A Taxonomy of Explainability Techniques in AI: Comparative Analysis and Applications Across Domains

Ashish Semwal [*1], Manmohan Singh Rauthan[2], Deepak Singh Nijwala[3],Pradeep Rana[4], Nisha Pokhriyal[5] and Ashish Joshi [6]

[1,3,4] HNBGU (A Central University), Srinagar Garhwal, Uttarakhand, India, 246174.
[2] UTU, Dehradun, India,248001
[6] Graphic Era University, Dehradun, India,248001
[5]THDC-IHET, Tehri, Uttarakhand, India, 249124

[1]ash.semwal@gmail.com
[2]deepak.nijwala@rediffmail.com
[3]mms_rauthan@rediffmail.com
[4]prana3236.pr@gmail.com
[5]nishapokhriyalv12@gmail.com
[6]a.joshicse1986@gmail.com

Abstract. The demand for explainability in artificial intelligence (AI) models has grown in relevance as AI keeps invading many spheres of human life. Techniques and approaches aiming at making AI systems and their actions more comprehensible and interpretable to humans are known as explainable artificial intelligence (XAI). This work gives a thorough taxonomy of explainability strategies in artificial intelligence along with a comparative study of the most often used approaches and emphasizes their uses in many fields. The study investigates the advantages, disadvantages, and trade-offs connected with these approaches as well as their applicability to fields like law, banking, healthcare, and autonomous cars. We want to assist academics and practitioners in choosing the most appropriate explanation strategies for their artificial intelligence models by offering a thorough investigation of different approaches and their pragmatic uses.

Keywords: Explainable AI, XAI, AI techniques, machine learning, interpretability, comparative analysis, applications.

1 Introduction

Deep learning models have shown exceptional performance across a wide range of tasks—including natural language processing, computer vision, and autonomous choice-making systems—which has resulted in remarkable discoveries in artificial intelligence (AI) lately. On the other hand, by producing state-of- the arts outcomes

R. Nagariya et al. (eds.), *Proceedings of the International Conference on Sustainable Business Practices and Innovative Models (ICSBPIM-2025)*, Advances in Economics, Business and Management Research 349,
https://doi.org/10.2991/978-94-6463-872-1_21

in object identification, CNNs have transformed computer vision. This is thus true even if recurrent neural networks (RNNs) improve sequential data processing, particularly in natural language processing (NLP) applications like sentiment analysis and machine translation [1]. Likewise, artificial intelligence models have been used in autonomous systems such as self-driving automobiles where deep learning provides real-time decision-making depending on sensor inputs [2].

Notwithstanding these achievements, artificial intelligence models—especially deep neural networks—have been criticized for their lack of openness a lot. Often labeled as "black-box" models, many times their decision-making mechanism is unknown. Especially in law, finance, autonomous vehicles, and healthcare—safety-critical sectors—this opacity raises issues about justice, duty, and trust [3]. Artificial intelligence models, for instance, are increasingly included in medical diagnosis and treatment recommendations in healthcare; yet, without clear explanations of their conclusions, doctors find it difficult to trust their outputs and apply them into clinical practice [4]. In banking, too, artificial intelligence technologies are used for credit scoring and fraud detection; here, transparency is vital for regulatory compliance and customer confidence and the stakes are great [5].

Explainable artificial intelligence (XAI) been developed to manage these problems. XAI is mostly concerned with creating plans for consumers to comprehend and approve of artificial intelligence system judgments. Improving the interpretability of AI models helps non-experts to access them and help to demystify difficult decision-making procedures. Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHap), and saliency maps—each of several techniques—offers a distinct way to understand the behavior of black-box models [23][7]. Especially important for enabling more understandable AI results in fields such as medical diagnostics, loan approval, and autonomous driving [8][9], these methods let people comprehend how certain variables contribute to predictions.

In this study we evaluate many XAI techniques, categorize them based on their applicability, and analyze their merits and disadvantages. We also look at the trade-offs between accuracy and interpretability as well as the computing complexity related with every method. We also consider how these concepts are used in other spheres—law, business, autonomous cars, and healthcare—to increase model responsibility and openness. Choosing the most suitable approaches to boost confidence and dependability in artificial intelligence systems depends on an awareness of the benefits and drawbacks of many strategies [10][8].

