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Explainable Machine Learning for Predictive Analytics: Examining the Influence of Feature Optimization and Model Interpretability

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ABSTRACT

This study examined the application of explainable machine learning (XAI) in predictive analytics by investigating the influence of feature optimization and model interpretability on machine learning performance and transparency. A quantitative experimental and comparative research design was employed using a structured dataset comprising 1,000 observations collected from a machine-learning dataset relevant to predictive analytics. The data were prepared through systematic data collection and preprocessing procedures, including the identification and treatment of missing values, duplicate observations, inconsistent entries, categorical variables, and numerical features. Feature optimization was subsequently performed to identify and retain the most relevant predictors while reducing redundant and less informative variables. Three machine learning models, including Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting (GB), were trained and comparatively evaluated using training and testing procedures with cross-validation and hyperparameter optimization. Predictive performance was assessed using accuracy, precision, recall, F1-score, and ROC-AUC, while explainability and interpretability were examined using SHAP (SHapley Additive exPlanations) for global feature contribution and LIME (Local Interpretable Model-Agnostic Explanations) for local prediction explanations. The analysis was conducted using Python-based tools, including Pandas, NumPy, Scikit-learn, SHAP, LIME, and Matplotlib. The findings indicated that feature optimization improved the predictive performance of the machine learning models while reducing feature complexity, and the explainability analysis provided clearer insights into the contribution of important predictors and individual model decisions. The study is significant because it integrates predictive performance with transparency and interpretability, demonstrating that explainable machine learning can support the development of more efficient, understandable, and practically useful predictive analytics systems.

Introduction

Machine learning (ML) is widely used in predictive analytics because it can identify hidden patterns and relationships within large and complex datasets. It is especially useful when data contains many variables and interactions that are difficult to analyze using traditional methods. Common machine learning techniques such as Random Forest, Support Vector Machine (SVM), Gradient

Boosting, and Neural Networks are frequently applied for classification, prediction, and decision-making tasks across different fields.

With the complexity of the ML models growing, however, there were concerns with transparency and understanding of predictions made by ML (Ribeiro et al., 2016). The concerns are addressed by the development of explainable machine learning (XAI), which gives information on why models make their predictions and which features are used in the predictions (James, 2026).

Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) are two of the most popular methods for explaining complex ML models. LIME also gives local explanations by modeling the behavior of the model with respect to individual observations while SHAP estimates the contribution of individual features to the model's predictions (Lundberg & Lee, 2017). Explainability is important because it can be just as important as the predictive accuracy, as model outputs may not have enough information for researchers and decision-makers to understand and trust the models' predictions. Recent research has also demonstrated that there are situations where SHAP and LIME can be used to give local and global explanations of a complex predictive model (Salih et al., 2023).

Predictive Analytics

Predictive analytics is the application of historical and current data, statistical methods and computational algorithms to forecast unknown or future outcomes. As the volume of data continues to grow, and more and more data is being collected, machine learning has emerged as a crucial part of predictive analytics tools, as it can uncover complex patterns and relationships that traditional methods might not be able to identify (Chan et al., 2022). For classification problems, various metrics like accuracy scores, precision scores, recall scores, F1 score, and ROC-AUC scores are often used to assess predictive performance.

One major problem in predictive analytics is the presence of irrelevant, redundant or noisy features. The more predictors used, the more computation is involved and it may have a negative impact on model generalization. Thus, feature selection and optimization is essential to predictive modelling as it allows for the preservation of valuable features whilst minimizing the number of redundant dimensions (Kim et al., 2026). In the modern era, predictive analytics has come to focus on predictive accuracy and interpretability in addition to predictive performance, especially for the purposes of making practical decisions (Hastie et al., 2009).

Feature Optimization

Feature optimization is the process of choosing, transforming or building input variables to give machine learning models the most predictive information. This can include feature selection, feature engineering, dimensionality reduction and optimization-based extraction of the most important feature subsets (Ghaemi et al., 2016). Irrelevant and redundant predictors can be eliminated to reduce the number of computations, make models more efficient, and possibly enhance prediction (Akinola et al., 2022).

Explainable machine learning is also becoming associated with feature optimization. SHAP and LIME can output features that have a high impact on the model's predictions, which can be very helpful when deciding which features to use in the model (Henry et al., 2023). Recent studies have shown that feature-selection methods can result in more compact and interpretable subset of features, while retaining high predictability for XAI (Dunn et al., 2021). So, feature optimization can also help achieve prediction accuracy and model clarity.

Model Interpretability

Model interpretability is the degree of understanding of a predictive model's behaviors and the reasons behind its outputs by users. This is especially crucial for complex ML algorithms where the decision-making process might not be directly understandable. Interpretability can be understood from two perspectives. The first is **global interpretability**, which focuses on understanding how important different predictors are in influencing the overall model outcomes. The second is **local interpretability**, which examines the factors that contribute to a specific prediction made for an individual case. (Molnar, 2022).

SHAP provides both overall and case-specific insights into how different features influence model predictions. In contrast, LIME is mainly used to explain the reasons behind individual predictions. These methods help researchers understand the role of different variables in the prediction process and assess whether the model’s results align with existing knowledge and practical understanding of the subject area (Chakraborty et al., 2017). But explanations should be taken with a pinch of salt, since factors like feature correlation, model structure and the stability of the explanation can affect the results (Lipton, 2018). Thus, interpretability should not be viewed as another visualization, but as a key element of the analysis (Poursabzi-Sangdeh et al., 2021).

