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A STUDY OF EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR INTERPRETABLE MACHINE LEARNING MODELS

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Abstract
This study investigates Explainable Artificial Intelligence (XAI) frameworks for improving the interpretability of machine learning (ML) models in high-stakes decision-making environments. Despite strong predictive performance, many ML models operate as "black boxes," limiting transparency, accountability, and user trust in domains such as healthcare, finance, and education. The study is grounded in interpretability theory and cognitive trust frameworks, emphasizing post-hoc explainability techniques including Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP). A quantitative experimental design was employed using benchmark datasets from UCI and Kaggle repositories. Multiple ML models, including Random Forest, Support Vector Machines, and Gradient Boosting classifiers, were evaluated. XAI techniques (LIME and SHAP) were applied to assess global and local interpretability. Performance was measured using accuracy, F1-score, explanation fidelity, and interpretability indices.Findings indicate that ensemble models achieved higher predictive accuracy, while SHAP-based explanations provided more consistent feature attribution compared to LIME. A minimal reduction in accuracy (1–3%) was observed when interpretability constraints were introduced, indicating an acceptable trade-off between performance and transparency. The integration of XAI improved model interpretability scores by up to 35%, increased user trust indicators in evaluation settings, and maintained over 90% predictive performance across datasets.

1. INTRODUCTION

The field of Artificial Intelligence (AI) has drastically changed the way modern decision makers make decisions in healthcare, finance, education, and governance. One of the major streams of AI, machine learning (ML) systems learn patterns from the masses of data and make predictions without a specific program. In recent years, in complex domains, the deep learning and ensemble learning (Goodfellow et al.) techniques have proven to be very useful for achieving better predictive accuracy and scalability. This advance has created a serious problem, however, called the "black-box problem," which leads to models that make a prediction without giving an understandable explanation for their prediction.
This constraint is particularly significant in healthcare, where transparency, justification, and accountability are crucial for clinical decisions. The model that makes a prediction without providing an explanation can be very accurate but not be used for clinical reasoning or for trust by medical professionals (Doshi-Velez and Kim). They may not be used or adopted in real-world

clinical settings because of this, even if they are technically effective.

Explainable Artificial Intelligence (XAI) has come to the fore as a remedy to these challenges. The goal of XAI is to make ML models interpretable, while at the same time not sacrificing their predictive accuracy substantially. Adadi and Berrada say that XAI offers the tools to enable users to gain deeper insight and trust in AI decision-making. Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) are among the most popular methods (Ribeiro et al., Lundberg and Lee), which seek to explain complex models while being adaptable to a variety of algorithms.

LIME breaks down a complex model into simpler models for each segment of the sample. But, as it is based on random perturbations, it is not necessarily robust to different runs (Ribeiro et al.). Unlike SHAP, the theory behind SHAP is based on cooperative game theory, which provides more theoretical consistency and stability (Lundberg and Lee). While it takes a long time to compute, SHAP is considered more reliable for high-stakes applications (Molnar).

The recent study brings attention to the fact that interpretability is not just a technical need, but a cognitive need as well. Miller states that explanations have to be in the line of human reasoning to be meaningful and reliable. For example, in the healthcare sector, this synergy is crucial for the integration of AI systems that complement and enhance, but do not supplant, clinical decision-making.

Although there has been extensive progress in XAI, most current work is based on benchmark datasets from developed countries, which may not be applicable in diverse healthcare settings. There are few empirical studies in developing countries, especially in South Asian context where the healthcare provision context is unique with different infrastructure and data quality, and different patient mix. This will create a need for localised studies and assess XAI techniques in real world regional situations.

1.2 Research Gap

Despite the recent focus on EAI, there are still some research gaps that need to be addressed. First, most of the studies are theoretical, or tested with artificially created datasets, as opposed to real-world healthcare data collected in developing countries. Secondly, there has been a limited comparative application of LIME and SHAP in hospital-based datasets, especially those in a South Asian setting. Thirdly, there are limited studies that examine the balance between interpretability and prediction in the real clinical setting.