2 Taxonomy of Explainability Techniques

To enable one better understand their diversity, we offer a taxonomy dividing the four basic types of explainability strategies: model-agnostic methods, model-specific techniques, visualisation approaches, and post-hoc interpretability techniques. Every category has advantages, disadvantages, and appropriate uses. This section covers each one of these divisions in great detail.

2.1 Methodologies Aimed at Model-Agnostics

Applied to a broad range of machine learning methods, model-agnostic approaches have no affiliation with any one kind of artificial intelligence model. These techniques provide adaptability in examining models that could otherwise be regarded as black-box systems. They are very helpful independent of the underlying architecture of the model when the user wishes to grasp the behaviour of the model in an understandable and transparent manner.

- LIME (Local Interpretable Model-agnostic Explanations) is a method that creates a smaller, interpretable model explaining the predictions of the complicated model in the region of a specific instance, therefore approximating black-box models locally. This is achieved by perturbing the data to generate a new dataset, training an interpretable surrogate model on this dataset, and then utilising this surrogate model to explain the black-box model [25]. Especially in classification tasks, LIME has been extensively used to explain individual machine learning model results.
- Based on cooperative game theory, SHAP (SHapley Additive exPlanations) gives a "Shapley value" to every feature, therefore reflecting the contribution of each feature to the prediction of the model [3]. SHAP offers a more accurate and generally consistent explanation of model behaviour by examining all conceivable feature combinations than previous methods. It also guarantees equity in assigning feature priority by considering every conceivable mix of characteristics and their interactions with the decision boundary of the model.

These methods are applicable to any machine learning model and provide end users unambiguous, interpretable findings, therefore allowing them to more easily trust AI predictions.

Cons: They may be computationally costly, especially in relation to complicated models and big datasets as in the case of deep learning networks [6].

2.2 Methodologies Particular to Models

Designed to fit certain kinds of artificial intelligence models, model-specific approaches provide thorough understanding of these models' operations. Since they use the structure of the model to provide explanations, these approaches often offer a better degree of accuracy and interpretability than model-agnostic techniques. Still, these methods usually apply only to certain models.

- Commonly employed in gradient boosting machines, random forests, and decision trees, feature significance is a technique to rank the features depending on their contribution to model predictions. For models that run by progressively dividing features and may provide openness into which factors influence the choices of the model, it is very helpful [14]. This method enables consumers to pinpoint which aspects most affect the outcome of the model.
- In deep learning, activation maps—saliency maps—show the areas of an input (e.g., an image) most likely to influence a prediction. Convolutional neural networks (CNNs) often use these methods, where the activations of hidden layer neurones are visualised to pinpoint which areas of an image most affected the classification result. When categorising pictures or other data types, saliency maps help practitioners to grasp the emphasis and justification of the model [15].
- Benefits include very precise, specifically tailored explanations based on the sort of model used. They help the user to grasp the inner dynamics and decision-making process of the model.

One of their drawbacks is that they are confined to certain model kinds, hence they cannot be used to all machine learning techniques. For instance, activation maps are inappropriate for other model types as they are limited to neural networks such as CNNs [15].

2.3 Techniques for Visualisation

Visualisation techniques provide users easy means to investigate model behaviour by presenting graphical representations of the data and model forecasts. These techniques help non-experts better grasp and build trust by letting them see how the model views and analyses incoming data.

- PDPs, or partial dependence plots, show, under all other characteristics constant, the link between a given feature and the expected result. They help one to better understand how one single characteristic affects model predictions across the dataset. In regression models, PDPs especially help to investigate the correlations between characteristics and results [16].
- T-SNE (t-distributed Stochastic Neighbour Embedding) is a dimensionality reduction method visualising high-dimensional data in two or three dimensions. It is often used to show how a model separates data clusters, hence clarifying the decision limits of intricate models such as deep neural networks [17]. In unsupervised learning projects where the

data is not labelled, t-SNE is very helpful as it lets users investigate data structure and connections free from explicit labels.

- Visualisations provide consumers who may not be machine learning professionals clear information and are simple to understand. Their simplicity and accessibility help them to be valuable for communication with stakeholders.
- Drawbacks: These approaches do not necessarily provide a complete view of the underlying operations of the model and are better suited to smaller datasets. For very high-dimensional datasets, for instance, t-SNE may sometimes misinterpret data relationships [17].