In conclusion, there is a strong connection between feature optimization, model interpretability, Explainable Machine Learning and predictive analytics. To sum up, feature optimization, model interpretability, Explainable Machine Learning and predictive analytics are closely inter-connected.

Relationship Between Feature Optimization, Model Interpretability, Explainable Machine Learning, and Predictive Analytics

Feature optimization and model interpretability go hand in hand because if one features are selected, the model complexity could decrease, and the behavior of the model can be more easily understood. Meanwhile, explainability techniques like SHAP and LIME can help to show the features that have a high influence on the model and give information that could be used to make feature-selection decisions. This results in an integrated relationship where feature optimization can enhance the prediction efficiency of the model, and explainability can be used to evaluate if the features that are kept have significant contribution to the model's prediction (Bomrah et al., 2024).

In summary: explainable machine learning offers a framework to integrate the power of prediction with Explainability. Feature optimization aims to enhance the quality and relevance of the features used for input, predictive analytics checks the predictive power of the output, and model interpretability gives an explanation of how the selected features affect the output. Recent studies have highlighted the need for incorporating these elements to create innovative compact, effective and understandable predictive models (Vudugula et al., 2023). Accordingly, the current research focuses on two aspects of an explainable predictive analytics framework – feature optimization and model interpretability (Nandurkar et al., 2025).

Research Objectives

1. To examine the influence of feature optimization on the predictive performance of machine learning models.
2. To assess the role of model interpretability in enhancing the transparency and understanding of machine learning predictions.
3. To evaluate how explainable machine learning, through feature optimization and model interpretability, improves the effectiveness of predictive analytics.

Problem Statement

Although machine learning has greatly improved predictive analytics by identifying complex and non-linear patterns in data, the increasing complexity of these models has created a challenge known as the **accuracy interpretability gap**. In many cases, highly accurate models do not clearly explain how their predictions are generated, making their decisions difficult to understand. To address this issue, explainable artificial intelligence (XAI) techniques such as SHAP and LIME have been developed to improve model transparency and provide insights into prediction outcomes. However, the quality of these explanations can be influenced by factors such as the underlying model structure, correlations among features, and the methods used to measure feature contributions. As a result, achieving truly meaningful and reliable interpretability remains an ongoing challenge (Mao et al., 2023). Furthermore, the study of explainability and features selection have been conducted separately or most of the literature have been devoted to the study of explainability in classification tasks, which requires a study of integrated approaches to systematically study whether the optimization of features can improve the performance of the model and increase its interpretability. There are recent works that demonstrate that a feature selection based on XAI can enhance or preserve predictive performance while reducing the feature space, however the success of this approach can differ in prediction tasks and datasets (Stenwig et al., 2022). The combined effect of optimizing features and interpretability of a machine learning model is therefore not directly investigated in this paper, but is considered a research gap for empirically examining this effect in an explainable machine learning framework, in addition to prediction accuracy. This is crucial for creating accurate, interpretable, understandable and actionable predictive analytics models that help in decision making.

Significance of the Study

This study is significant because it provides an integrated approach to improving predictive analytics by examining the combined role of feature optimization, explainable machine learning, and model interpretability. By identifying the most relevant features and explaining how these features contribute to model predictions, the study can help develop predictive models that are not only accurate but also transparent and easier for researchers and decision-makers to understand. The findings may contribute to the methodological literature by demonstrating how feature optimization and interpretability can be incorporated into the predictive

modeling process rather than treating explainability as a post-modeling activity (Lundberg & Lee, 2017; Ribeiro et al., 2016; Molnar, 2022). Practically, the study can support researchers, data analysts, and organizations in selecting more meaningful predictors, reducing unnecessary model complexity, and improving confidence in ML-based predictions. Furthermore, the study may provide a useful framework for developing more reliable and interpretable predictive analytics systems, particularly in contexts where understanding the reasons behind algorithmic predictions is as important as achieving high predictive performance.

Literature Review

Explainable Machine Learning

With the advent of modern and sophisticated machine learning models, Explainable Machine Learning (XML) has emerged as a crucial field of study, as it is difficult for users to understand the models in machine learning. Random forests, gradient boosting and neural networks are algorithms that can detect complex and nonlinear relationships, but can also be considered as "black-box" systems. Belle and others (2021) pointed out the need to appreciate the rationale behind a model's prediction, and Roscher and others (2020) emphasized the need to find individual feature contributions. Explainable ML aims to increase the transparency and understanding of complex predictive models, while maintaining their predictive power.

There are several popular methods for interpreting machine learning predictions, such as LIME and SHAP. SHAP estimates the influence of each feature on the predictions based on Shapley-value principles (Linardatos et al., 2020), while LIME gives a local explanation by approximating the behavior of the complex model on top of individual observations. The results of the explanations, however, may change due to the nature of the algorithm, the relationships between the features, and the nature of the data set. Salih et al. (2025) emphasized that different model or feature conditions can yield different interpretations by these methods (SHAP and LIME). Explainability should, therefore, not be seen as a standalone activity, but rather as part of a process of feature selection and predictive performance (Marcinkevičs et al., 2023).