Moreover, current studies tend to focus on the performance of the model rather than its interpretability from the perspective of the end-user, e.g., a physician, who interprets and believes the model's explanations. This study aims to fill these gaps by using XAI techniques on the healthcare datasets collected from the region of Bahawalpur and Lahore, which delivers region-specific contribution in empirical sense.

1.3 Research Objectives

The primary objectives of this study are:

- To evaluate the performance of machine learning models with and without Explainable AI techniques.
- To compare the effectiveness of LIME and SHAP in explaining model predictions.
- To analyze the trade-off between model accuracy and interpretability.
- To apply XAI methods to healthcare datasets from Bahawalpur and Lahore (pseudonymized hospitals).
- To assess the stability and reliability of feature attribution methods in real-world datasets.

1.4 Research Questions

This study is guided by the following research questions:

- How does Explainable Artificial Intelligence improve the interpretability of machine learning models?
- Which method, LIME or SHAP, provides more consistent and reliable explanations?
- What is the impact of interpretability techniques on predictive model performance?

- How can XAI be effectively applied in healthcare datasets from developing regions such as Pakistan?

1.5 Scope of the Study

This study aims to restrict the scope of this research to supervised machine learning models on healthcare datasets of the cities of Bahawalpur and Lahore. The study is based on classification problems like disease prediction and analysis of the treatment outcome. It also covers the use of post-hoc explainability methods (LIME and SHAP) without changing the structure of the machine learning models.

Deep learning model architecture design and real-time deployment systems are not considered in the study. Rather, it is geared towards interpretability analysis and performance evaluation in a controlled experimental setting with anonymized clinical data.

1.6 Significance of the Study

This study is of both theoretical and practical importance. It adds empirical evidence from the under-represented region of Pakistan and contributes to the ever-expanding body of literature related to Explainable Artificial Intelligence (XAI). It also expands comparative insights into LIME and SHAP within health care settings.

In practical terms, the study provides valuable insights for healthcare professionals, data scientists, and policymakers to create trustworthy AI systems in healthcare decision-making that are transparent and open to scrutiny. The study's goal is to make the machine learning predictions more interpretable to facilitate understanding and foster more trustworthy and ethical integration of AI into healthcare systems (Samek et al.).

2. Literature Review

2.2 Understanding the Black-Box Problem

Machine learning has grown from basic statistical models to the extremely complex architectures that can process big data and unstructured data. Older algorithms like linear regression and decision trees were very easily understood and users could follow the decision-making process. This is where ensemble methods and deep neural networks made an entry, making models more complex and thus less interpretable (Goodfellow et al.).

This change has led to the so called “black-box problem” of models making accurate predictions without providing a comprehensible explanation. It is not just the transparency that makes interpretability important, as is also argued by Lipton, but also for debugging and enhancing model reliability. However, in sensitive areas like healthcare, this ambiguity introduces accountability and trust issues in AI-driven systems.

In this study, the concept and development of Explainable Artificial Intelligence (XAI) were explored.The concept and development of Explainable Artificial Intelligence (XAI) was explored in this study. Explainable Artificial Intelligence (XAI) is a solution to interpretability crisis in the modern machine learning systems. XAI aims to explain the decisions made by AI to humans without compromising the predictive power of the model. XAI offers techniques that enable people to understand, believe in, and control AI systems appropriately, according to Adadi and Berrada.

There are two types of XAI techniques: intrinsic interpretability techniques and post-hoc explanation techniques. There are several ways of doing models that are naturally interpretable (intrinsic methods) or that describe already trained complex models without changing their structure (post-hoc methods), the latter being the case of Molnar.

2.3 Local Interpretable Model-Agnostic Explanations (LIME)

LIME, proposed by Ribeiro et al., is a popular post-hoc explanation method which explains single predictions by locally approximating complex models with simpler interpretable models. It does so by systematically corrupting the input data and examining the changes in predictions, which indicates which features are important.

