International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN (Online): 2347-5552, Volume-13, Issue-6, November 2025
DOI: https://doi.org/10.55524/ijircst.2025.13.6.2
Article ID IRP-1686, Pages 8-19
www.ijircst.org

Explainable Artificial Intelligence (XAI) for Distributed Systems: A Survey

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Received: 8 October 2025 Revised: 23 October 2025 Accepted: 6 November 2025

ABSTRACT- Black-box artificial intelligence (AI) models and their nature are such that it does not permit end-users to perceive or sometime reliance the outputs created by that type of model. Artificial Intelligence applications, where not only the solutions but also the selection paths that are lead to the solution are also important, like black-box Artificial Intelligence models, are not enough. Explainable Artificial Intelligence delivers that type of job and specifies a bundle of Artificial Intelligence models which are explainable by the end users. Freshly, A number of Explainable Artificial Intelligence models have addressed this issue surrounded by deficiency of explainability and interpret-ability of the black-box models in several application domains like energy, healthcare, and financial areas. The idea of Explainable Artificial Intelligence has increased and is gaining for high attraction. Freshly, its combination into the different Distributed systems is under described and need attention. This paper contains a detailed systematic review of past studies by using Explainable Artificial Intelligence models in the environment of Distributed system domains. We grouped these findings and studies in accordance to their methodological analysis and domains. Our focus is on the problems, challenges plus different issues and provide different future directions to provide guidelines for the researchers and the developers for potential upcoming scenarios and investigations.

KEYWORDS- Explainable Artificial Intelligence (XAI), Distributed Systems, Distributed computing, Explain-ability, Decentralization, Federated Learning

I. INTRODUCTION

The rapid proliferation of a domain called Artificial Intelligence (AI) in modern computing infrastructures enhancing the autonomy, adaptability, and intelligence of software systems [1]. Particularly, the fusion of AI with distributed **systems**—such as cloud computing, edge computing, and federated learning—has opened new frontiers in large-scale data processing, decision-making, and automation [2]. These systems enable real-time and decentralized intelligence in diverse domains, including smart cities, industrial automation, healthcare, finance, and cyber security. However, despite their impressive performance, many AI models, particularly, deep learning areas and architectures, directs as black boxes**,** offering limited transparency into decision making. this poses a major obstacle in military and security sensitive application in trust accountability, fairness and regulatory compliance.users always demands in AI applications that can justify their output in human readable and understandable form. Particularly when these systems are integrated into distributed environment [3]. To address these challenges the XAI has emerged a solid and very vital research area focus on enhancing the interpretability and transparency of AI models. XAI methods intent to make up the actions of AI systems more flexible and easier to understandable by humans without lowering down performance. Indifferent distributed environments, the combination of explainable artificial intelligence is more complex because of causes such as unsimilar computing resources, distributed data storage, dynamical topology, on spot processing requirement, and different constrained devices at the edge [4]. these elements make new technicality and operationality challenges in designing, styling and delivering explainable Artificial Intelligence solutions. By applying explainable artificial intelligence in the relation to distributed systems presents specific challenge and constraints. Distributed AI systems often affect multiple factors operating asynchronously across the diverse circle with varied computational capabilities, network conditions, and data privacy requirements [5]. Moreover, different edge devices and integrated systems may have short memory and processing power, making it difficult to implement complex explain-ability models. Additionally, the decentralized nature of these systems can track to inconsistent or incomplete access to data and model parameters, further complicating the task of generating accurate and coherent explanations [6].In this survey we discuss a detailed and well-structured review in explainable artificial intelligence techniques designed for distributed systems. We start with the starting concept that are important both in XAI and distributed computing and goes on deep for detailed architecture, Next we present a taxonomy of XAI methods applicable to several architectures of distributed systems such as cloud edge hierarchies, different distributed and federated learning platforms, different peer to peer systems, and block chain based AI systems [7]. We studied how various learning models—supervised, unsupervised, and reinforcement learning—affect the design of explain-ability ways in distributed environment contexts. Furthermore, we cover system level constraints and resource constraints, each of which causal factor of the feasibility of delivering XAI mechanisms. We also dig in into privacy and security of XAI and distributed systems, and examine how different techniques like differential privacy, secure multi-party computation, and homomorphic encryption intersect with explain-ability in sensitive environments [8]. To elaborate practical relevancy, we survey a wide range of applications that performs for explainable distributed AI, including different smart grids, autonomous and robotics environment, cooperative robotics, tel-medicine, and distributed financial systems. With the help of these studies, we investigated that how XAI boost user trust understanding and control in complex and distributed systems [9]. This survey facilitates a wide range of summary of XAI techniques and their practice in distributed systems We classify the existing literature based on types of distributed architectures, levels of model interpret-ability, and learning paradigms. Furthermore, we discuss the trade-offs between explain-ability, scalability, resource efficiency, and system latency, which are critical in distributed environments. We also examine practical applications and highlight emerging trends**,** such as XAI in federated learning, edge AI, and privacy-aware explain-ability [10]. By identifying significant challenges, different open-end research issues, and upcoming directions**,** this paper is important for researchers, practitioners, and system designers aiming to build trustworthy and transparent distributed AI systems**.** However, according to our knowledge and understanding, there is not any existing survey paper related the use of Explainable Artificial Intelligence methodologies in Distributed systems area. To accomplish this gap, in this paper, we furnish a complete transparent and understandable review of current and recent studies and theories on Explainable Artificial Intelligence in the distributed systems Environment. The primary parts and contributions of this paper are as follows:

We justify Explainable Artificial Intelligence terminology and methodologies in simplex and clear-cut manner for new researchers in this domain. A comprehensive and complete review of the actual studies that addresses Explainable Artificial Intelligence methodologies in distributed systems environment. Different emerging challenges and newly opened issues in Explainable Artificial Intelligence from a Distributed appearance and sum-up different future research aspects. The structured is as follows.

Part II, we discuss the taxonomies, terminologies and methodologies of XAI.

Part III, contains needs and benefits XAI and Distributed systems.

Part IV, consist of ongoing research which addresses Explainable Artificial Intelligence with respect to Distributed System application domain.

Part V contains different open-end challenges and upcoming directions and Part VI ends the paper.

A. XAI

i) Terminology and its Definitions

There is a problem called interpreting and explaining and its very common angstrom all domains specially in computer science and it's been faced since 1970s. As time goes and it's the age of AI applications particularly since 2016, a term explain-ability gaining more attention and consideration. Different academia's used this term XAI and IML regularly in literature . IML is used to described the sense of machine learning algorithms and it's a part of Explainable artificial Intelligence[11].even though some systems are explainable by itself. particularly determining what is a great quality explanation or not is a debatable matter in the literature [12]. the IML and XAI are same terms and used in literature[11] and both focuses on interpret-ability and explain-ability but there is a foundational difference between these two terminologies.To sort out the similarity and the differences between these similar terminologies, we furnish brief explanations of this which is as follows [5][9][12][13].

- Explain-ability: Explains the workings of the model internally.
- Interpret-ability: Termed as a model's ability to extend its prediction which can be understandable by humans and this can be described with the help of transparency.
- Understandable: It contains the details that shows how this working done without explaining internal details.
- Comprehensibility: It expresses the ability learned information to create it understandable near to humans.
- Transparency: Understood easily by humans.
- Faithfulness: The power of always selecting the relevant and related features.
- Informativeness: Its basically provides the information fro humans
- Explicitness: To provide clear transparent and short form explanation.

These all terms are draw in Figure 1.

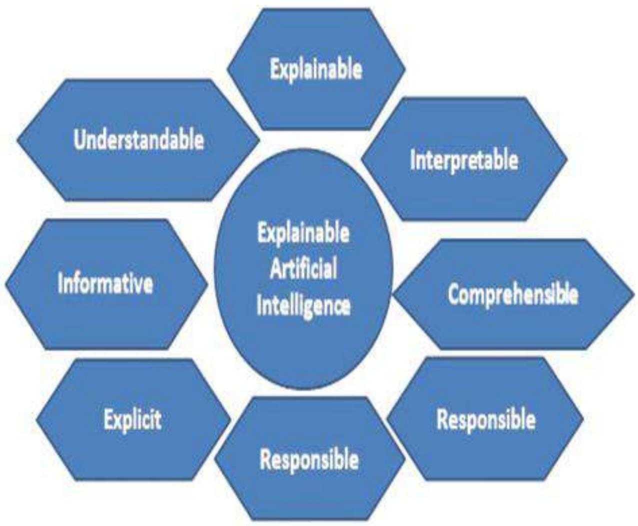

Figure 1: Terms in XAI

ii) *XAI Taxonomy*

Explainable Artificial Intelligence can be gouped up from several viewpoints [11], [14], as described in Figure 2. It is necessary to record that these categorizations may sometimes intersect, meaning a singular term could suit into multiple groups at once. For instance, an XAI method may be model-agnostic, post-hoc and deliverable at a localized level simultaneously. Therefore, to guarantee precision, every formulation should be measure on a case-by-case ground within its single sub-group. The figures stated in the hierarchy service as examples, and other visible states may also effectively carry the aforesaid structural associations.

iii) Ante-hoc vs. Post-hoc

XAI methods can be mixed at different states of model creation methods—before training, during training, or after training. Ante-hoc methods provide interpretability either before training begins or while the model is being trained, resulting in model that is inherently explainable by designing. Examples contain (DT) decision trees and (SLRM) sparse linear regression model, which artificially show their decision logic.