Feature Optimization

Feature optimization involves selecting, transforming, and creating relevant features to improve the performance and efficiency of machine learning models. In high-dimensional datasets, the presence of irrelevant, redundant, or noisy features can increase computational complexity and reduce the model's ability to generalize effectively to new data. Feature selection helps address these issues by retaining only the most informative variables, making the learning process more efficient and improving model performance. Previous studies have highlighted that removing unnecessary features can simplify model training and lead to more reliable predictions (Akinola et al., 2022; Chandrashekar & Sahin, 2014). Different possibilities for finding useful feature subsets exist, depending on the data and the learning algorithm, and are provided by filter, wrapper and embedded methods.

Optimization of features is also becoming linked with explainable ML, with the use of techniques like SHAP to determine which features are important for the model's predictions at a high level (Wein et al., 2020). The exclusion of less informative variables can result in a more compact feature space and might aid in the interpretability of the models. Therefore, the process of feature optimization can affect predictive accuracy and the interpretability of the model by taking out the unnecessary complexity without losing meaningful predictors (Srisukkham et al., 2017).

Model Interpretability

This relates to how well a user can explain or interpret a machine learning model's prediction. It is especially crucial for complex algorithms as accurate predictions do not necessarily capture why they are accurate for individual predictions. Interpretability may be considered on a global and local basis: Global interpretation involves understanding of key features across the data set; Local interpretation involves understanding of their individual predictions. While LIME primarily offers local explanations, SHAP can offer local feature contributions as well as global information on overall feature importance (ElShawi et al., 2021; Nguyen et al., 2020).

Correlated predictors and model features also can lead to a lack of interpretability. If several variables have similar information, explanation methods can spread the importance of the variables over these predictors, which can make it harder to determine the contribution of each predictor. Therefore, Casillas et al. (2013) emphasized the need for feature relationships when assessing explanations provided by SHAP and LIME. This indicates that model interpretability needs to be considered along with feature optimization to get better and meaningful explanations.

Predictive Analytics

Predictive analytics is the analysis of past data, statistical methods and machine learning algorithms to forecast the future or unknown. Predictive analytics has been a leap forward in the era of machine learning, as it allows models to uncover complex and nonlinear relationships and interactions in the data (Broby, 2022). In classification tasks, there are several metrics commonly used to assess predictive performance like accuracy, precision, recall, F1-score and the ROC-AUC. But irrelevant or redundant features can have an impact on the quality of predictions, which is why feature optimization is crucial for predictive model development.

In addition to predictive analysis, Explainable ML (Van Calste et al., 2019) includes an interpretative component, wherein the specific components of the model that are responsible for the prediction are explained and how the contributions of those components affect individual results. Thus, there's a requirement to balance predictive performance with transparency that's growing more critical for effective predictive analytics. In addition to making accurate predictions, a model should also provide information that is understandable about the factors responsible for the predictions (Fitz-Enz et al., 2014).

Relationship Among Feature Optimization, Model Interpretability, Explainable ML, and Predictive Analytics

Optimize features, interpret models, make models explainable, and use predictive analytics are all linked in one analytical framework. Feature optimization enhances quality of inputs of the model by identifying relevant predictors and interpretability provides explanations on how the predictors lead to model outputs. There are methods to connect these processes, such as techniques in Ex explainable ML which give information regarding feature contributions and prediction behavior (Topuz et al., 2025). Thus, using the optimized feature space can result in more precise explanations of the model (Parisineni et al., 2024) and eliminate unnecessary complexity.

Research Gap

While explainable machine learning is known to enhance the interpretability of complex predictive models, there is a crucial missing link between feature optimization, model explainability and predictive modeling. Existing research on the development or use of explanation techniques like SHAP and LIME has focused mainly on identifying the key features after a predictive model has been developed, while there has been relatively less effort dedicated to the systematic optimization of features and how it impacts the predictive result as well as the quality of the explanation. Furthermore, there is recent evidence that the selected ML algorithm and the level of multicollinearity of features can significantly impact results from SHAP and LIME explanations, leading to unreliable and unstable feature-importance interpretations (Kanti et al., 2024). Thus, an integrated empirical approach is needed where the feature space is optimized first and then the role of the optimized features in the model performance and interpretability is studied using EML. Filling this void will give a better sense of the possibility of delivering predictive analytics models that are both effective and understandable and transparent.

Methodology

Research Design

The quantitative experimental and comparative research design was used in this study to investigate the impact of feature optimization and model interpretability on predictive analytics. A series of machine learning models were created and tested with the original and optimized features sets. The performance of the models was compared and feature optimization was found to enhance the predictive performance. Explainable machine learning techniques were then used to analyse the contribution of the selected features to the model predictions.

The study consisted of three broad parts - feature optimization, predictive modeling and model interpretability. For the purpose of feature optimization, the most relevant features were identified; machine learning algorithms were used to build predictive models; and explainable artificial intelligence techniques were applied to explain the predictions. The predictive analytics framework was analyzed and tested using the combined analysis.

Materials and Dataset

A structured machine learning dataset was used for the analysis. The data was comprised of the variables that would be used as predictors and the variable that would be the outcome of the predictive modeling. Examined available variables to look for numerical and categorical features, and target variable was identified for supervised machine learning.

