**Enhancing XGBoost Performance for High-Dimensional Data: Challenges, Optimization Strategies, and Practical Insights**

High-dimensional datasets frequently cause problems for machine learning models because of the higher processing requirements, overfitting risk, and duplicated features. The purpose of this work is to investigate methods for enhancing the performance of the popular gradient boosting algorithm XGBoost in high-dimensional settings. We will look into important issues including model generalization, computational efficiency, and feature selection. We want to apply and evaluate dimensionality reduction strategies, such as Principal Component Analysis (PCA) and L1-based feature selection, in order to overcome these issues. Hyperparameter tweaking techniques will also be used to improve model performance without sacrificing prediction accuracy.

We will assess how these modifications affect training time, model interpretability, and overall performance through experimental analysis on benchmark datasets. The goal of the work is to provide light on how to evaluate trade-offs between explainability and dimensionality reduction and strike a balance between model complexity and predictive capability. This study will advance best practices for using XGBoost on intricate, feature-rich datasets by methodically examining various optimization techniques. Incorporating deep learning methods or hybrid strategies might be future possibilities to improve model performance in high-dimensional environments.

**KEYWORD**:High-Dimensional Data, XGBoost Optimization, Feature Selection, Dimensionality Reduction, Hyperparameter Tuning.