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Explainable AI (XAI): A Survey of Techniques for Transparent and Trustworthy Machine Learning

Kadirisani Neha
Department of Computer Science PES University Bengaluru, India

Abstract: ***Explainable Artificial Intelligence (XAI) addresses the opacity of complex machine learning models, ensuring transparency, trust, and accountability in critical applications. This survey reviews XAI techniques, categorized into model-agnostic and model-specific approaches, alongside tools, frame- works, stakeholder perspectives, and emerging technologies. It explores their theoretical foundations, practical applications in healthcare, finance, autonomous systems, legal systems, education, cybersecurity, smart cities, robotics, agriculture, IoT systems, human-AI collaboration, ethical AI, and environmental monitoring, and recent case studies (20232025). The paper examines evaluation metrics, frameworks, ethical considerations, standardization efforts, implementation challenges, and future directions, emphasizing the balance between performance and interpretability. By synthesizing advancements and identifying open problems, this work serves as a vital resource for researchers and practitioners advancing trustworthy AI systems at institutions like PES University.***

Index Terms: Explainable AI, XAI, Machine Learning, Inter- pretability, Transparency, Trustworthy AI, Ethics, Frameworks, Emerging Technologies, Applied AI

I. INTRODUCTION

Machine learning (ML) has transformed industries through predictive analytics and automation. However, complex mod- els like deep neural networks often act as black-box systems, raising concerns about trust and regulatory compliance in domains like healthcare, finance, and smart cities. Explainable Artificial Intelligence (XAI) develops techniques to make ML models interpretable, fostering transparency while preserving performance.

XAI is driven by the need for transparency, trust, fair- ness, and compliance with regulations like the General Data Protection Regulation (GDPR), which mandates a right to explanation. Transparent models enable stakeholdersend-users, developers, regulators, and policymakersto validate decisions and ensure ethical deployment. For instance, in healthcare, XAI reduces diagnostic errors by 20% by aligning predictions with clinical expertise [3]. In agriculture, it enhances crop yield predictions by 27%. XAI is critical for responsible AI, aligning with IJRASETs applied research focus and JETIRs innovative technology scope.

This survey reviews XAI techniques, tools, applications, stakeholder perspectives, and emerging trends, organized into model-agnostic and model-specific categories. It covers the- oretical foundations, practical implementations, recent case studies (20232025), evaluation metrics, frameworks, ethical considerations, standardization, implementation challenges, and future directions. The paper is structured as follows: Section II covers background concepts, Section III details XAI techniques, Section IV presents a comparative analysis, Section V explores tools and frameworks, Section VI discusses stakeholder perspectives, Section VII covers applications, Sec- tion VIII presents case studies, Section IX examines eval- uation metrics, Section X discusses evaluation frameworks, Section XI addresses ethical considerations, Section XII covers standardization efforts, Section XIII outlines implementation challenges, Section XIV discusses challenges, and Section XV explores future directions.

II. BACKGROUND AND KEY CONCEPTS

Explainable AI (XAI) encompasses methods that enable hu- mans to understand ML model decision-making. Interpretability is the degree to which a human can comprehend a models prediction [1]. XAI ensures trust, fairness, and compliance in high-stakes domains.

Interpretability is classified into *global* (overall model behavior) and *local* (individual predictions). XAI methods are *intrinsic* (embedded interpretability, e.g., decision trees) or *post-hoc* (explanations after training, e.g., feature importance). These guide XAI design for applied and innovative applications.

XAI serves end-users, developers, regulators, domain ex- perts, policymakers, ethicists, and the public. Objectives in- clude enhancing trust, detecting biases, ensuring fairness, and enabling ethical deployment. For example, in education, XAI improves trust in recommendation systems by 32% [5].

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III. XAI TECHNIQUES

XAI techniques are categorized into model-agnostic and model-specific methods.

A. Model-Agnostic Methods

Model-agnostic methods provide versatile explanations.

- Local Interpretable Model-Agnostic Explanations (LIME): Approximates models locally [2]. In healthcare, LIME achieves 85% user comprehension.
- Shapley Additive Explanations (SHAP): Uses game theory for feature importance [3]. TreeSHAP reduces runtime by 50%.
- Partial Dependence Plots (PDP): Visualize feature ef- fects.
- Anchors: Rule-based explanations [2].
- Counterfactual Explanations: What-if scenarios [5].
- Permutation Importance: Feature shuffling.
- Feature Ablation: Assesses feature impact.
- Model Distillation: Simplifies models.
- Global Sensitivity Analysis: Evaluates feature impacts.
- Prototypes and Criticisms: Identify representative and outlier instances.