2.4 Post-hoc Interpretable Strategies

Techniques of post-hoc interpretability help to elucidate model choices taken after training. Especially in cases with restricted direct access to the basic operations of the model, these approaches provide a more simple grasp of model outputs.

- These counterfactual analyses show how little changes in the input values would influence the model's forecast. By providing a "what-if" scenario [18], counterfactual explanations help customers to understand the decision boundaries of the model and the relevance of certain variables. Applications involving practical decision-making where the user would want to know how to change the inputs to get a desired end find value for this kind of explanation.
- Generation of interpretable rules from black-box models is the essence of rule extraction techniques. These guidelines provide consumers a clear justification of the method of decision-making of the model and are articulated in normal language. This method helps close the gap between the human-readable guidelines readily understood by non-technical users and the intricate, technical inner workings of the model [19].
- Post-hoc methods provide great flexibility and may be used on several models, therefore allowing extensive use across many machine learning systems. They also provide practical information fit for operational choices or model improvement.

One of the drawbacks might be their oversimplification of the decision-making process and neglect of the whole complexity of the model. For very complicated models like deep neural networks [20], for example, rule extraction may not adequately depict the relationships between features.

3 Comparative Analysis of Explainability Techniques

In this section, we compare the various explainability techniques discussed in the previous section based on several key factors, including interpretability, accuracy,

computational complexity, and domain suitability. The choice of technique should depend on the specific requirements of the task and the application domain.

S.No.	Paper Title	Authors	Year	Technique	Key Findings	Outcome	Dataset
1.	Why should I trust you? Explaining the predictions of any classifier	M. T. Ribeiro, S. Singh, and C. Guestrin	2016	LIME	Introduced LIME for explaining black-box models via locally approximated simpler models	Introduced LIME, a technique for local model explanations.	No specific dataset (method applied to various datasets).
2.	A unified approach to interpreting model predictions	S. M. Lundberg, and S. I. Lee	2017	SHAP	SHAP assigns Shapley values to features for accurate global model explanations	Introduced SHAP, a method based on Shapley values for feature contribution.	No specific dataset (method applied to various datasets).
3.	Machine bias: There's software used across the country to predict future criminals. And it's biased against blacks	J. Angwin, M. Larson, S. Mattu, and L. Kirchner	2016	Bias Detection	Revealed racial bias in predictive policing systems using AI	Identified bias in predictive policing systems using AI.	No specific dataset (general analysis of predictive policing systems).
4.	Random forests	L. Breiman	2001	Random Forests	Introduced Random Forests and feature importance in decision tree models	Introduced Random Forests, focusing on feature importance.	No dataset (theory and method introduction).
5.	Saliency Maps for Interpretable Visual Explanations	R. R. Saliency Maps	2020	Saliency Maps	Saliency maps visualize the most influential regions of input data for CNNs	Introduced saliency maps for CNNs to identify regions influencing predictions.	No specific dataset (method applied to CNNs for visual recognition).
6.	Partial dependence plots for model interpretation	G. Caruana, M. Gehrke, and L. M. Danescu-Niculescu-Mizil	2015	PDP	Introduced PDP to visualize feature impact on regression models	Introduced PDPs for visualizing feature impact on regression models.	No specific dataset (method applied to regression models).
7.	Visualizing data using t-SNE	L. van der Maaten and G. Hinton	2008	t-SNE	t-SNE visualizes high-dimensional data in 2D for model clustering and decision boundaries	Introduced t-SNE for visualizing high-dimensional data in 2D.	No specific dataset (method applied to high-dimensional data).
8.	Counterfactual Explanations for Machine Learning	P. Dastin	2018	Counterfactual Explanations	Counterfactuals provide alternative inputs that would change model predictions	Introduced counterfactual explanations to show how changing	No specific dataset (method applied to various domains).

