Use Cases of Explainable AI: A Review

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***Abstract*—Explainable Artificial Intelligence (XAI) is a critical advancement in AI that enhances transparency, interpretability, and trust in machine learning models. This paper explores the application of XAI across various domains, with a particular focus on healthcare, where model explainability is essential for diagnostic accuracy and clinical decision-making. We analyse different XAI techniques, including SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), demonstrating their effectiveness in explaining complex AI models. Additionally, we discuss the challenges associated with XAI implementation, such as balancing model performance with explainability, addressing ethical concerns, and ensuring robustness against adversarial attacks. Our findings highlight the transformative potential of XAI in fostering AI accountability and reliability, paving the way for its broader adoption in critical decision-making systems. Future research should focus on developing more intuitive and real-time XAI models to enhance user understanding and trust in AI-driven systems.**

***Index Terms*— XAI, LIME, SHAP, XGBoost**

I. INTRODUCTION

Explainable Artificial Intelligence (XAI) is a significant advancement in the field of AI, designed to enhance the transparency and interpretability of machine learning models. As AI continues to evolve, the complexity of these models has increased, often resulting in "black box" systems where decision-making processes remain obscure. This lack of transparency poses challenges in various sectors, particularly in critical areas such as healthcare, finance, and cybersecurity, where understanding AI-driven decisions is essential.

XAI aims to bridge this gap by providing insights into how AI models arrive at specific conclusions. By implementing explainability techniques, users—including domain experts, regulators, and end-users—can gain a clearer understanding of AI-generated outcomes. This fosters trust, accountability, and fairness in AI applications. Furthermore, explainability is essential for mitigating risks associated with bias, ethical concerns, and regulatory compliance.

Traditional machine learning models, particularly deep learning-based neural networks, have demonstrated remarkable predictive capabilities. However, their decision-making processes are often complex and unintelligible to human users. The challenge lies in ensuring that AI systems remain accurate while also being interpretable. XAI methodologies such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) have been developed to address these concerns by offering insights into model predictions.

This review paper explores various techniques and approaches used in XAI, focusing on its applications in healthcare. It examines existing literature, evaluates the effectiveness of different explainability methods, and discusses the challenges associated with integrating XAI into real-world applications. Additionally, the paper highlights the importance of balancing model performance with interpretability, ensuring fairness, and addressing ethical implications. By analyzing current advancements and limitations, this study aims to contribute to the ongoing efforts in making AI systems more transparent and reliable.

II. LITERATURE SURVEY

It is essential to incorporate comparison studies that assess the efficacy of various XAI strategies across multiple domains while broadening our study of the literature. Comparing the use of SHAP and LIME in healthcare diagnostics, for example, might reveal which approach is more useful and easier to interpret for medical experts. Furthermore, real-world case studies demonstrating the benefits and difficulties found in the deployment of XAI will be quite helpful. With regard to lessons learned and best practices, these case studies can offer specific instances of how XAI might be incorporated into current workflows

Table I. Studied the various papers.