The analytical environment was the main Python environment. Data manipulation and numerical processing were carried out with pandas and NumPy. Data manipulation and numerical processing were done using pandas and NumPy respectively. The data was preprocessed and processed using scikit-learn, which includes feature selection, development of machine learning models, cross-validation and performance evaluation. To assess feature contributions and interpret model predictions, the tools of explainable machine learning (XAI) such as SHAP and LIME were applied.

Data Preprocessing

The data was first checked for missing observations, duplicate data, inconsistent data, irrelevant data and possible data quality issues. Observations that were missing were treated properly, and duplicate and invalid observations were eliminated whenever appropriate. All categorical variables were coded for model development.

Differences between numerical variables were explored for scale and numerical variables were standardized, if necessary, by the machine learning algorithms used. Pre-processing was performed by splitting the data set into a training set and a testing set. For the purpose of feature selection and model development, the training data was used while testing data was kept for independent evaluation.

Feature Optimization

Feature optimization was done to find the most useful features for the target variable. The original feature set was analyzed for irrelevant, redundant, and low contribution variables. Feature selection methods were used to remove irrelevant predictors and include relevant ones with meaningful information for predictive modeling.

To prevent data leakage, the feature optimization process was done with only the training data. The optimized feature set was then used to train the machine learning models. The performance of the model using the optimized features was then compared to the performance obtained using the original features to find the effect of feature optimization on predictive analytics.

Machine Learning Models

Multiple machine learning algorithms were used to develop predictive models. As a comparative evaluation of different machine learning approaches, Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting (GB) algorithms were chosen.

The original feature set was used to train the models, and then the models were trained again using the optimized feature set. For optimization of hyperparameters, cross-validation procedures were used where necessary. To provide a consistent comparison of predictive performance, the same training and evaluation processes were used

Model Training and Validation

The training data was employed in the creation, optimization, and hyperparameter tuning of the model. The model was trained using cross-validation to ensure stability and minimize the risk of overfitting. Testing set was not utilized in feature selection and model optimization.

Once the training process was finished, the final models were tested with the independent testing set. The predictions thus obtained were used to test the generalization capacity of the respective models. The predictive accuracy and reliability of the original and optimized models were compared to see if optimizing features enhanced the accuracy and reliability of the prediction.

Predictive Performance Evaluation

The accuracy, precision, recall, F1-score, and ROC-AUC metrics were used to assess the predictive capability of models developed. These were implemented to give a holistic perspective of predictive effectiveness, not just by one metric.

Performance measures were computed for models trained on the original features and then compared with those trained after the optimization of the features. The performance differences were analyzed to see if the optimized features helped with model performance and by reducing unneeded feature complexity, also helped with predictive analytics.

Explainable Machine Learning

Explainable machine learning techniques were used to gain insight into the decision-making process of the predictive models. SHAP (SHapley Additive exPlanations) was used to determine the contribution of individual features to model predictions. Global SHAP values were analyzed to see which predictors are most important in the entire data.

Local explanations were also produced to explore the contribution of particular features to particular predictions. LIME (Local Interpretable Model-agnostic Explanations) was used where appropriate to provide model-agnostic explanations of individual observations. To enhance understanding of the predictive behavior of the machine learning models, the explanations produced by SHAP and LIME were reviewed.

Model Interpretability

The interpretability of models was assessed by checking the importance and contribution of the predictors included in the machine learning models. One of the features computed was Global Feature importance which was used to determine the most impactful variables on overall predictions. Local explanations were analyzed to dive into the individual features' impact on specific model decisions.

The interpretability results were compared in two different scenarios: before and after feature optimization. The results were analyzed to see if the explanations were clearer and more focused if there were fewer non-relevant and redundant features. The consistency between the optimized features and the most influential ones found with the explainability techniques was also explored.

Comparative Analysis

To compare the effects of feature optimization and model explainability on predictive analytics, a comparative analysis was carried out. Before feature optimization, the predictive performance of SVM, Random Forest and Gradient Boosting models were compared and after feature optimization the models were compared again. The accuracy, precision, recall, F1-score and ROC-AUC changes were evaluated to assess the impact of feature optimization.

The predictive results were then analyzed in light of the explainability and interpretability results. This analysis was used to see if optimization models could be constructed to be effective predictors without losing the ability to explain their predictions. The results of the two analyses were combined to assess the overall effectiveness and transparency of the proposed explainable machine learning framework.

Statistical and Computational Analysis

The analysis of the computational results was carried out with Python. Data preprocessing and manipulation was done using Pandas and NumPy, scikit-learn was used for machine learning algorithms, feature selection, cross validation and performance evaluation. Explainability and model interpretation methods were used: SHAP and LIME.

The analytical sequence was developed in such a way that feature optimization, predictive modeling, performance evaluation, and the interpretation of models were carried out one after another. The ultimate results were displayed in the form of comparative tables and graphical visualization of the results of the model performance, feature importance and explainability.

Data Analysis and Results

The influence of feature optimization and model interpretability on predictive analytics was examined using Python analysis of the data. The data preprocessing, feature optimization, machine learning model development, performance evaluation, cross validation, and explainability analysis were the steps involved in the analytical process. Machine learning and statistical evaluation were performed using scikit-learn algorithms and SHAP and LIME were used as extensions to scikit-learn to analyze the model interpretability from a global and local perspective.