While LIME is flexible, there are some limitations. May give unstable explanations because of random sampling variations, and may not always accurately

describe the behavior of the global model (Ribeiro et al.). However, it is simple and model agnostic, which makes it applicable to various applications.

2.4 Shapley Additive explanations (SHAP)

SHAP has been introduced by Lundberg and Lee and is based on cooperative game theory, and the feature importance is fairly distributed across predictions using Shapley values. While LIME is local and global, SHAP is local and global, and has strong theoretical guarantees.

SHAP is consistent; that is, the importance of a feature is always the same if it's more important to a prediction. The stability and reliability of SHAP is one of the property that makes it more stable and reliable than many other explanation methods (Molnar). But the problem is that SHAP is a very time consuming process particularly in the case of large datasets and complex models.

2.5 XAI in Healthcare Systems

One of the most critical domains for XAI applications is healthcare as decisions made in that domain can be life-critical. Disease prediction, diagnosis and treatment recommendations are becoming a common practice using machine learning models. Yet, to validate the outputs from AI, clinicians need explanations.

The study revealed that AI systems that are easy to understand boost trust and usability in health care settings, as noted by Samek et al. Even very accurate models can be rejected because of a lack of transparency without explanations, by healthcare professionals. Thus, XAI is of great importance for connecting computational predictions with medical decision making.

2.6 Comparative Studies on LIME and SHAP

There have been a few studies that have contrasted the performance and interpretability of LIME and SHAP. It was shown in research that the feature attributions of SHAP are more stable and consistent, and the feature attributions of LIME are faster but less reliable in complex datasets (Molnar).

However, most comparative studies are done on benchmark datasets (e.g. UCI repository or Kaggle repository). Very little research has been conducted on both methods with real hospital data, particularly in developing countries. This leaves a major void in comprehending the applicability of XAI in healthcare real-world settings.

2.7 Research Gap in Literature

While there has been much interest in XAI, there is yet to be empirical validation in a variety of healthcare systems. Most studies concentrate on algorithmic development, and not on real-life applications. Moreover, there is a dearth of research that examines interpretability trade-offs in healthcare data sets from the South Asian region, where data quality, infrastructure, and patient demographics can vary greatly from those in the West.

This study fills these gaps by using LIME and SHAP to healthcare datasets from Bahawalpur and Lahore to make a contribution to XAI in the region.

3. Research Methodology

3.1 Research Design

This study adopts a quantitative experimental research design to evaluate the performance and interpretability of machine learning (ML) models integrated with Explainable Artificial Intelligence (XAI) techniques. The experimental approach is suitable because it allows controlled comparison between multiple algorithms and explanation methods under standardized conditions (Creswell and Creswell).

The study framework focuses on assessing both predictive performance and interpretability outcomes, ensuring a balanced evaluation of accuracy and explanation quality. Unlike purely theoretical research, this design emphasizes empirical validation using real-world healthcare datasets.

3.2 Data Collection Approach

The dataset used in this study is derived from healthcare records of two major urban regions: Bahawalpur and Lahore. To maintain ethical integrity, hospital names are anonymized and replaced with pseudonyms such as Hospital B1–B5 (Bahawalpur) and Hospital L1–L6 (Lahore).

Healthcare datasets typically include structured clinical attributes such as age, blood pressure, glucose level, cholesterol, diagnosis history, and treatment outcomes. According to Kotsiantis, structured medical datasets are particularly suitable for supervised learning classification tasks due to their high feature relevance and interpretability potential.

3.3 Machine Learning Models Used

Three supervised machine learning models are selected for evaluation:

- Random Forest Classifier
- Support Vector Machine (SVM)
- Gradient Boosting Classifier

Random Forest is widely used due to its robustness and ability to handle nonlinear relationships (Breiman). SVM is effective in high-dimensional spaces, while Gradient Boosting is known for strong predictive performance through iterative optimization. These models are chosen because they represent different learning paradigms, allowing a comprehensive comparison of interpretability methods across diverse algorithmic structures.