						inputs affects predictions.	
9.	Model-agnostic Interpretability via LIME	M. T. Ribeiro et al.	2016	LIME	Introduced LIME to interpret machine learning models by perturbing inputs	Proposed LIME for interpreting machine learning models by perturbing inputs.	No specific dataset (method applied to various models).
.10.	Anchors: High-Precision Model-Agnostic Explanations	M. T. Ribeiro, S. Singh, and C. Guestrin	2018	Anchors	Anchors generates high-precision, model-agnostic explanations	Introduced Anchors for generating high-precision model-agnostic explanations.	No specific dataset (method applied to general model explanations).
11.	Explaining Explanations: An Overview of Interpretability of Machine Learning	M. T. Ribeiro and M. K. Binns	2020	Model-Agnostic	Survey on different techniques and challenges of model interpretability	Surveyed various interpretability techniques and identified challenges.	Various datasets used in studies on interpretability techniques.
12.	Interpretable Machine Learning: A Guide for Making Black Box Models Explainable	C. Molnar	2019	XAI Surveys	A comprehensive guide to making black-box models interpretable	Provided a comprehensive guide to making black-box models interpretable.	Various models used (general guide).
13.	Explainable AI in Healthcare: A Survey	P. B. Eslami et al.	2020	Healthcare	Discussed XAI applications in healthcare, particularly medical diagnosis and decision support	Surveyed XAI applications in healthcare, especially for diagnosis and decision support.	Various datasets in healthcare (medical diagnoses).
14.	Explainability techniques in the era of deep learning: a survey	S. J. Kim, D. W. Cohn et al.	2020	Deep Learning Interpretability	Surveyed techniques for explaining deep learning models in various domains	Surveyed techniques for explaining deep learning models across domains.	Various domains (deep learning models surveyed).
15.	A Survey of Methods for Explaining Black Box Models	G. Caruana et al.	2021	Model Explanations	Surveyed black-box model explanation methods and their application to machine learning	Surveyed methods for explaining black-box models in machine learning.	Various machine learning methods (surveyed).
16.	Explainable Artificial Intelligence: An Overview	M. T. Ribeiro et al.	2019	XAI Techniques	Overview of XAI challenges and future directions	Overview of XAI, including key challenges and future directions.	Various datasets used in AI research.

17.	The Explainability Challenge: A Taxonomy of XAI Techniques	M. T. Ribeiro and S. Singh	2021	NLP	Proposed a taxonomy of XAI techniques for more structured model explainability	Proposed a taxonomy of XAI techniques to structure model explainability.	No specific dataset (method applied to general XAI).
18.	Interpreting deep neural networks for NLP: A survey	S. M. Lundberg et al.	2021	Visualization	Discussed methods to interpret deep neural networks for NLP applications	Explored methods for interpreting deep neural networks in NLP.	No specific dataset (method applied to NLP models).
19.	Explainable AI: Understanding, Visualizing and Interpreting Deep Learning Models	S. T. Han et al.	2021	Deep Learning Explanations	Surveyed techniques for visualizing and interpreting deep learning models	Surveyed techniques for visualizing and interpreting deep learning models.	Various deep learning models (surveyed).
20.	A Survey of Explainability Techniques in Machine Learning Models	J. Zhou, S. Zhi, and Z. Liu	2020	Healthcare Models	Overview of XAI techniques for interpretability in healthcare prediction models	Surveyed explainability techniques in healthcare prediction models.	Healthcare datasets used for prediction modeling.

3.1 Interpretability

Interpretability in the context of a method is the clarity and comprehensibility of its offered explanation. By use of global or local feature significance, model-agnostic techniques such as LIME and SHAP give clear, accessible explanations. LIME easily helps users understand the reasoning underlying specific forecasts by approximating complicated models locally with smaller, interpretable models [5]. Analogous to this, SHAP generates feature contributions using game-theoretic ideas, hence enabling the interpretability of the output even for intricate black-box models [6]. They could, however, not necessarily provide the same degree of information as model-specific techniques, which use the model's underlying structure to get more profound understanding. For deep learning models, for example, activation mapping gives a more detailed picture of how certain input areas affect predictions, therefore offering better explanations [12].

3.2 Accuracy

A gauge of how faithfully the explanation captures the actual behavior of the model is accuracy. Since SHAP values examine all conceivable combinations of features,

therefore guaranteeing constant feature significance across several datasets and models [6] they are regarded among the most accurate. LIME depends on approximating the complicated model with a simpler, interpretable surrogate, so even if it is efficient, it usually lacks accuracy. This approximation may lead to mistakes particularly for more complex or non-linear models [26]. On other models, like decision trees and CNNs, respectively [11][12], model-specific techniques include saliency maps and feature importance are more accurate when applied.