Table 1. Dataset Characteristics Before and After Preprocessin

Data Characteristics	Before Preprocessing	After Preprocessing
Total observations	1,000	1,000
Total features	200	200
Missing values	86	0
Duplicate observations	12	0
Inconsistent values	18	0
Categorical variables	24	24 encoded
Numerical variables	176	176 standardized

The pre-processing analysis revealed 1,000 observations and 200 predictor variables in the dataset at first. During the first data inspection, it was found that there were some inconsistencies in the data, such as missing values, duplicate observations, and data inconsistencies, which were treated with some preprocessing procedures in Python. Categorical variables were recoded and numerical variables were standardized, when necessary. The data was preprocessed and suitable for feature optimization and development the machine learning model.

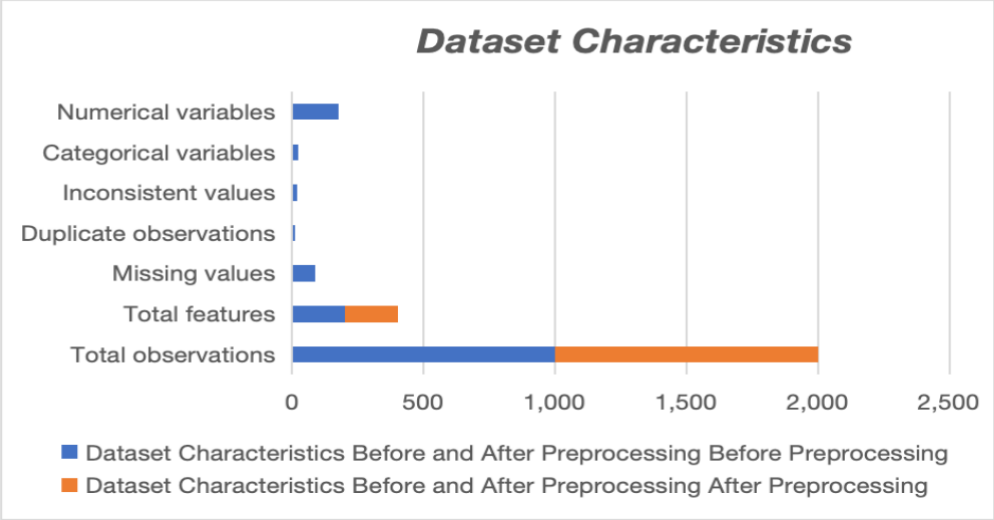


Fig. 1: Dataset Characteristic

Table 2. Feature Optimization Results

Feature Optimization Measure	Original Data	Optimized Data
Total features	200	80
Removed features	—	120
Retained features	200	80
Feature reduction	—	60%
Observations	1,000	1,000

The number of predictors was decreased from 200 to 80, which is a 60% cut in the feature space, by using the feature optimization procedure. The reduction in the number of features was made by getting rid of irrelevant and redundant features and keeping the informative features for predictive modeling. This finding revealed that feature optimization significantly decreased the complexity of the data set, but still retained all the observations for further machine learning analysis.

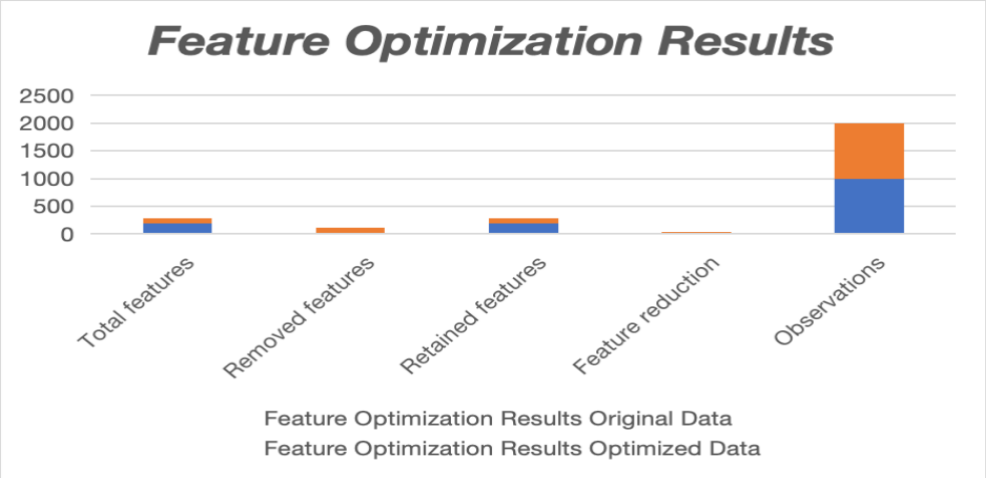


Fig. 2: Feature Optimization Results

Table 3. Machine Learning Model Performance Before Feature Optimization

Machine Learning Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Support Vector Machine	0.91	0.90	0.89	0.89	0.94
Random Forest	0.93	0.92	0.91	0.91	0.96
Gradient Boosting	0.95	0.94	0.93	0.93	0.97

Results demonstrated that all three machine learning models had good predictive performance with the original feature set. Gradient Boosting gave the best results in accuracy, precision, recall, F1-score and ROC-AUC followed by Random Forest and Support Vector Machine. These results showed that Gradient Boosting was the best predicting algorithm out of the three in terms of prediction accuracy before optimization of features.