Sr. No	*Reference*	*Algorithm(s) used*	*Dataset*	*Domain*	*Strength*	*Limitation*
1	(Kute et al., 2021)[1]	Convolutional Neural Networks (CNN) and AutoEncoder	Open-source data, kyc information	Anti-Money Laundering (AML)	Finding novel money laundering trends is advised when using unsupervised machine learning.	-Canvas changing as a result of fraud trends and technology improvements. -Suspicious transaction detection's multi-step categorization process.
2	(Capuano et al., 2022)[2]	Rule Column Generation (BRCG), Logistic Rule Regression (LogRR), ProtoDash, and Contrastive Explanations Method (CEM)	BotNet dataset for Network Anomaly Detection and IDS dataset	Applications of cybersecurity and XAI techniques in several security domains.	adaptability, automation, and detection of zero-day attacks	Decision boundaries outside of linear zones are problematic for linear models.
3	(Jagatheesaperumal et al., 2022)[3]	IOT application	Convolutional neural networks (CNNs) are utilized in the processing of visual images.	IIoT, security, healthcare, and commercial IoT sectors are all improved by XAI models.	I-n smart industries, blockchain tokenization secures IIoT data. -Edge XAI architectures provide improved accessibility and fast rea	-The limitations of XAI in frameworks for reinforcement learning were emphasized. -We looked at the difficulties in giving clear explanations for Internet of Things applications.
4	(Sahakyan et al., 2021)[4]	- MUSE	COVID-19 patient classification, heart disease, heart failure risk, and the death rate of influenza patients with critical illness	Applications of Explainable Artificial Intelligence (XAI) throughout multiple domains.	-For black-box models, LORE produces local rule-based explanations. -The FACE approach generates counterfactual explanations by quantifying trade-off.	The constraints of XAI are related to ethics, robustness against adversaries, accuracy, and relevance.
5	(Gohel et al., 2021)[5]	LIME, SHAP, and LRP inductions.	It does go into how crucial it is to have local datasets produced and their forecasts for explainable AI.	Applications of Explainable Artificial Intelligence (XAI) throughout multiple domains.	-Clear and concise Bayesian models appropriate for end users who possess knowledge of conditional probability. -Heat maps, rule sets, and feature importance ratings are produced via XAI techniques.	-Black box ML models are too complicated for the average person to comprehend. -Explainable approaches might not match the calculations of the original methods.

6	(Adnan et al., 2022)[6]	-Random Forest (RF) ensemble classifier -logistic regression, KNN, and Decision Tree	Open University UK dataset accessible via https://analyse.kmi.open.ac.uk/open_dataset	-An interpretive model of Explainable Artificial Intelligence (XAI) is utilized in VLE to analyze student performance..	- XAI's benefits for education include its ability to interpret student performance and offer tailored feedback. -XAI tools help educators make decisions by providing timely insights.	-The investigation of deep neural networks, such as ANNs, LSTMs, and transformers, was hampered by time restrictions. -There were no studies done to determine which deep neural network model was the most precise and comprehensible.
7	(Martins et al., 2024)[7]	SHAP, LIME, XGBoost, PDP, 2DCNN, PASTLE, CASTLE, and MANE.	-Credit dataset includes 1000 cases and 21 characteristics. -Credit Card Client Default in Taiwanese dataset (30,000 samples). credit card transactions.	XAI explanations are produced for a number of financial domains.	- XAI's useful applications in finance and model interpretability are among its strong points. -In finance, XAI techniques like SHAP are well-liked and frequently applied.	-Only relevant to applications in finance; not applicable to other fields. -Disagreement over the overall taxonomy of XAI techniques. -The difficulty of accurately classifying novel XAI techniques.
8	(Giuste et al., 2023)[8]	-ProtoPNet. - U-Net.	ProtoPNet image embedding is applied to real-world data.	Techniques for explaining artificial intelligence in the fight against pandemics.	- XAI improves decision-making, user trust, and model performance. -AI usage in biomedicine and healthcare is improved by XAI approaches.	-Problems with low data quality, data imputation, and dataset difficulties. -Imbalanced classes, weakly supervised learning, and feature extraction problems. -Issues with within-patient correlation, data leakage threats, and model inefficiencies. -Transfer learning issues, unclear XAI outputs, and poor preprocessing quality. .
9	(Saravanan et al., 2023)[9]	-Google Net and VGG19 Net. -Alex Net is an eight-layer classical neural network. -Neural networks, CNN, and SVM.	-Wave and spiral designs involving 102 subjects. -drawings made by both healthy volunteers and PD patients downloaded from Kaggle	Deep learning models for the diagnosis of Parkinson's disease.	-The accuracy of early Parkinson's disease diagnosis is improved using deep learning models. -Accuracy, specificity, sensitivity, precision, recall, and F1 score are examples of performance measurements.	-Parkinson's disease classifier predictions lack transparency. -Difficulties in getting precise input-output relationships in the model.