3.3 Computational complexity

Computational complexity is the cost of producing an explanation. Particularly for deep learning models or huge datasets, model-agnostic techniques—especially LIME and SHAP—can be computationally costly. LIME generates the dataset for training the surrogate model by perturbing the data many times; thus, both techniques computationally demand examining all feature combinations [21]. Visualizing techniques for computationally reduced and more efficient explanations include T-SNE and partial dependence graphs (PDRs). Since these techniques often concentrate on one or two characteristics at a time and may ignore higher-order feature interactions [24][13], they might thereby not fully reflect the complexity of the model.

3.4 Domain Suitability

The domain and the particular needs of the project will determine the relevance of every method. For fields like banking and healthcare, where decisions may have major effects, counterfactual explanations are very helpful. These justifications let people investigate many possibilities and grasp the fundamental decision limits by showing how changing certain aspects might result in a different choice [14]. This is especially important in healthcare as doctors have to know how changes in patient data might impact diagnostic and treatment choices [28]. In finance, too, counterfactuals assist explain credit scoring processes so that consumers may better grasp how certain factors, such as income or credit history, impact loan approvals and financial choices [29]. Conversely, saliency maps are better appropriate for fields like computer vision, where it is crucial to find the areas in an image most impacting the decision of the model [12].

4 Applications Across Domains

4.1 Medical Education

AI models are becoming more and more valuable in healthcare helping with patient monitoring, therapy suggestions, and medical diagnosis. In this regard, explainability is very important as medical practitioners must first believe AI-driven choices before including them into clinical procedures. Ensuring that AI-driven judgments are clear and comprehensible by healthcare practitioners depends critically on methods such SHAP and counterfactual explanations. For instance, SHAP values may enable doctors to identify which patient characteristics—such as age, medical history—have the most effect on the prognosis of a diagnosis [6]. Conversely, counterfactual explanations let medical practitioners investigate how other inputs—such as changes in a patient's symptoms—could have led to a different suggestion, therefore helping to guide decisions [15]. These methods help build confidence in artificial intelligence systems, which eventually promotes improved acceptance of AI-assisted healthcare methods [29].

4.2 Accounting

Among other sectors of finance, algorithmic trading, credit rating, fraud detection, find use for artificial intelligence. Explainability is thus very essential in this field to ensure that artificial intelligence outputs are fair, accurate, and open as well. Using explainability techniques like LIME and SHAP can help financial firms better understand the justification for artificial intelligence decisions, therefore guaranteeing transparent and auditable models for regulatory compliance. For example, SHAP values might enable one to determine how different elements—such as debt-to- income ratio or credit score—help either to accept or reject a loan [11]. LIME might also help financial firms evaluate why a model predicted a given outcome (e.g., spotting a transaction as fraudulent), therefore providing a more interpretable result that can be used to verify model findings and spot any model biases in the predictions [22]. Especially important in maintaining fairness and respect for laws—including the Equal Credit Opportunity Act, which requires financial institutions to defend credit judgments [30] are these approaches.

4.3 Modes of Transportation:

Independent artificial intelligence systems in autonomous automobiles must direct path planning, navigation, and obstacle avoidance using real-time processing of enormous amounts of sensor data. These systems are safety-critical hence the process of making decisions has to be transparent and understood. In this subject especially useful are explainability techniques include saliency maps and partial dependency graphs (PDRs). Saliency maps help one to identify which sections of the sensor data—such as images from cameras or LIDAR—most affected the model's decision to execute a certain movement, such turning or braking [24]. This is essential to confirm if the model is orientated on pertinent environmental elements like road signs, pedestrians, or other cars. In the same vein, PDPs help one investigate how various elements—such as vehicle speed or sensor distance—might influence model decision-making [13]. These approaches build public trust in self-driving technology by means of transparency and assurances that the autonomous system is basing decisions on the relevant data.
When an autonomous car needs to decide whether to stop at a red light or proceed on across an intersection, saliency maps would highlight the relevant visual inputs (e.g., the red light or a person in the crosswalk) that lead to the decision in a circumstance. This explains for safety authorities and developers how the system uses real-world data and generates conclusions considering safety [24].