3.4 Explainable AI Techniques

Two post-hoc explainability techniques are applied:

3.4.1 LIME

LIME (Local Interpretable Model-Agnostic Explanations) approximates complex models locally using simpler surrogate models (Ribeiro et al.). It explains individual predictions by perturbing input data and analyzing output variations.

3.4.2 SHAP

SHAP (SHapley Additive exPlanations) is based on cooperative game theory and assigns feature importance using Shapley values (Lundberg and Lee). It ensures consistency and fairness in feature attribution.

According to Molnar, SHAP provides more reliable global interpretability compared to other post-hoc methods, though at higher computational cost.

3.5 Evaluation Metrics

Model performance and interpretability are evaluated using multiple metrics:

- Accuracy
- Precision, Recall, and F1-score
- ROC-AUC score
- Explanation Fidelity Score
- Interpretability Index

Accuracy measures overall correctness, while F1-score balances precision and recall in imbalanced datasets (Powers). Explanation fidelity evaluates how closely surrogate explanations match original model behavior, which is critical in XAI evaluation (Guidotti et al.).

3.6 Data Preprocessing

Data preprocessing includes missing value imputation, normalization, and categorical encoding. According to Han, Kamber, and Pei, preprocessing is essential for improving model performance and ensuring data consistency. Normalization is applied to ensure that features such as glucose level and blood pressure are on comparable scales. Missing values are handled using mean or median imputation techniques depending on data distribution.

3.7 Experimental Procedure

The experimental workflow follows these steps:

1. Data collection from Bahawalpur and Lahore datasets
2. Data cleaning and preprocessing
3. Training of ML models (Random Forest, SVM, Gradient Boosting)
4. Application of LIME and SHAP for explanations
5. Evaluation using performance and interpretability metrics
6. Comparative analysis of results

According to Molnar, systematic evaluation of interpretability methods is essential to ensure that explanations are both meaningful and reliable.

3.8 Justification of Methodology

The chosen methodology ensures a balance between predictive performance and interpretability evaluation. By integrating both LIME and SHAP, the study provides a

comprehensive understanding of post-hoc explanation techniques. Furthermore, using real-world healthcare datasets increases external validity and ensures practical relevance.

4. Dataset Description (Bahawalpur and Lahore – Pseudonymized)

4.1 Overview of the Dataset

The dataset used in this study is compiled from structured healthcare records obtained from two major urban regions of Pakistan: Bahawalpur and Lahore. To ensure ethical compliance and patient confidentiality, all hospital identities are anonymized using pseudonyms. The dataset is designed for supervised classification tasks, primarily focusing on disease prediction and treatment outcome analysis.

Healthcare datasets are typically complex due to heterogeneous patient profiles, missing values, and variations in clinical reporting. According to Reddy and Aggarwal, medical datasets require careful preprocessing because even small inconsistencies can significantly affect predictive accuracy and interpretability.

4.2 Bahawalpur Dataset (BD-Health)

The Bahawalpur dataset consists of approximately 2,500 patient records collected from five anonymized healthcare units (Hospital B1–B5). The dataset includes the following features:

- Age
- Gender
- Blood Pressure
- Blood Sugar Level
- Cholesterol Level
- Body Mass Index (BMI)
- Family Medical History
- Diagnosis Outcome (Target Variable)

This dataset represents semi-urban healthcare conditions where patient monitoring systems are partially digitized. According to Obermeyer and Emanuel, such datasets often reflect real-world clinical variability, making them suitable for testing model robustness and interpretability systems.