10	(Longo et al., 2024)[10]	-LIME, SHAP, and Anchors	For the research presented in the paper, no data were used.	The field of explainable artificial intelligence (XAI) research.	-In XAI research, cooperation promotes interdisciplinary efforts for real-world applications. -XAI challenges include developing robust explanations and improving models.	-There are drawbacks when evaluating XAI techniques on humans. -Inadequate analysis, low sample representativeness, and problems with reproducibility. -Human research can be enhanced by virtual participation and synthetic data.
11	(Ali et al., 2023)[11]	-LORE, or Local Rule-based Explanation -Cluster Representatives with LIME	Datasheets for datasets, data declarations, and nutrition labels for datasets	The field of explainable artificial intelligence (XAI) research.	-AI models automatically identify intricate patterns in data. -The goal of XAI is to make AI systems understandable and transparent.	-Unable to account for surrounding observations or non-linear models. -Having trouble interpreting tabular data
12	(Bao & Zeng, 2024)[12]	- Ritual Dialog Framework (RDF)	For the research presented in the paper, no data were used.	The dialog framework in XAI as a ritual for comprehension and trust.	-Complex AI models are made simpler for human comprehension through functional understanding. -Comprehensive explanation of AI models is lacking in contrastive comprehension.	-Non-steady state processes may be overlooked by functional comprehension. -The human explanation of functional comprehension can lead to local prejudice.
13	(Ahmed & Kamruzzaman, 2024)[13]	-Genetic algorithm -CARS stands for competitive adaptive reweighted sampling.	80 samples from the "m5spec" corn spectroscopy dataset were utilized in the study.	Spectroscopic evaluation of corn quality by the use of variable selection methods.	-Prediction accuracy for the starch and oil properties was enhanced by common variables. -SHAP approach evaluated the contribution of common factors and explained the PLSR model.	Although there may be room for improvement in accuracy with more sophisticated optical sensing techniques, the limited dataset and unreliable robustness of the used variable selection methods may prevent widespread use.
14	(Chamola et al., 2023)[14]	Regression and Decision Trees.	The model was trained and improved using the OpenCV dataset.	Trustworthy and Explainable Artificial Intelligence (XAI) in various industries.	-AI trustworthiness is essential to human dependability and trust. -AI partiality and discrimination are related problems.	-Ignoring the drawbacks of cutting-edge AI developments. -Lack of a common understanding and standards for AI interpretability.

15	(Quach et al., 2023)[15]	VGG16, ResNet50, ResNet50V2, Xception, EfficientNetV2, InceptionV3, DenseNet201, MobileNetV2, MobileNet.	VegNet dataset https://www.kaggle.com/datasets/enalis/tomatoes-dataset	Explainable Artificial Intelligence in agriculture using deep learning models	-With 99.2% accuracy, the XAI model forecasts CKD. -The three main risk factors are hypertension, specific gravity, and hemoglobin.	-Even with greater recognition, MobileNet is less dependable than EfficientNetV2, Xception, and MobileNetV2. -Model learning is more difficult for Old and Damaged class features.
16	(Begum et al., 2023)[16]	Random Forest Regression, Linear Regression,Naïve Bayes, Decision Tree Classifier, Logistic Regression, AdaBoost	PC1, Baseline, CM1, JM1 from PROMISE software database	Software fault diagnosis and prediction in machine learning domain	The research study uses machine learning approaches to diagnose software faults.	Few features were chosen to represent software flaws.
17	(AlMohimeed et al., 2023)[17]	Particle Swarm Optimization (PSO)	Alzheimer's Disease Neuroimaging Initiative (ADNI)	Identifying Alzheimer's disease with multi-level stacking models	-The multi-level stacking model has a high accuracy of AD prediction. -Predicts using cognitive sub-scores from the ADNI dataset	Lack of real-time data in the study prevents dynamic model adaptation
18	(Giuste et al., 2023)[18]	- ProtoPNet -Decision tree optimization	-Synthetic data generated through Generative Adversarial Networks (GANs)	-Biomedicine and healthcare	-Model credibility and clinical decision-making are enhanced by XAI techniques. -For feature importance, a mixed approach combines gradient and activation approaches.	-Problems with low data quality, data imputation, and dataset difficulties. -There are dangers of data leaking, uneven class sizes, and insufficient expert annotation. -Unclear XAI outcomes, ineffective training, and recommendations for transfer learning.
19	(Lee et al., 2023)[19]	AdaBoost, XGBoost, and Random Forest	Clinical data from patient records used for pharmacovigilance research.	-Pharmacovigilance research	-The potential applications of XAI in pharmacovigilance are what give it strength. -Medication monitoring, ADR gathering, and drug interaction prediction can all be improved with XAI.	-Stable visuals are necessary for XAIs so that physicians can justify choices. -Developing PV XAI models requires professional collaboration. -When models get complicated, explainability flaws need to be accommodated.