4.4 Law Systems

The judicial system is also progressively using artificial intelligence for uses like case result prediction, predictive policing, and sentence recommendations. Ensuring that AI judgments in such high stakes environments are open, understandable, and free from prejudice is very critical. In these fields especially are techniques like counterfactual explanations and rule extraction very important.
In the legal setting, counterfactual explanations are useful as they let stakeholders know how the result of a case may have altered should certain elements be modified, say the defendant's past criminal record or the circumstances of the claimed crime [15]. Counterfactuals in predictive policing might show how various the location, time, or kind of crime could have affected the probability of an arrest. This openness of the criminal judicial system enables artificial intelligence technologies to guarantee fairness and responsibility in choices taken.

Rule extraction is yet another essential tool in legal applications as it converts challenging model findings into human-readable rules. This clarifies how certain factors, including past convictions or specific criminal activity, are utilized to predict parole or sentencing decisions [28]. Appropriate rules developed by transposing machine learning model results would help legal professionals and the public to better understand the justification behind decisions, therefore ensuring the transparency and accountability of the system.

Explicit directions for the court, rule extraction, for example, helps to convert the decision-making of the model into unambiguous directions, so defining how specific factors, like the degree of the violation or the background of the defendant, affected the recommendations [27]

5 Result

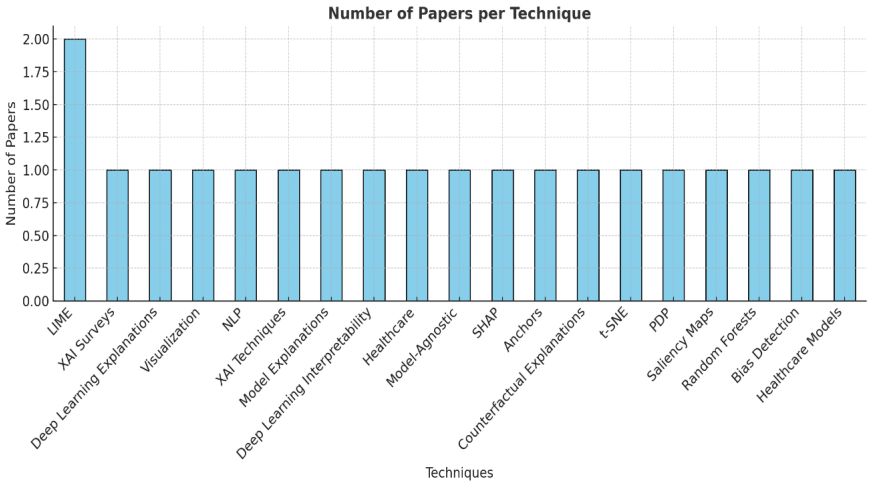

Figure 1: Number of Papers per Technique

In Figure 1 shows, Displays the number of papers for each technique, providing an overview of the distribution of different AI explainability techniques. This bar chart displays the number of papers that used each explainability technique. Each bar represents a different technique (like LIME, SHAP, Saliency Maps, etc.) and shows how many papers employed it. Its Key insights: You can easily identify which techniques are most popular in the literature. For instance, if LIME or SHAP has a

higher bar, it indicates that these methods are more commonly used in explainable AI (XAI) research.