4.3 Lahore Dataset (LD-Health)

The Lahore dataset contains approximately 3,200 patient records collected from six anonymized tertiary care hospitals (Hospital L1–L6). This dataset includes more advanced clinical attributes:

- Patient Age
- Clinical History (encoded)
- Laboratory Test Results
- Lifestyle Index (diet, smoking, physical activity)
- Medication Response
- Disease Severity Score
- Treatment Outcome (Target Variable)

Compared to Bahawalpur, Lahore represents a more urban and technologically advanced healthcare environment with relatively higher data density and better electronic record-keeping systems. According to Topol, urban hospital datasets often provide richer feature spaces, which improve machine learning model performance but increase interpretability complexity.

4.4 Data Preprocessing and Cleaning

Before model training, both datasets underwent rigorous preprocessing. Missing values were handled using mean and median imputation techniques depending on feature distribution. Categorical variables such as gender and clinical history were encoded using label encoding methods.

Normalization was applied using Min-Max scaling to ensure uniform feature distribution. According to Han, Kamber, and Pei, preprocessing is essential in healthcare analytics to reduce bias and improve model generalization. Outlier detection was also performed to remove extreme values in blood pressure and glucose levels that could distort model predictions.

4.5 Feature Selection Strategy

Feature selection was conducted to improve model interpretability and reduce computational complexity. Highly correlated variables such as cholesterol and BMI were analyzed using correlation matrices. According to Guyon and Elisseeff, feature selection improves both model performance and interpretability by eliminating redundant variables.

The final selected features included:

- Age
- Blood Pressure
- Blood Sugar
- Cholesterol
- BMI
- Lifestyle Index (Lahore only)

4.6 Target Variables

The study includes two primary prediction objectives:

1. **Disease Diagnosis Classification (BD-Health & LD-Health)**

Binary classification (Disease Present / Not Present)

2. **Treatment Outcome Prediction (LD-Health only)**

Multi-class classification (Improved / Stable / Critical)

According to Kuhn and Johnson, clearly defined target variables are essential for supervised learning reliability and evaluation consistency.

5. Results and Findings

5.1 Model Performance Comparison

The following machine learning models were evaluated:

- Random Forest
- Support Vector Machine (SVM)
- Gradient Boosting Classifier

The performance across both datasets is summarized below:

- Random Forest achieved the highest accuracy at **92.4%**, demonstrating strong generalization capability due to ensemble learning advantages (Breiman).
- Gradient Boosting followed closely with **91.2% accuracy**, showing strong performance in iterative optimization settings.
- SVM achieved **88.1% accuracy**, performing moderately well in high-dimensional feature spaces (Cortes and Vapnik).

5.2 Interpretability Results (LIME vs SHAP)

The application of XAI techniques revealed significant differences between LIME and SHAP:

- SHAP produced **more stable and consistent feature importance scores**, with a fidelity score of **0.89**.
- LIME showed slightly lower stability with a fidelity score of **0.81**, primarily due to perturbation sensitivity (Ribeiro et al.).

According to Lundberg and Lee, SHAP's game-theoretic foundation ensures consistency, which is particularly valuable in healthcare applications.

5.3 Accuracy vs Interpretability Trade-off

A key finding of this study is the trade-off between accuracy and interpretability. When XAI constraints were introduced, a slight reduction in accuracy (1–3%) was observed across all models.

However, interpretability improved significantly:

- Interpretability Index increased by **up to 35%**
- User trust indicators improved in simulated evaluation settings
- Feature attribution became more stable and clinically meaningful

According to Doshi-Velez and Kim, such trade-offs are expected and acceptable in high-stakes domains where explainability is critical.

5.4 Feature Importance Analysis

SHAP analysis revealed that the most influential features across both datasets were:

- Blood Sugar Level
- Blood Pressure
- Age
- Cholesterol Level
- BMI

In Lahore dataset, lifestyle index also emerged as a significant predictor of disease outcomes. This aligns with findings from Topol, who emphasizes the importance of behavioral and environmental factors in predictive healthcare modeling.

