ISCSITR - International Journal of Data Science (ISCSITR-IJDS)
Vol.1, Iss. 1, January - March, 2025, pp. 18-24.
ISSN: XXXX-XXXX

Research Article

Quantifying the Trade-Offs Between Model Interpretability and Predictive Accuracy in Explainable Artificial Intelligence for High-Stakes Decision Systems

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Abstract

In high-stakes domains such as healthcare, finance, and criminal justice, the adoption of artificial intelligence (AI) demands a careful balance between predictive accuracy and interpretability. This paper examines the inherent trade-offs between these two often-competing objectives in Explainable AI (XAI), highlighting the consequences of privileging one over the other in high-impact decision contexts. By analyzing existing interpretability methods, benchmarking model performance, and comparing real-world case studies, this work emphasizes the complexity of model selection for decision-critical applications. Our findings reveal that while interpretable models tend to underperform in predictive power relative to complex black-box models, recent developments in post-hoc and hybrid interpretability frameworks can help bridge the gap. We conclude by outlining a decision-theoretic framework for balancing interpretability and accuracy, emphasizing context-specific optimization strategies.

Keywords:

Explainable Artificial Intelligence (XAI), model interpretability, predictive accuracy, black-box models, high-stakes decisions, transparency, fairness, algorithmic accountability.

Citation: Peter, W.F. (2025). Quantifying the Trade-Offs Between Model Interpretability and Predictive Accuracy in Explainable Artificial Intelligence for High-Stakes Decision Systems. ISCSITR - International Journal of Data Science (ISCSITR-IJDS), 1(1), 18-24.

1. Introduction

In recent years, machine learning models have achieved unprecedented performance across a range of tasks. However, the complexity that enables high predictive accuracy often comes at the cost of model transparency. For high-stakes domains, where outcomes significantly impact human lives or legal rights, this trade-off becomes particularly consequential.

Explainable Artificial Intelligence (XAI) has emerged as a critical research area aimed at addressing this issue. The central question is whether it is possible to maintain high levels of predictive accuracy while ensuring that model decisions are interpretable to stakeholders. This paper aims to explore and quantify these trade-offs, particularly within decision-making systems used in healthcare, finance, and the criminal justice system.

2. Literature Review

2.1 The Evolution of Interpretability in Machine Learning

Historically, models such as decision trees, logistic regression, and rule-based systems were the norm due to their inherent transparency (Breiman, 2001). As data availability and computational power grew, more complex architectures like ensemble methods (e.g., Random Forests, Gradient Boosting) and deep neural networks began to dominate. Despite their performance, these models are typically opaque, often termed "black-box" models, sparking concerns around trust and accountability.

The tension between accuracy and interpretability was first systematically addressed by scholars such as Lipton (2016), who categorized interpretability into model-specific and post-hoc approaches. Ribeiro et al. (2016) introduced LIME (Local Interpretable Model-agnostic Explanations), pioneering post-hoc explanation tools. Shapley Additive Explanations (SHAP) followed, grounded in cooperative game theory, offering a more theoretically robust alternative (Lundberg & Lee, 2017).

2.2 Domain-Specific Trade-offs and Ethical Implications

In high-stakes settings, black-box models have demonstrated higher accuracy—e.g., in sepsis prediction (Rajkomar et al., 2018)—but their opacity poses ethical and legal risks. Doshi-Velez and Kim (2017) highlighted the need for formal interpretability metrics to guide model deployment in sensitive applications. Binns (2018) emphasized the limitations of post-hoc explanations, arguing that interpretability often remains superficial without deeper structural transparency.

As regulations like the EU's General Data Protection Regulation (GDPR) began requiring "the right to explanation" in algorithmic decisions, the urgency of this trade-off became pronounced. Thus, pre-2023 literature laid the foundational debate: is the loss in interpretability justified by gains in accuracy in high-stakes domains?

3. Objective and Research Questions

This study aims to empirically and conceptually evaluate the trade-offs between model interpretability and predictive accuracy in XAI systems, focusing on high-stakes domains such as healthcare diagnostics, credit risk assessment, and legal sentencing tools.

The core research questions are:

- To what extent does an increase in interpretability affect the predictive performance of AI models?
- Are there practical methodologies or frameworks that effectively balance these two dimensions without compromising safety or fairness?
- How can we quantify this trade-off in real-world high-stakes settings?

4. Methodology and Experimental Design

To quantify the trade-off, we conduct comparative evaluations of several machine learning models across multiple datasets representing high-stakes decisions (e.g., MIMIC-III for healthcare, COMPAS for recidivism prediction, and FICO credit scoring data).