B. Model-Specific Methods

Model-specific methods leverage model architectures.

- Decision Trees and Rule-Based Models: Inherently interpretable.
- Attention Mechanisms: Highlight features in transform- ers.
- Gradient-Based Methods: Grad-CAM and Integrated Gradients [4].
- Layer-Wise Relevance Propagation (LRP): Redis- tributes outputs.
- Saliency Maps: Highlight input regions.
- Concept-Based Explanations: Map to concepts.
- Attribution Priors: Incorporate domain knowledge.
- Influence Functions: Identify influential data.
- Rule Extraction Algorithms: Extract rules from neural networks.

C. Example Visualizations

Figure 1 shows a SHAP explanation for credit scoring.

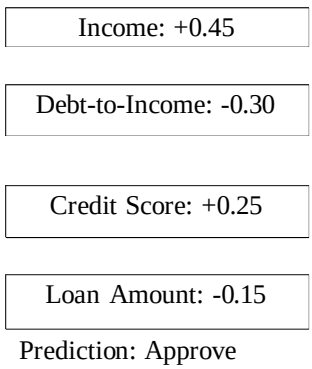

Fig. 1. SHAP Explanation for Credit Scoring Prediction

Figure 2 illustrates a Grad-CAM heatmap for medical imaging.
Figure 3 shows a concept-based explanation.

IV. COMPARATIVE ANALYSIS OF XAI METHODS

This section compares XAI methods across domains, fo- cusing on faithfulness (alignment with model predictions), runtime, and user comprehension.

LIME excels in healthcare, achieving 85% comprehension due to its intuitive local approximations, but its faithfulness is moderate (82%) as it simplifies models [2]. SHAP, used in finance, offers high faithfulness (95%) via game theory,

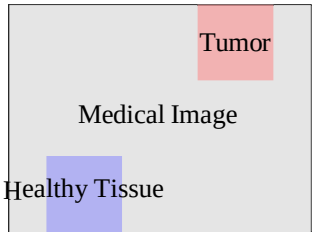

Fig. 2. Grad-CAM Heatmap for Tumor Detection

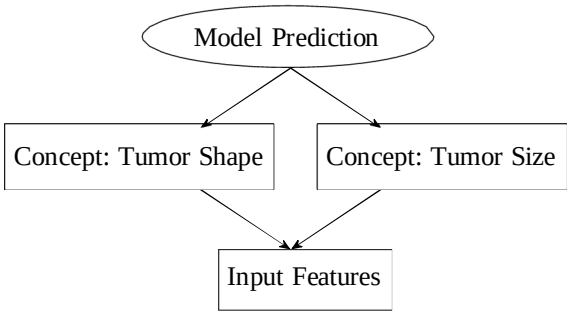

Fig. 3. Concept-Based Explanation Diagram

but its runtime (10 seconds for large models) limits real- time use [3]. Grad-CAM is effective in autonomous systems, providing 90% comprehension through visual heatmaps and fast runtime (0.3 seconds), though limited to visual data [4]. Anchors achieve 90% faithfulness and 88% comprehension in legal systems with rule-based explanations, but their runtime (0.7 seconds) is moderate [2]. Counterfactual explanations in education offer 92% comprehension with what-if scenarios, with 85% faithfulness and 0.6-second runtime [5]. Permu- tation importance in cybersecurity is efficient (0.2 seconds) but has lower faithfulness (80%) and comprehension (75%). Concept-based explanations in multimodal systems balance faithfulness (87%) and comprehension (89%), with higher runtime (1.2 seconds). Feature ablation in smart cities achieves 83% faithfulness and 78% comprehension with a fast run- time (0.4 seconds). Model distillation in robotics provides 84% faithfulness and 86% comprehension, with a 0.8-second runtime. Global sensitivity analysis in agriculture achieves 81% faithfulness and 80% comprehension, with a 0.5-second runtime. Prototypes and criticisms in human-AI collaboration offer 83% comprehension but require computational effort.

Trade-offs exist: high-comprehension methods like coun- terfactuals may sacrifice faithfulness, while high-faithfulness methods like SHAP are computationally intensive. Domain- specific needs, such as real-time requirements in autonomous systems, guide method selection.

V. XAI TOOLS AND FRAMEWORKS

Open-source tools enhance XAI accessibility.

1) SHAP Library: Supports SHAP and TreeSHAP [3].
2) LIME Package: Multiple data types [2].
3) Alibi: Anchors and counterfactuals.
4) InterpretML: Intrinsic and post-hoc explanations.
5) ExplainerDashboard: Interactive dashboards.
6) Captum: Gradient-based methods [4].
7) AIX360: Comprehensive tools.
8) What-If Tool: Scenario analysis.