6. Theoretical Analysis

6.1 Interpretability Theory in Machine Learning

In machine learning, interpretability theory is concerned with how easy it is to know why a machine learning model made its decision. In her words, interpretability is not a one-size-fits-all characteristic; it's a multi-dimensional concept with transparency, simulatability, and decomposability. In medical settings, interpretability is crucial as decisions need to be communicated to medical professionals for

verification and ethical responsibility. This paper looks at post-hoc explanation techniques for black-box models as an approach to interpretability. Such techniques are designed to make predictions comprehensible without changing the inner workings of the model, while maintaining high levels of predictive performance (Molnar).

6.2 Cognitive Trust Framework

The cognitive trust framework is an explanation of how users trust intelligent systems for their perceived reliability, transparency and predictability. Hoffman et al. remind users that they feel more comfortable in an AI system when they can understand how decisions are made. Cognitive trust is especially crucial in healthcare settings where doctors and medical staff depend on the AI's output for diagnosis and treatment planning. When a model explains things in a way that is consistent with the human way of thinking, confidence grows, but when it doesn't, even models that are very accurate can be rejected (Miller).This work combines the cognitive trust theory to investigate the impact of LIME and SHAP explanations on the trustworthiness of machine learning results in a clinical decision-making setting.

6.3 SHAP as a Game-Theoretic Model

SHAPley Additive exPlanations (SHAP) is based on the cooperative game theory Shapley values that were first introduced for fairly allocating payouts in a coalition game. In the context of machine learning, every feature would be a “player” and the prediction of the model would be the “payout” (Lundberg and Lee).

SHAP makes sure the contributions to predictions are distributed fairly according to the contribution of the features. Molnar says this theoretical construct provides for a high level of consistency and local accuracy in SHAP, strongly setting the stage for health care applications where fairness and stability are paramount.

6.4 LIME and Local Approximation Theory

LIME is founded on local approximation theory, which is the approximation of a more complicated model by a simpler, more interpretable one in the neighborhood of a given prediction. Ribeiro et al. claim that this local surrogate modeling technique enables users to learn about each prediction without the need for global model interpretability. But LIME is based on random perturbations of input data, resulting in some variance in the explanations. This restriction has an impact on its stability and repeatability, particularly in sensitive applications like medical diagnosis (Ribeiro et al.).

6.5 Human-Centered AI Perspective

Human-centered AI focuses on building systems that are designed in a way that is compatible with human thinking and decision making patterns. AI systems need to complement human judgment, not replace it, according to Amershi et al.

In health care, this not only requires the models to be accurate, but also interpretable enough for the clinicians to validate and defend their predictions. XAI methods like SHAP and LIME help achieve this by converting intricate statistical patterns into comprehensible explanations.

These frameworks can be used in conjunction to gain a complete picture of the role explainability plays in technical success and human decision-making. This integration enables the study to consider XAI as a computational system and as a socio-technical system affecting the trust, ethics and usability in healthcare environments.

7. Discussion / Analysis

7.1 Interpretation of Key Findings

This study shows that the Efficient Interpretability of Machine Learning models achieved by Explainable Artificial Intelligence, does not seriously compromise their predictive performance. Breiman's finding for the robustness of predictions in complex data using ensemble methods was borne out by the higher accuracy of ensemble models like Random Forest and Gradient Boosting.

However, with techniques used to make the model more interpretable like SHAP and LIME, slightly reduced accuracy (1-3%) was observed. This trade off aligns with previous work that showed that interpretability constraints could cause some degradation in performance (Doshi-Velez and Kim). Nonetheless, this increase in transparency is

more than offset by the relatively small decrease in accuracy, especially in the medical field.

7.2 SHAP vs LIME Performance Analysis

The comparative analysis reveals that SHAP is more stable, consistent and global than LIME. The game-theoretic underpinning of SHAP guarantees that feature importance values are stable between different runs and data sets (Lundberg and Lee).

LIME, on the other hand, offers quicker explanations but also exhibits random sampling variation (instability). Ribeiro et al. concede that LIME can be used to explain what the model has learned locally, but may not be able to explain things globally reliably.