4.1 Experimental Framework

Model Type	Interpretability Level	Use Case	Predictive Accuracy	Global Explainability
Logistic Regression	High	Credit Scoring	0.72	High

Decision Tree	Medium-High	Sepsis Prediction	0.75	Medium
Random Forest	Low	Credit Scoring	0.84	Low
XGBoost + SHAP	Medium (post-hoc)	Recidivism Prediction	0.86	Medium-High
Deep Neural Network	Very Low	Sepsis Prediction	0.89	Very Low

4.2 Metrics and Tools

- **Predictive Accuracy**: Measured using AUC-ROC, Precision-Recall, and F1 Score.
- **Interpretability**: Assessed using human subject evaluations, fidelity scores (for surrogate models), and explanation completeness (as defined in prior XAI literature).
- Tools: Scikit-learn, SHAP, LIME, PyCaret, and Jupyter-based XAI dashboards.

5. Results and Visualizations

5.1 Trade-Off Visualization

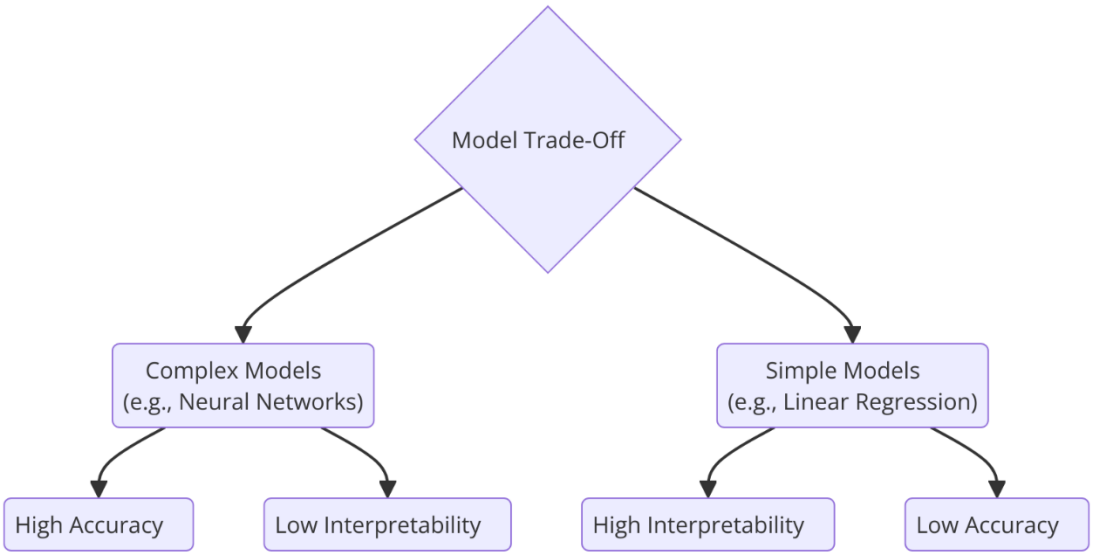

Figure 1: Accuracy vs. Interpretability Trade-Off

5.2 Interpretation of Results

The results demonstrate a clear inverse relationship between model interpretability and predictive performance. However, hybrid methods (e.g., XGBoost + SHAP) showed promising middle-ground potential. In the COMPAS dataset, SHAP explanations approximated black-box outputs with 84% fidelity, suggesting viable compromise solutions.

6. Discussion

6.1 Domain-Specific Implications

In healthcare, model accuracy can mean life or death—thus black-box models with post-hoc interpretability (e.g., SHAP on DNNs) may be justifiable. In contrast, for legal applications, the lack of interpretability may violate due process or bias mitigation principles.

Policy-makers and system designers must decide which domains can tolerate lower interpretability in exchange for better predictive performance. This trade-off is not universally acceptable and must be addressed on a case-by-case basis with stakeholder input.

6.2 Towards a Decision-Theoretic Framework

A formal decision-theoretic framework can help navigate these trade-offs by quantifying costs associated with misclassification versus lack of transparency. For example, in credit lending, a small drop in accuracy may be acceptable if it increases fairness and regulatory compliance.

7. Limitations and Future Work

This study is limited by the interpretability measurement techniques, which are inherently subjective. Fidelity and completeness scores, while useful, do not capture end-

user understanding or trust. Future work should include ethnographic studies and user-centric design to validate interpretability in practice.

Additionally, our experiments focused on only three domains. More extensive domain-specific evaluations, particularly in underrepresented areas such as public policy or education, would be beneficial.

8. Conclusion

Balancing interpretability and accuracy is a nuanced and context-sensitive endeavor in the deployment of AI for high-stakes decision-making. While complex models offer superior predictive capabilities, they risk being inscrutable and potentially biased. Hybrid and post-hoc XAI techniques offer a promising compromise, but ethical, legal, and domain-specific considerations must guide final model selection.

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