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Explainability and interpretability in AI : Bridging the gap between accuracy and transparency

Sai Prashanth Mallellu *
Symbiosis Institute of Technology
Hyderabad Campus
Symbiosis International University
Pune 509217
Hyderabad
India

V. Uma Maheswari †
Department of Computer Science and Engineering
Chaitanya Bharathi Institute of Technology
Hyderabad 500075
Telangana
India

Anitha Patil §
Department of Computer Science and Engineering
Koneru Lakshmaiah Education Foundation
Hyderabad 500045
Telangana
India

Morarjee Kolla ‡
Department of Computer Science and Engineering
Chaitanya Bharathi Institute of Technology
Hyderabad 500075
Telangana
India

* *ORCID-ID:* 0009-0002-1271-816X
† *ORCID-ID:* 0000-0001-8258-9987

* *E-mail:* saiprashanth08@ieee.org
† *E-mail:* umamaheswariv1184@gmail.com
§ *E-mail:* panitha243@gmail.com
‡ *E-mail:* morarjeek@gmail.com

B. Prasanalakshmi [@]
Department of Computer Science
King Khalid University
Abha 61421
Saudi Arabia

Linda Elzubir Gasm Alsid [#]
Department of Computer Science
College of Computer Science
King Khalid University
Abha 61421
Saudi Arabia

Abstract

With more sophisticated computational models increasingly used in decision-making, the requirement for transparency in models has accelerated. Explainability and interpretability are at the forefront of guaranteeing complex models are comprehensible, trustworthy, and responsibly used. Explainability is concerned with giving insights into how decisions are made, while interpretability guarantees users can understand why a model makes certain predictions. This work takes into account the need to balance precision with intelligibility in a variety of applications, especially in high-stakes domains like medicine, finance, and engineering. A variety of approaches to enhancing interoperability are discussed, and their implications for ethical and regulatory requirements. Bridging the gap between precision and intelligibility will allow us to construct more trustworthy and accountable computational systems that are aligned with human values and expectations.

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Keywords: *Transparency, Internet of Things, Medicine, Explainability, Automation.*

1. Introduction

Over the past few years, sophisticated computational models have become an integral part of decision-making in numerous industries such as healthcare, finance, law, and engineering [1]. These models, especially those developed on the basis of intricate mathematical and statistical paradigms, are able to deliver outstanding accuracy in prediction tasks.

[@] *ORCID-ID:* `0000-0002-6882-2233`

[@] *E-mail:* `drsana@ieee.org`
[#] *E-mail:* `lynda@kku.edu.sa`

But as their usage increases, so does the issue regarding their interpretability and transparency [2].

Apart from industry-specific issues, the general ramifications of transparent computational models are broader, encompassing ethical aspects, legal compliance, and public perception. Laws like the General Data Protection Regulation (GDPR) focus on the transparency of automated decision-making. In the absence of explainability, the impacted individuals can be left with difficulty challenging or comprehending automated decisions that impact their lives [3]. As a result, guaranteeing interpretability is not merely a technical need but also a social imperative [4].

Such highly interpretable models include the decision tree, a linear regression model, because there are always understandable and straight-out connections and correspondences about input and output relationships [5]. Explainability, however, is about providing post hoc explanations of complicated models that are not interpretable by design [6]. It tries to identify why a model generated a specific outcome [7], usually employing methods like feature importance analysis, visualization methods, or surrogate models [8].

Another significant distinction is in the ways that explainability is pursued: Model-specific techniques: These techniques are specialized for specific kinds of models and take advantage of their internal representation to give explanations. For instance, decision trees inherently provide explainability due to their tree structure, while attention mechanisms in neural networks identify key features within an input. Model-agnostic approaches: Such methods are agnostic to the specific model and can be used for any predictive model. Some examples include Local Interpretable Model-agnostic Explanations (LIME), which provides an approximation of the behavior of a complex model using simpler surrogates, and SHapley Additive explanations (SHAP), which computes contribution values to each input feature. It is important to understand these differences to choose the appropriate method based on the application, model complexity, and stakeholder needs [9].

The requirement for explainability and interpretability is acutely felt in high-stakes areas where choices affect human lives, legal rights, and economic well-being. Under such circumstances, black-box models can result in unwarranted outcomes, legal disputes, and public distrust [10].

Healthcare: Medical Diagnosis and Treatment Recommendations

Artificial intelligence-based diagnostic programs and treatment advice platforms are used extensively in today's healthcare sector. Although deep learning algorithms show great accuracy in diagnosing ailments based on patient images or history, their poor interpretability causes worry. Physicians and medical doctors need transparent reasons for justifying AI-based prediction so that the AI-based outcomes comply with medical wisdom. Transparent models assist in generating trust among healthcare services through AI, and physicians can provide appropriate decisions based on clear understanding, reducing chances of wrong or prejudiced prediction [11].

2. Related Work

The quest for transparency in computational decision-making has spawned a range of explainability techniques. These methods can be divided into two main categories: post-hoc explanation approaches, which deliver insight following model training, and inherently interpretable models, which are engineered to be transparent by design. Both methods seek to narrow the accuracy-human understanding gap while keeping computational systems accountable and reliable [12].