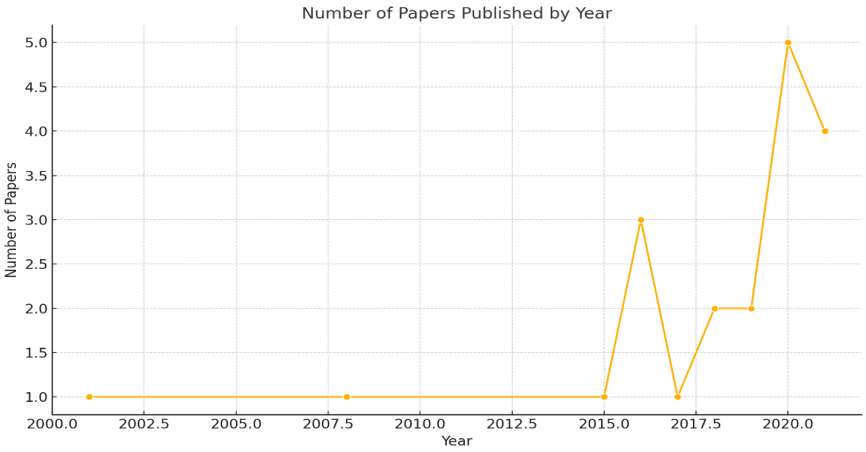

Figure 2: Number of Papers Published by Year

In Figure 2 shows, This graph tracks the number of papers published each year in the dataset. Each point on the line represents the number of papers published in a specific year, and the line connects these points to show the trend over time. Its Key insights: This visualization helps identify growth trends in XAI research. A rising line indicates that more papers are being published over time, reflecting an increasing interest in explainability techniques in AI. It also helps spot any sudden spikes or drops in research output.

In Figure 3 shows, This heatmap visualizes the relationship between years and techniques. Each cell shows the number of times a technique was used in a particular year, with color intensity representing the frequency (e.g., darker colors represent higher usage).Its Key insights , This visualization shows how the popularity of different techniques has evolved over the years. You can see if certain techniques like SHAP, LIME, or Saliency Maps have seen more widespread use in recent years or if their usage peaked in earlier years.