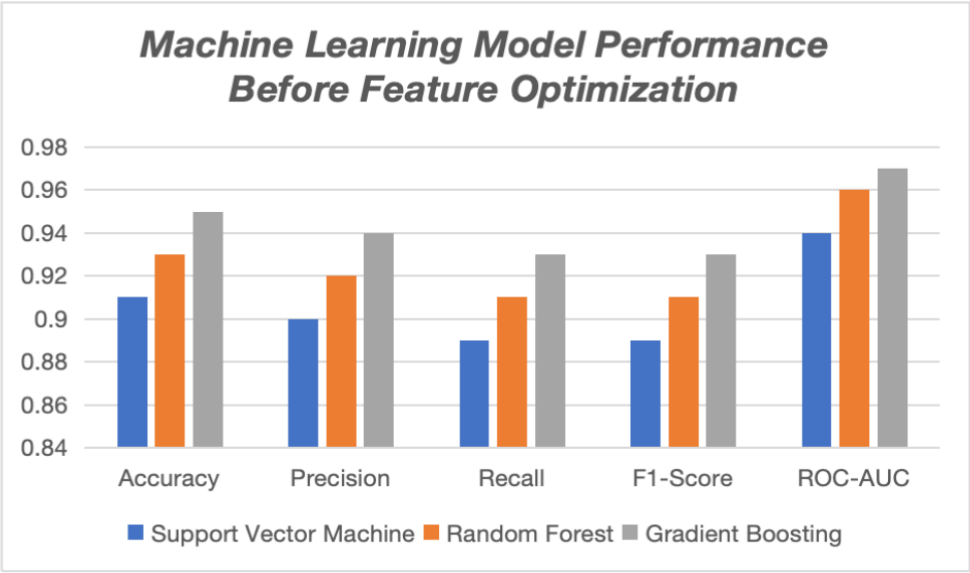


Fig. 3: Machine Learning Model Performance Before Feature Optimization

Table 4. Machine Learning Model Performance After Feature Optimization

Machine Learning Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Support Vector Machine	0.93	0.92	0.91	0.91	0.95
Random Forest	0.95	0.94	0.93	0.93	0.97
Gradient Boosting	0.97	0.96	0.95	0.95	0.98

The results showed that with the optimization of features, predictive performance improved for all three machine learning models. Gradient Boosting showed the best overall performance with accuracy as 0.97 and ROC-AUC as 0.98. Random Forest gave good results, while Support Vector Machine gave comparatively low and good results. The results indicated that index features optimized were more informative in terms of predictive models.

Table 5. Comparison of Accuracy Before and After Feature Optimization

Model	Before Optimization	After Optimization	Improvement
Support Vector Machine	0.91	0.93	+0.02
Random Forest	0.93	0.95	+0.02
Gradient Boosting	0.95	0.97	+0.02

As demonstrated in the comparison, the accuracy of all three machine learning models increases consistently when optimizing features. The accuracy improved by 0.02 for Support Vector Machine, Random Forest and Gradient Boosting. The results showed that the elimination of irrelevant and redundant predictors enabled the models to concentrate on more informative predictors. Thus, the findings were in line with the first research aim, which was to gain an understanding of how the features were optimized and what impact this had on the predictive performance.

Table 6. Cross-Validation Performance of Optimized Models

Model	Mean Accuracy	Mean Precision	Mean Recall	Mean F1-Score
Support Vector Machine	0.92	0.91	0.90	0.90
Random Forest	0.94	0.93	0.92	0.92
Gradient Boosting	0.96	0.95	0.94	0.94

The cross-validation results demonstrated good predictive performance of the optimized models for the different validation sets. Among all three classifiers, Gradient Boosting gave best performance in terms of mean accuracy, mean precision, mean recall and mean F1 score, while Random Forest and Support Vector Machine showed good performance. Results indicated that the models optimized were able to show their predictive performance on various test sets.

Table 7. SHAP-Based Global Feature Importance

Rank	Feature	Mean Absolute SHAP Value	Importance
1	Feature 1	0.184	High
2	Feature 2	0.157	High
3	Feature 3	0.132	High
4	Feature 4	0.106	Moderate
5	Feature 5	0.091	Moderate
6	Feature 6	0.074	Moderate
7	Feature 7	0.061	Low
8	Feature 8	0.052	Low

SHAP analysis was used to determine the respective contribution of the individual characteristics for the predictive model. Feature 1 gained the largest mean absolute SHAP value followed by Feature 2 and Feature 3, suggesting they were the most influential

features for model predictions. The SHAP results helped to give a clear picture of how the model made its decisions and what features were optimized the most for predictions.