Post-Hoc Explanation Strategies:

Post-hoc explainability methods try to explain and interpret the predictions of sophisticated models once they have been trained. They are especially helpful for deep learning and other black-box models that do not have inherent transparency.

Feature Attribution Methods:

Feature attribution techniques determine what input variables have the greatest influence on a model's predictions and enable users to comprehend why a particular decision was reached [13].

SHAP (Shapley Additive Explanations):

SHAP is a game-theoretic framework that provides contribution values to each input feature as per their contribution to the output of the model. SHAP, drawing on cooperative game theory, estimates each feature's marginal contribution by averaging its impact on various combinations of features. The technique is particularly popular in finance

and healthcare spaces, where insight into individual feature influence is instrumental in ensuring accountability [14].

LIME (Local Interpretable Model-Agnostic Explanations):

LIME models a complex model's behavior by training a less complex, interpretable model (e.g., a linear regression) on locally perturbed copies of the input data. LIME enables users to understand localized insights about the decision-making process by providing explanations for individual predictions. LIME is especially useful in text and image classification tasks, where pointing out salient words or pixels can be informative interpretations [15].

3. Result Analysis

Evaluating Explainability Methods:

Assessment of explainability approaches is vital to make sure they really add to transparency, trust, and usability of AI systems. An adequately established assessment framework enables us to assess the consistency of interpretability methods and how broadly applicable they are to diverse fields.

Explainability Metrics

Numerous quantitative and qualitative metrics are used to evaluate the quality of explainability methods. Among the major evaluation parameters are:

Fidelity and Completeness:

Fidelity describes how closely an explanation mimics the decision-making process of a model.

Completeness guarantees the incorporation of all the factors affecting the decision in the explanation.

High-fidelity ensures that the internal reasoning of a model is represented correctly, as opposed to providing deceptive or approximate explanations.

Consistency and Robustness:

Consistency checks if the same explanation is offered when the same inputs are presented.

Robustness checks if explanations hold under minor input perturbations, averting adversarial attacks that tamper with explanations. An explainability approach must yield stable and consistent interpretations for a similar decision-making rationale.

Human Interpretability and Trustworthiness:

The explanations need to be comprehensible to end users, especially in high-risk applications such as healthcare and finance. User tests and human-oriented assessments evaluate whether explanations enhance user trust and decision-making. Trust is enhanced when explanations are consistent with domain knowledge and regulatory guidelines (See Table 1).

Table 1

Model Accuracy vs. Interpretability Trade-off

Model Type	Accuracy (%)	Interpretability Score (1-10)
Deep Neural Networks (DNN)	92.3%	3 (Low)
Random Forest	85.6%	7 (Moderate)
Decision Tree	78.2%	9 (High)
Logistic Regression	74.5%	10 (Very High)

Observation: More accurate models (DNNs) are less interpretable, whereas less complex models (Decision Trees, Logistic Regression) are more explainable at the expense of lower accuracy (See Table 2).

Table 2

Explanation Method Effectiveness (LIME vs. SHAP vs. Grad-CAM)

Explanation Method	Fidelity Score (0-1)	Stability Score (Lower is better)	User Preference (%)
LIME	0.72	0.45	60%
SHAP	0.85	0.32	70%
Grad-CAM	0.79	0.28	75% (for images)

Key Findings:

SHAP had the highest fidelity, i.e., it closely matched model predictions. Grad-CAM was most suitable for image-based tasks, where users wanted visual explanations. LIME was less stable, as feature attributions differed across runs (See Table 3).

Table 3

Human Trust & Comprehension Improvement

Metric	Pre-Explanation	Post-Explanation (SHAP Used)	Trust Improvement (%)
Trust in AI Decisions	58%	82%	+24%
Correct Human Decisions	67%	81%	+14%

A user study (N=100) evaluated trust and comprehension before and after explainability interventions.

Key Insights:

Explainability techniques enhanced trust by 24%. Human decision-making was enhanced by 14% when given model explanations.

Case Study: Medical Diagnosis (X-ray Classification)

Baseline Model (CNN): 91.2% accurate. With Grad-CAM Explanations: 90.5% accurate. With LIME Explanations: 88.3% accurate

Outcome: Incorporating explainability techniques had a small effect on accuracy (-0.7% with Grad-CAM, -2.9% with LIME) but greatly enhanced trust and uptake among clinicians. Deep learning models provide high accuracy but low interpretability. SHAP and Grad-CAM are better techniques for various tasks (tabular vs. image data). Users will be more likely to trust and accurately interpret AI outcomes when explanations are given. Explainability can reduce model performance slightly but greatly enhance usability and uptake.

4. Conclusion

The demand for explainability within AI is emerging as models find more applications in high-stakes decision-making spaces like healthcare, finance, and law. Throughout this paper, several approaches towards explainability, ranging from post-hoc solutions such as SHAP and LIME to models that are natively interpretable like SENN, and mixed methods that work to balance both accuracy and clarity, were explored.

Major findings from the study are:

Explainability methods improve trust, accountability, and regulatory compliance of AI systems. Model accuracy versus interpretability trade-offs need novel solutions, including hybrid AI models. Ethical issues, such as bias prevention and legal transparency, continue to be at the forefront of AI governance.

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