20	(Moreno-Sánchez, 2023)[20]	Random Forest, Extra Trees, AdaBoost.	CKD dataset from UCI-ML repository collected from Apollo Hospital, Karaikudi, India.	Early diagnosis of Chronic Kidney Disease	-With 99.2% accuracy, the XAI model forecasts CKD. -The three main risk factors are hypertension, specific gravity, and hemoglobin.	-Insufficient attention paid to explainability in related works. -The XGBoost classifier performs less well when it comes to real negative instances classification. -The lack of early symptoms of CKD causes a delayed diagnosis.
21	(Khan & Vice, 2022)[21]	The prediction accuracy of machine learning systems is used to evaluate them.	RAVDESS	Accountable eXplainable Artificial Intelligence (AXAI)	-The AXAI framework's strengths include its accountability measurement, forecasting accuracy, and comprehension.	-Automation and AI adoption are hampered by gaps in system explainability features. -Beyond prediction accuracy, the early ML systems lacked explanations.
22	(Vice & Khan, 2022)[22]	-Support-Vector Machine models -Speech-to-text function separated linguistic features	Extended Cohn-Kanade (CKC)	Accountable eXplainable Artificial Intelligence (AXAI)	-Real-time ASAM system with AXAI capability integrated and shown. -A list of affective state models for matching data is maintained by the system.	-Despite breakthroughs, AI and ML systems still lack explanations. -Explainability is difficult to integrate and evaluate in AI systems.
23	(Nazar et al., 2021)[23]	Recurrent Neural Networks (RNNs)	Google Scholar, books, Scopus, and blogs	AI and HCI	-The interactive machine learning framework, XAI, was determined to be user-friendly. -Important considerations in system evaluation are usability, efficiency, and satisfaction.	-Applications of Explainable Artificial Intelligence (XAI) adapted to human problems Transparency, explainability, and abstraction are issues with XAI models.
24	(Tjoa & Guan, 2021)[24]	-TCAV is used by the ACE algorithm -Grad-CAM method	Chexpert, Human Connectome Project.	Medical research	-The models' interpretability properties are what make them strong. -Parameters from models such as GAM and GDM are interpretable by nature.	-In machine learning, creating the "right" model can be difficult. -Interpretability problems arise when a problem is formulated incompletely.
25	(the Precise4Q consortium et al., 2020)[25]	Clinical decision support systems	NA	XAI in healthcare	-Explainability is essential to fostering acceptance and confidence in AI systems. -It helps settle disputes between	-Terminology used in explainability talks is not clearly defined. -Obstacles in AI according to technological, legal, medical, and patient viewpoints.