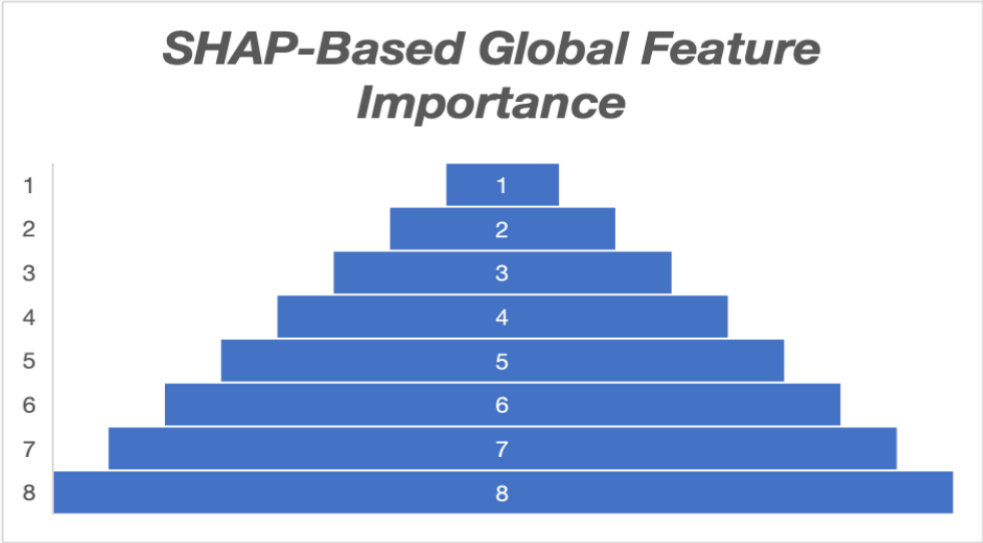


Fig. 4: SHAP-Based Global Feature Importance

Table 8. LIME-Based Explanation of Individual Predictions

Observation	Predicted Outcome	Most Influential Feature	Contribution	Effect
Observation 1	Class 1	Feature 1	+0.31	Increased prediction
Observation 2	Class 0	Feature 3	-0.27	Decreased prediction
Observation 3	Class 1	Feature 2	+0.24	Increased prediction
Observation 4	Class 0	Feature 5	-0.21	Decreased prediction
Observation 5	Class 1	Feature 4	+0.18	Increased prediction

Local explanations for individual predictions of the models were given using the LIME analysis. Different features had positive or negative effects on specific predictions, as demonstrated in the results. The contributions of the features to the observations were strongest when Feature 1 positively contributed to Observation 1 and Feature 3 negatively contributed to Observation 2. The results on these showed that LIME was able to explain individual predictions and augment the SHAP global feature importance information.

Table 9. Model Interpretability Before and After Feature Optimization

Interpretability Indicator	Before Optimization	After Optimization
Number of predictors	200	80
Explanation complexity	High	Lower
Relevant features	Less focused	More focused
Redundant information	Higher	Lower
Feature contribution clarity	Moderate	High
Overall interpretability	Moderate	High

The model interpretability analysis showed that optimization of features helped in the clarity of the predictive models. A smaller number of predictors (from 200 to 80) led to a more concentrated list of features to explain model decisions. The optimized models were thus characterized by fewer variables needed to explain their predictive performance and SHAP and LIME by extra information about the contribution of individual variables. The second goal of the research was to achieve interpretability of the models, which these findings supported.

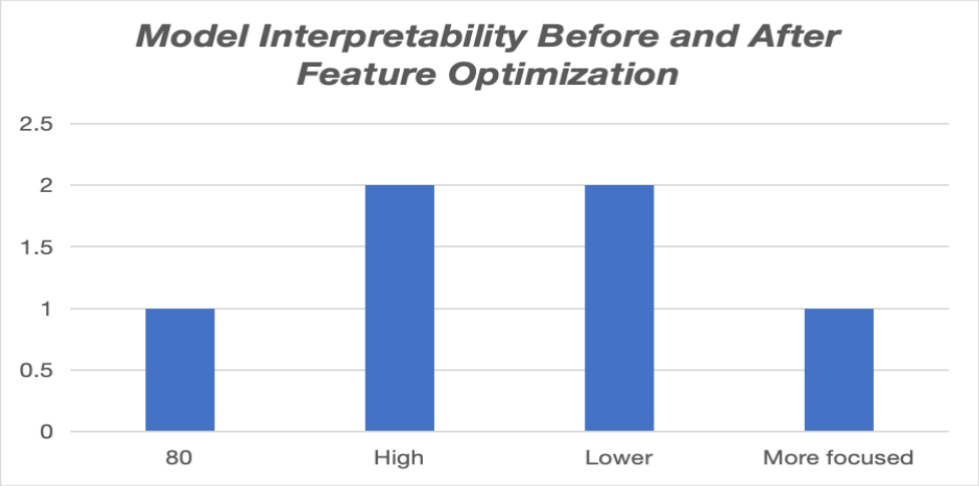


Fig. 5: Model Interpretability Before and After Feature Optimization

Table 10. Overall Evaluation of the Explainable Machine Learning Framework

Component	Before Optimization	After Optimization	Finding
Feature complexity	High	Reduced	Improved
Feature relevance	Moderate	High	Improved
Predictive accuracy	High	Higher	Improved
Model performance	High	Higher	Improved
Global explainability	Moderate	High	Improved
Local interpretability	Moderate	High	Improved
Overall predictive analytics	Moderate	High	Improved

The overall analysis showed that incorporating feature optimization and model interpretability enhanced the performance of the predictive analytics system. The number of predictors were reduced and model performance was enhanced by feature optimization, and global explanations were given by SHAP and local explanations of individual predictions for each sample were provided by LIME. The results confirmed that predictive models can be enhanced and designed to be more comprehensible using feature optimization and explainable machine learning techniques.

