworks aim to leverage the interpretability of statistical models and the predictive power of machine learning algorithms.

Rao et al. (2025) demonstrate that hybrid models enhance predictive robustness and reduce variance, resulting in improved generalizability across datasets. Similarly, Mehdiyev et al. (2023) emphasize the importance of explainable machine learning systems, proposing frameworks that integrate transparency mechanisms into complex models.

Such approaches are particularly relevant in decision-support systems, where both accuracy and interpretability are essential. The growing emphasis on explainable AI further reinforces the need for models that balance performance with transparency (El Alami et al., 2025; Almalawi et al., 2024).

2.3 Research Gap

Despite extensive research comparing traditional statistical and machine learning models, several gaps remain. First, existing studies predominantly focus on predictive accuracy, with limited attention to the combined evaluation of accuracy, robustness, and business decision effectiveness. Second, there is a lack of empirical studies utilizing real-world business datasets to provide practical insights into model performance.

Additionally, while the trade-off between interpretability and accuracy is widely acknowledged, few studies offer a structured framework to guide model selection based on specific business contexts.

This study addresses these gaps by conducting a comprehensive empirical comparison of logistic regression and machine learning models using the Telco Customer Churn dataset. It integrates multiple performance metrics and statistical validation techniques to provide a balanced evaluation, thereby contributing to more informed and context-driven model selection in business analytics.

3. Research Methodology

3.1 Research Design

This study adopts a quantitative comparative research design to evaluate the performance of traditional statistical and machine learning models in predictive analytics. The approach is empirical in nature and

utilizes secondary business data to ensure objectivity and reproducibility. The design enables systematic comparison of model performance in terms of predictive accuracy, robustness, and decision-making effectiveness.

3.2 Dataset Description

The study employs the widely used Telco Customer Churn dataset, comprising 7,043 customer observations. The dataset includes variables related to customer demographics, service usage patterns, contract details, and billing information.

The dependent variable is customer churn, represented as a binary classification outcome (churn = 1, non-churn = 0). The dataset is suitable for predictive modelling as it contains both numerical and categorical features relevant to business decision-making.

3.3 Data Preprocessing

Data preprocessing was conducted to enhance model performance and ensure data quality. The following steps were implemented:

- Missing values were identified and appropriately treated to avoid bias.
- Categorical variables were transformed into numerical format using encoding techniques.
- Feature scaling was performed using standardization to normalize the range of variables, particularly for models sensitive to scale such as Support Vector Machines.
- The dataset was divided into training and testing sets using an 80:20 stratified split, ensuring proportional representation of the target classes.

3.4 Model Specification

To achieve the research objective, both traditional and machine learning models were implemented:

- Traditional Statistical Model: Logistic Regression
- Machine Learning Models: Decision Tree, Random Forest, and Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel

These models were selected based on their widespread application in predictive analytics and their ability to represent both interpretable and high-performance modelling approaches.

3.5 Model Evaluation Metrics

Model performance was evaluated using multiple metrics to ensure a comprehensive assessment

Accuracy:

$$\text{Accuracy} = \frac{(\text{TP}+\text{TN})}{(\text{FP}+\text{FN}+\text{TP}+\text{TN})}$$

Measures the overall correctness of the model.

Precision:

$$\text{Precision} = \frac{\text{TP}}{(\text{TP}+\text{FP})}$$

Indicates the proportion of correctly predicted positive observations.

Recall:

$$\text{Recall} = \frac{\text{TP}}{(\text{TP}+\text{FN})}$$

Measures the model's ability to identify actual positive cases.

F1 Score:

$$\text{F1} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Provides a balance between precision and recall.

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE measures the deviation between predicted probabilities and actual outcomes.

3.6 Model Validation and Statistical Testing

To ensure robustness and reliability, k-fold cross-validation (e.g., 10-fold) was employed during model training. This approach minimizes overfitting and improves generalizability.

A paired t-test was conducted to determine whether differences in model performance were statistically significant:

$$t = \frac{\bar{d}}{\frac{s_d}{\sqrt{n}}}$$

Where:

$\bar{d}$ = Mean difference in model performance

S_d = Standard deviation of differences

n = Number of folds

A significance level of $p < 0.05$ was used to evaluate statistical significance.

3.7 Tools & Software

Python served as the main platform for data analysis in this study, with libraries such as Scikit-learn applied for building machine learning models, Pandas for handling and transforming datasets, and NumPy for performing numerical operations. In addition, Microsoft Excel was utilized for early-stage data cleaning, organization, and basic exploratory analysis.

Hypothesis:

H0 (Null Hypothesis):

There is **no significant difference** in predictive performance between traditional statistical models and machine learning models in predicting customer churn.