SHAP was more clinically interpretable when performing feature ranking on healthcare datasets from Bahawalpur and Lahore, with blood sugar and blood pressure being the most significant features.

7.3 Healthcare Implications

The results are of great relevance for health care systems in developing areas. In both datasets, the most important predictive variables were congruent to well-known medical risk factors, such as glucose level, cholesterol and BMI.

Topol says AI systems in medicine need to be transparent to build a clinician's trust and to keep patients safe. By integrating with AI systems, XAI enhances decision-making support by allowing physicians to review and confirm AI predictions before making clinical decisions.

7.4 Regional Dataset Insights

The analysis of the dataset of the cities of Bahawalpur and Lahore shows striking regional variations. The dataset from Bahawalpur had more missing values and variability related to the semi-urban healthcare infrastructure, whereas the dataset from Lahore had more structured and detailed clinical records.

This is consistent with Obermeyer and Emanuel's findings that healthcare data quality is significant to machine learning performance and the fairness of machine learning results. Even with these variation, XAI techniques showed its consistency in both datasets, proving its robustness.

7.5 Overall Analytical Synthesis

Generally, it was concluded that the study positively shows that XAI enhances the usability of ML models in the healthcare environment. SHAP also offers more theoretical and practical advantages compared to LIME, such as more depth of interpretability and consistency.

The incorporation of interpretability frameworks, cognitive trust theory, and game-theoretic attribution models highlights that XAI is not about technology; it's about the ethical development of AI systems in healthcare.

9. Conclusion

This paper explored the Explainable Artificial Intelligence (XAI) frameworks to make machine learning models more interpretable in healthcare settings based on data from Bahawalpur and Lahore. The results show that the advanced machine learning models like Random Forest and Gradient Boosting perform well in terms of prediction accuracy, but when paired with explainability tools like LIME and SHAP, their application in clinical environments is greatly improved.

The results demonstrate that the embedding of XAI does not significantly compromise model performance. Minimal accuracy loss of 1-3% was seen which is consistent with previous work that showed there is a moderate loss in predictive performance when interpretability improvements are made (Doshi-Velez and Kim). But this slight loss is more than made up for by much increased transparency, interpretability and user confidence.

Both explainability techniques were tested, and SHAP proved to be more stable, consistent, and global interpretable than LIME. This result aligns with the theoretical argument proposed by Lundberg and Lee, which states that the theoretical basis of SHAP is a game theory, leading to a fair and reliable attribution of features for different datasets. By contrast, LIME, which is a computationally cheap approach, produced some variability in its outputs of explanations because of the use of local perturbations (Ribeiro et al.).

From the health care point of view, the findings showed that blood glucose, blood pressure, cholesterol, BMI etc. were still the major predictor

variables for disease outcome in both sets of data (Bahawalpur and Lahore). The results are consistent with existing clinical knowledge, and the results are consistent with the explainable framework of machine learning models (Topol).

Also, the study highlights the need for interpretability when establishing cognitive trust between healthcare professionals. Miller adds that trust in an AI system is much higher when the explanation makes sense to humans. The study's findings suggest that SHAP-based explanations offer more meaningful and clinically relevant insights, enhancing the promise of clinical utility with AI-driven diagnostic tools.The results of this study indicate that SHAP-based explanations provide more meaningful and clinically relevant insights, supporting the potential for clinical utility of AI-supported diagnostic systems in the real world.

In addition, the regional analysis shows that the healthcare datasets are not uniform in terms of their data structures and data quality; however, the XAI technique is still effective across the two regions. This shows that explainable machine learning models can be used effectively in developing country healthcare systems even with the limitation of infrastructure resources (Obermeyer and Emanuel).

In sum, this research finds that EAI is not only an add-on feature, but a must-have for current and future ML systems in healthcare. XAI's ability to reconcile the accuracy and transparency aspects is making it a key ingredient in safer, more ethical, and more reliable AI utilization.

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