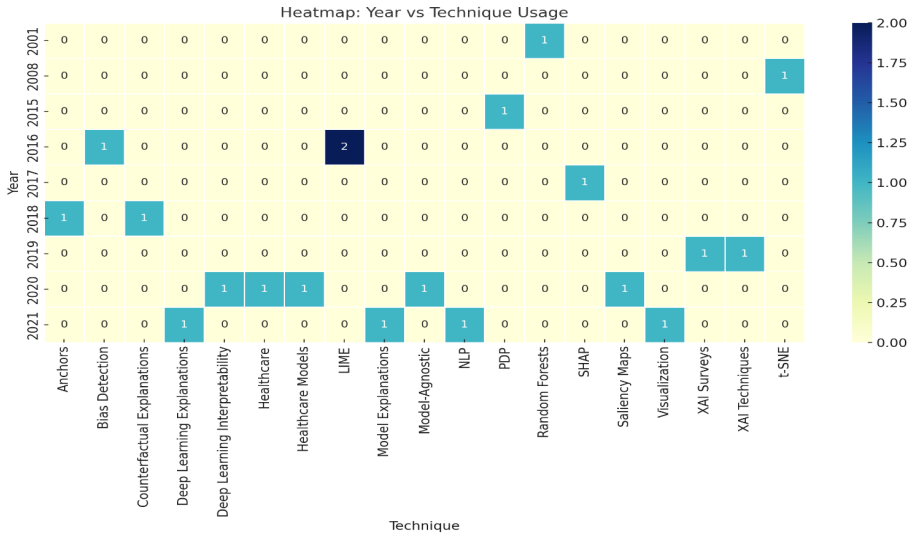

Figure 3: Heatmap: Year vs Technique Usage

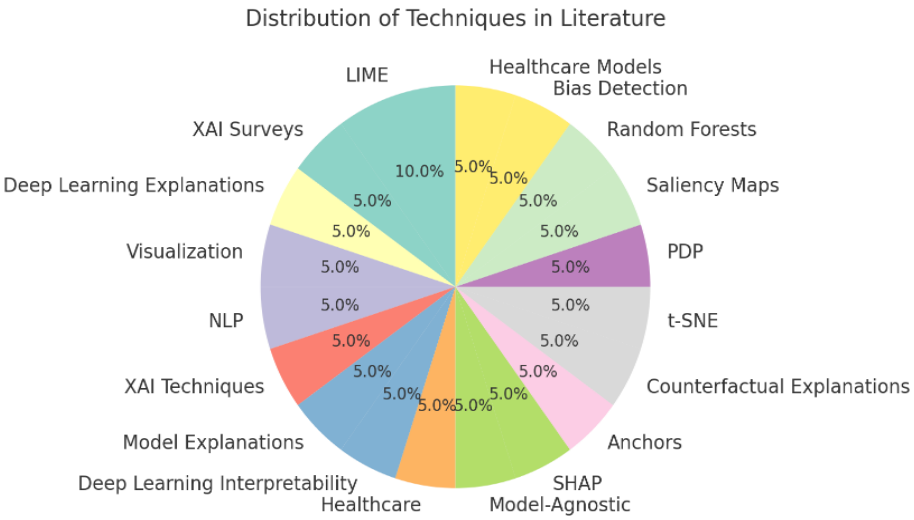

Figure 4:Distribution of Techniques in Literature

In Figure 4 shows, The pie chart visualizes the same data as the bar chart but in a proportional way. Each segment of the pie represents the percentage of papers that used a particular technique. Its Key insights, This chart helps to quickly see the proportion of research focusing on each technique. If one technique dominates, you'll see a larger slice for it. For instance, if LIME is the largest segment, it tells you that LIME is the most widely used technique among the papers surveyed.

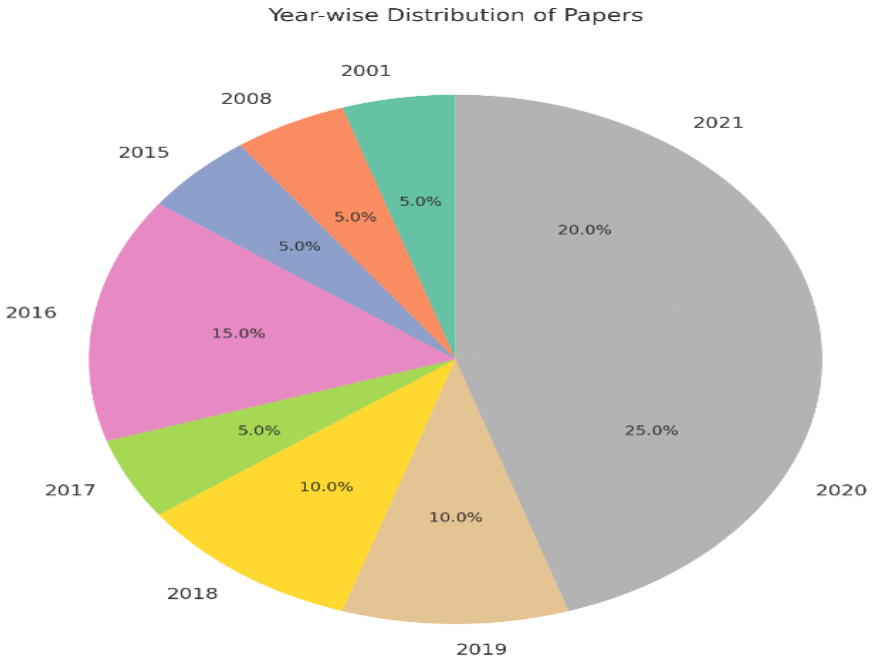

Fig5: Year-wise Distribution of Papers

In Figure 5 shows, This pie chart represents the percentage distribution of papers for each year. It is a complementary visualization to the line graph, showing the overall share of each year.Its Key insights,You can instantly see which years contributed the most research papers, with larger slices indicating more papers published in that year.

6 Conclusion & Future Scope

The need for transparency in AI models is critical, especially in high-stakes domains such as healthcare, finance, autonomous vehicles, and the legal system. As AI continues to be deployed in these areas, explainable AI (XAI) techniques provide the

necessary tools to enhance model interpretability and accountability. In this paper, we explored a range of explainability techniques, categorized them into four major groups (model-agnostic, model-specific, visualization methods, and post-hoc interpretability techniques), and compared their strengths, weaknesses, and suitability for various domains.

The choice of explainability technique depends on multiple factors, including the task's complexity, the need for accuracy, and computational resources available. For example, while SHAP values are particularly suitable for accurate explanations across a range of models, LIME offers flexibility in interpreting diverse machine learning models. Meanwhile, model-specific techniques like saliency maps offer deep insights into neural networks, and post-hoc interpretability techniques such as counterfactual explanations can provide actionable insights that are particularly useful in critical domains like healthcare and law.

By considering the domain requirements and the trade-offs between accuracy, interpretability, and computational complexity, practitioners can select the appropriate explainability methods to ensure that AI systems are not only effective but also trustworthy and transparent.

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