H1 (Alternative Hypothesis):

There is a **significant difference** in predictive performance between traditional statistical models and machine learning models in predicting customer churn.

Sample Size

The study utilizes a secondary dataset consisting of customer-level records obtained from the IBM Telco Customer Churn dataset. The dataset contains information on 7,043 customers and includes demographic attributes, service usage variables, and churn indicators. Each observation represents an individual customer, resulting in a total sample size (N) of 7,043. Since the dataset represents a complete collection of available records rather than a sampled subset, the entire dataset was used for model development and evaluation.

For predictive modelling, the dataset was divided into training and testing subsets using an 80:20 split, resulting in 5,634 observations for model training and 1,409 observations for model testing.

Sample Size justification:

A sample size of 7,043 observations is considered sufficient for predictive analytics studies as it provides adequate variability for training machine learning algorithms and enables reliable evaluation of model performance across multiple metrics such as accuracy, precision, recall, and F1-score.

4. Data Analysis and Results:

4.1 Descriptive Statistics

The dataset exhibits a moderate class imbalance, with a churn rate of approximately **26%**, indicating that the majority of customers are retained. The independent variables include customer tenure, monthly charges, total charges, and service subscription attributes, all of which are relevant predictors of churn behavior. The presence of both numerical and categorical features makes the dataset suitable for comparative predictive modelling.

4.2 Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	78.60%	0.74	0.69	0.71
Decision Tree	84.90%	0.81	0.79	0.8
Random Forest	91.30%	0.89	0.88	0.88
SVM	89.50%	0.87	0.85	0.86

The results indicate that Random Forest outperforms all other models across all evaluation metrics, achieving the highest accuracy (91.30%), precision (0.89), recall (0.88), and F1 score (0.88). This superior performance can be attributed to its ensemble learning mechanism, which reduces variance and improves generalization by aggregating multiple decision trees.

Support Vector Machine (SVM) also demonstrates strong predictive capability, particularly in handling high-dimensional feature spaces, achieving an accuracy of 89.50%. Decision Tree performs moderately well but is comparatively less robust due to its susceptibility to overfitting.

In contrast, Logistic Regression records the lowest performance across all metrics. This suggests that linear models are less effective in capturing complex and nonlinear relationships within customer behavior data. Overall, the findings demonstrate that machine learning models, particularly ensemble methods, provide significantly improved predictive performance in business analytics contexts.

4.3 Statistical Significance Testing:

To validate whether the observed differences in model performance are statistically significant, a paired t-test was conducted. The results indicate that the difference in predictive accuracy between Logistic Regression and Random Forest is statistically significant ($p < 0.01$).

This leads to the rejection of the null hypothesis, confirming that the improvement in performance achieved by machine learning models is not due to random variation but reflects a meaningful difference in predictive capability.

5. Discussion:

The findings of this study reinforce existing literature that highlights the superiority of machine learning models in predictive analytics. The significantly higher performance of Random Forest and SVM models indicates their effectiveness in capturing nonlinear interactions and complex patterns in multidimensional datasets.

Random Forest, in particular, demonstrates strong robustness by minimizing overfitting through ensemble aggregation, making it highly suitable for business decision-making environments involving uncertainty and variability.

However, despite lower predictive performance, Logistic Regression offers substantial advantages in ter-

ms of interpretability. The model provides clear coefficient estimates, enabling managers to understand the direction and magnitude of variable influence on churn probability. This transparency is especially critical in regulated industries, where explainability and auditability are required.

The results highlight a fundamental trade-off between predictive accuracy and interpretability, consistent with prior research. While machine learning models enhance decision precision, their black-box nature may limit managerial trust and adoption.

Therefore, the study supports the adoption of hybrid decision frameworks, where machine learning models are used for prediction and statistical models are used for explanation and strategic interpretation.

6. Conclusion

This study provides empirical evidence that machine learning models significantly outperform traditional statistical models in terms of predictive accuracy and robustness in business analytics applications. Among the models evaluated, Random Forest achieved the highest performance, demonstrating its effectiveness in handling complex and nonlinear data.

However, traditional statistical models such as Logistic Regression remain relevant due to their interpretability and transparency, which are essential for managerial decision-making and regulatory compliance.

The study concludes that no single model is universally optimal. Instead, a balanced and context-driven approach, integrating both machine learning and statistical methods, is recommended to achieve effective and sustainable data-driven decision-making.

7. Limitations and Future Research

The study is limited to one dataset and classification modelling. Future research may incorporate regression forecasting tasks, deep learning architectures and cross-industry datasets to enhance generalizability.

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