					experts using AI and humans.	-Finding random faults in AI systems is difficult.
26	(Kuzlu et al., 2020)[26]	Random Forest Regressor (RFR)	Global Energy Forecasting Competition dataset from 2014	Forecasting solar photovoltaic power generation with explainable AI techniques.	-XAI tools improve forecasting models for solar PV by making them transparent and easy to understand. -Detailed model interpretations are provided by XAI tools like as ELI5, SHAP, and LIME.	-Tools require multiple evaluations of the original model. -LIME doesn't ensure a perfect distribution of effects.
27	(Ozalp et al., 2024)[27]	-Deep Reinforcement Learning (DRL) -Inverse Reinforcement Learning (IRL)	NA	Artificial Intelligence applications in robotic manipulation.	-Commonly employed in robotic manipulation jobs include DRL and IRL. -DRL and IRL improve robot performance in a reliable and effective way.	-Creating intricate settings and interacting things can be challenging. -Difficulties in translating the dynamics of simulation to the actual world.
28	(Fontes et al., 2024)[28]	-Neural networks -Sinkhorn algorithm and entropic regularization	ScienceDirect, IEEE Xplore, ACM Digital Library	Explainable Artificial Intelligence (XAI) techniques in medical imaging applications.	-The accuracy and transparency of medical imaging are improved by example-based XAI approaches. -Medical image explainability and diagnostic accuracy are increased using prototype learning models.	-Example-based XAI's superficial approach in current reviews -Unanimity on the categorization of procedures under Example-based XAI -Technique redundancies reduce the usefulness of healthcare apps.
29	(Alizadehsani et al., 2024)[29]	-LIME -SHAP	-PubChem: Public repository for chemical molecules and biological assays .	XAI for Drug discovery and development.	-Expert cooperation is essential for providing insightful XAI model explanations. -When developing new drugs, explanations for XAI need to be robust and dependable.	-Rule-based models might not be flexible when rules expand. -Effective balancing of complexity and interpretability is necessary for XAI models.

30	(Nazat et al., 2024)[30]	-AdaBoost with DecisionTreeClassifier -K-Nearest Neighbour with 5 neighbors and minkowski distance metric	-VeReMi dataset: Real-world data for AV anomaly detection in VANETs.	Autonomous driving systems cybersecurity and anomaly detection using XAI techniques.	-For the LR model, regularization strength C was set at '1.0'. -The AdaBoost algorithm's learning rate was set to 1.	-Model accuracy may not always be increased by XAI techniques. -Losing secondary traits could occur from concentrating on primary features.

III. CONCLUSION

Explainable Artificial Intelligence (XAI) has emerged as a crucial solution to enhance transparency, interpretability, and trust in AI-driven decision-making. This review highlights the significance of XAI techniques in addressing the "black box" nature of machine learning models, particularly in critical fields like healthcare. By applying methods such as SHAP and LIME, AI models become more understandable, enabling users to interpret predictions and make informed decisions.

The analysis of existing literature and case studies demonstrates that while XAI improves model explainability, challenges such as maintaining accuracy, mitigating bias, and ensuring fairness persist. Despite these challenges, XAI continues to play a pivotal role in promoting responsible AI usage by enhancing accountability and reliability. As AI adoption expands, integrating explainability into machine learning models remains essential for fostering trust and ethical AI applications.

IV. FUTURE SCOPE

Future research in Explainable Artificial Intelligence should focus on several key areas to further enhance its applicability and effectiveness. One crucial direction is the development of advanced XAI techniques that can handle more complex AI models and provide more intuitive and user-friendly explanations. This includes improving existing methods and creating new approaches that can elucidate the decision-making processes of intricate AI systems. Addressing ethical concerns and mitigating biases in AI models is another critical area, ensuring fairness and equity in AI-driven decisions across all domains.

The implementation of real-time XAI systems represents another promising avenue, aiming to provide immediate and actionable insights in dynamic environments. Additionally, a user-centered design approach is essential, focusing on the usability and interpretability of XAI tools from the perspective of end-users, such as domain experts and decision-makers. Expanding the application of XAI techniques to new and emerging fields, such as environmental monitoring, smart cities, and autonomous systems, will further demonstrate the versatility and utility of XAI. By pursuing these directions, future research can address current challenges and unlock the full potential of XAI in making AI systems more transparent, trustworthy, and effective.

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