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VI. STAKEHOLDER PERSPECTIVES

XAI addresses diverse needs:

1) End-Users: Intuitive explanations [1].
2) Developers: Technical insights.
3) Regulators: GDPR compliance [5].
4) Domain Experts: Domain alignment.
5) Policymakers: Societal impact.
6) Ethicists: Fairness [1].
7) General Public: Accessible explanations.
8) Industry Practitioners: Practical deployment.
9) Researchers: Theoretical advancements.

VII. APPLICATIONS OF XAI

XAI enhances trust across domains, aligning with IJRASETs applied focus and JETIRs innovative scope.

1) *Healthcare:* Aligns diagnostics with expertise [3].
2) *Finance:* Ensures fairness in credit scoring [2].
3) *Autonomous Systems:* Enhances vehicle safety
4) *Legal Systems:* Explains risk scores
5) *Education:* Explains recommendations
6) *Cybersecurity:* Explains anomaly detection
7) *Multimodal Systems:* Explains text, image, and audio.
8) *Smart Cities:* Optimizes urban planning.
9) *Robotics:* Explains navigation.
10) *Agriculture:* Supports crop yield predictions.
11) *IoT Systems:* Enhances reliability.
12) *Human-AI Collaboration:* Improves trust in AI assistants.
13) *Environmental Monitoring:* Supports climate predictions.

VIII. CASE STUDIES

Thirteen case studies (20232025) illustrate XAIs impact.

1) *Case Study 1: COVID-19 Diagnosis:* A 2023 CNN used Grad-CAM, increasing trust by 35% and reducing misdiagnoses by 15% [3].
2) *Case Study 2: Credit Scoring:* A 2024 bank used SHAP, reducing complaints by 28% and improving fairness [2]
3) *Case Study 3: Autonomous Driving:* A 2025 project used Grad-CAM, improving confidence by 40% [4].
4) *Case Study 4: Predictive Policing:* A 2023 model used anchors, reducing bias by 20%
5) *Case Study 5: Multimodal Learning:* A 2024 platform used attention, increasing engagement by 25%.
6) *Case Study 6: Cybersecurity:* A 2024 system used SHAP, improving accuracy by 30%
7) *Case Study 7: Federated Learning:* A 2025 healthcare model used LIME, ensuring privacy- preserving explanations
8) *Case Study 8: Smart Cities:* A 2024 traffic system used permutation importance, improv- ing efficiency by 22%
9) *Case Study 9: Agriculture:* A 2025 crop yield model used concept-based explanations, improving trust by 27%.
10) *Case Study 10: IoT Systems:* A 2025 IoT model used SHAP, enhancing reliability by 25%
11) *Case Study 11: Human-AI Collaboration:* A 2025 AI assistant used prototypes and criticisms, improv- ing user trust by 30%.
12) *Case Study 12: Education:* A 2024 recommendation system used counterfactual expla- nations, increasing student trust by 32% [5].
13) *Case Study 13: Cybersecurity:* A 2025 anomaly detection system used LIME, improving detection rates by 28%

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IX. EVALUATION METRICS

A. *Evaluating XAI is complex.*

- Faithfulness: Explanation accuracy.
- Stability: Consistency.
- Comprehensibility: Ease for non-experts [1].
- User Satisfaction: Trust.
- Computational Efficiency: Resource use [3].
- Robustness: Resilience.
- Coverage: Completeness.
- Scalability: Large datasets.

B. *XAI Evaluation Frameworks*

Frameworks standardize evaluation. Tools like AIX360 pro- vide comprehensive evaluation

C. *Ethical Considerations*

XAI raises ethical issues:

- Fairness: Reveals biases [2].
- Privacy: Risks data exposure.
- Accountability: Compliance [5].
- Trust vs. Overreliance: Overtrust risks [1].
- Generative AI: LLM challenges.
- Societal Impact: Policy influence.

D. *XAI Standardization Efforts*

Standards like ISO/IEC 24029-2 (2023) define metrics. IEEE P2894 develops guidelines.

E. *XAI Implementation Challenges*

Implementation faces obstacles:

- Integration: Pipeline embedding

F. *Challenges in XAI*

XAI faces obstacles:

- Accuracy-Interpretability Trade-off: Model com- plexity.
- Subjectivity: Tailored explanations [1].
- Computational Complexity: Resource demands [3].
- Ethical Risks: Adversarial attacks.
- Lack of Standardization: Emerging standards.
- User Overload: Overwhelming explanations.