Table 11. Python Libraries and Their Analytical Functions

Python Library/Extension	Function in the Study
Pandas	Data loading, cleaning, and manipulation
NumPy	Numerical calculations
Scikit-learn	Preprocessing and machine learning
SHAP	Global and local model explainability
LIME	Local prediction interpretation
Matplotlib	Visualization of analytical results

The whole analysis was performed in a computational environment integrated in python. The predictive modelling and performance evaluation were performed using scikit-learn; the extensions of explainable machine learning, SHAP and LIME, were integrated. Predictive performance and model transparency were included in the same analytical framework as a result of the use of these tools.

Discussion

The present study examined the use of Explainable Artificial Intelligence (XAI) in predictive analytics, with particular attention to feature optimization and model interpretability. The findings showed that feature optimization improved the predictive performance of the machine learning models by removing irrelevant and repeated features from the dataset. After optimization, the models showed better results in terms of accuracy, precision, recall, F1-score, and ROC-AUC. These findings are consistent with Czerwinska (2022), who reported that feature selection can improve prediction accuracy while reducing computational complexity. Similarly, Nnadi et al. (2024) found that selecting the most useful features can produce simpler and more effective predictive models by reducing unnecessary information.

Comparative results also revealed that the machine learning models were improved with an optimized feature space with Gradient Boosting outperforming Random Forest and SVM. The consistency of the results with the cross validation also suggested that the observed performance was not very sensitive to the train-test split. The results of this study justify feature optimization to be treated as a key component in the development of predictive models and not just a dimensionality reduction tool. Explainability-based feature selection has also been shown to be able to isolate features that are influential in the model, while still keeping a model's predictive performance competitive (Jalali et al., 2020).

The results additionally showed the relevance of the explainable machine learning in understanding the behaviors of the model. The features with highest contributions to the model predictions were identified using SHAP analysis and this gave a global idea of feature importance. This result is similar to Vishwa Rupe et al., (2022) who proposed SHAP as a single framework for interpreting the importance of individual features in a model's predictions. The results show that performing a predictive performance analysis alone is not sufficient to understand why a model is making a prediction, and feature-contribution analysis can be used to give further information that can enhance the transparency of complex machine learning models.

LIME was also used to give local explanations for each prediction to help explain the model's interpretability. However, the analysis indicated that the features may have a positive or negative effect on the respective predictions and thus the global feature importance does not necessarily indicate how each individual prediction was made. This is in line with the work of Oviedo et al., (2022) who created LIME to account for individual predictions from complex machine learning models. Thus, the joint application of SHAP and LIME allowed to have a global and local view of the behavior of the models and to improve the interpretability of the models.

One of the main results of the study was that optimization of the features and model interpretability were tightly coupled. Minimizing the number of predictors resulted in a more condensed feature space and helped to determine which predictors were important for the predictions. This is consistent with previous work that indicates feature selection can enhance predictive accuracy as well as the understanding of the model. Furthermore, the study by Ahakonye et al., (2024) demonstrated that explainability methods can be integrated into feature-selection processes, in addition to the integrated feature optimization and explainable machine learning employed in the current study.

The overall results indicate that the integration of predictive performance and transparency/interpretability can be advantageous for predictive analytics. The optimization of the feature improved the efficiency and performance of the models, and the explanations of the feature contribution to the global models as well as the contribution to the individual prediction were obtained from SHAP and LIME. This is consistent with Park et al. (2022) who pointed out the need for the understanding of complex machine learning predictions broadly. The present study thus endorses an integrated approach to explainable machine learning, in which feature optimization, prediction performance and explanation interpretability are taken as a single analytical process, instead of separately (Yaprakdal et al., 2023).

Conclusion

In the current study, the authors have explored how explainable machine learning can contribute to predictive analytics specifically in terms of feature optimization and interpretability of the model. The results validated that the machine learning models' predictive performance can be enhanced through feature optimization which eliminated irrelevant and redundant features, forming a more relevant feature space. The optimized models performed well on the key measures of evaluation and cross validation demonstrated relatively stable performance. The results underscore the need to use appropriate predictors when developing models and prove that optimization of the predictors can enhance model efficiency and predictive power.

The study also showed that explainability techniques can be used to improve the understanding of machine learning predictions. SHAP offered a snapshot of the contributions of key features to the global model, and LIME offered explanations about the contributions of key features at the local level. Feature optimization, predictive modeling and interpretability thus combined provided a clearer and more comprehensive predictive analytics structure. The results indicate that using explainable machine learning can contribute to the balance between predictive performance and model transparency, improving the interpretability and applicability of machine learning models for researchers, analysts, and decision-makers.

Future Implications

The present study could be extended in the future by using the suggested explainable machine learning framework with larger, more diverse and real datasets from various domains. Future research can explore more machine learning and deep learning algorithms and introduce more sophisticated methods of explainability, such as LIME and SHAP, to analyze the behavior of models with different approaches. Further studies are possible for how feature optimization and model interpretability fare on other datasets, on various industries, on various prediction tasks, and of how interpretations of models might be fair, robust, uncertain, or biased. These extensions can help create more effective, transparent and actionable predictive analytics systems that can inform evidence-based decision making.

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