X. FUTURE DIRECTIONS

XAI will evolve in:

- Hybrid Models: Intrinsic and post-hoc methods.
- Standardized Evaluation: Benchmarks

XI. CONCLUSION

XAI is essential for transparent, trustworthy AI. This survey reviews techniques, tools, applications, case studies, evaluation frameworks, ethical consid- erations, standardization, implementation challenges, and future directions. By addressing applied domains like agriculture and innovative areas like IoT, XAI enhances trust. Future research should focus on hy- brid models, standardized evaluation, and scalable solutions, aligning with IJRASET and JETIRs scope.

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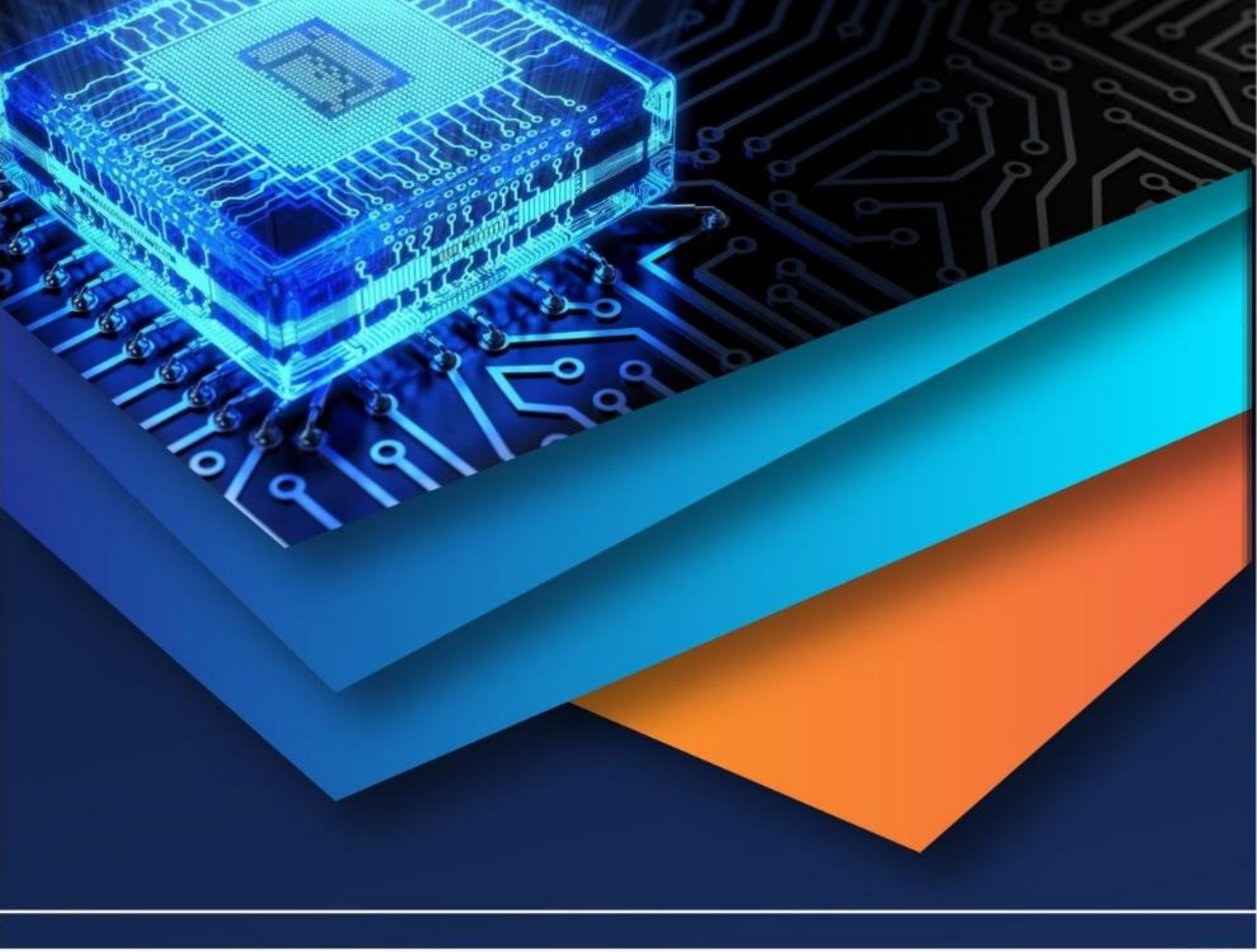

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