On the other hand, post-hoc when our model needs to be trained, we apply this technique. These methods retrospectively describe black-box model's behaviour and can also complement ante-hoc approaches to improve overall interpret-ability.

Model-specific vs. Model-agnostic- Explainable Artificial intelligence processes can also be grouped on their relevance to various model types.

Model-specific- A particular model style and architecture is explained by creating these types of methods. Like, some methods are explicitly plan to examine deep neural networks (DNN) by leveraging their style, structure and factors to produce explanations.

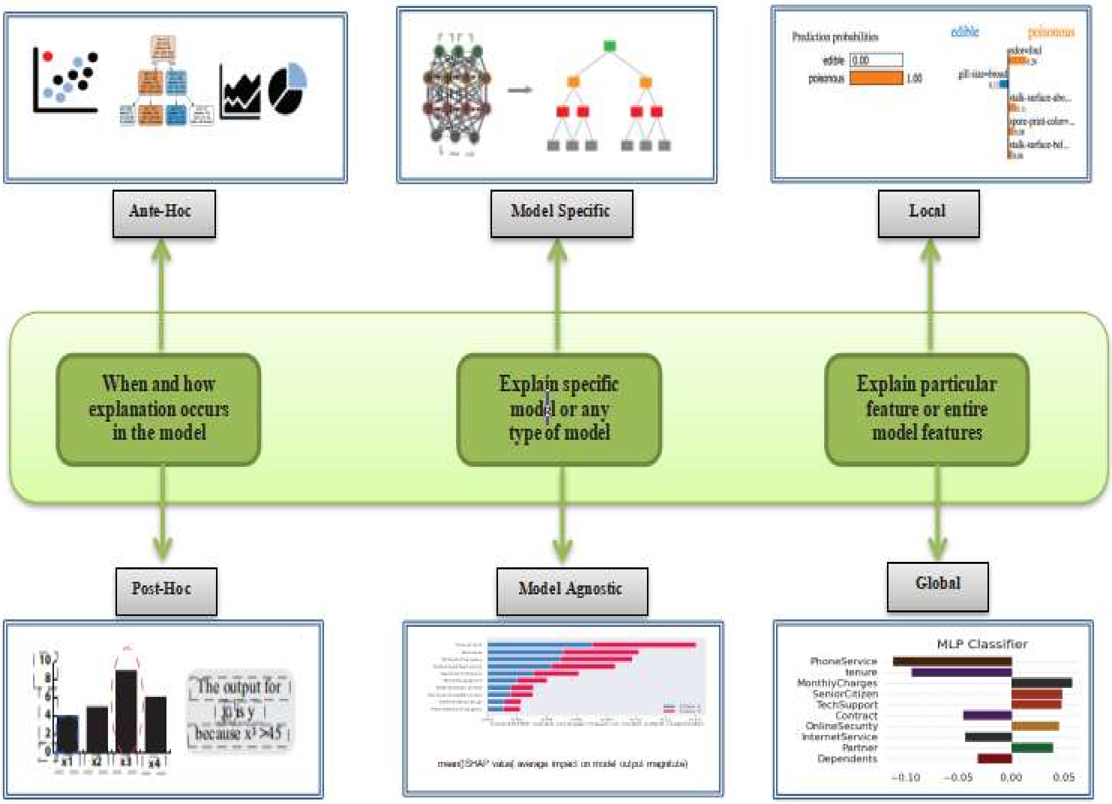

Figure 2: Taxonomy of XAI

Black-box models almost achieve higher predictive accuracy and performane, their complexness produces them integrally opaque. Model-specific interpretability methods are created to justify specific architectures by leveraging their interior structures, but this specialization bounds their adoption when other explanation designs are needed.

Model-agnostic approaches get over this restriction through their flexible platform. This methodology operates openly of framework architecture, enabling conformable interpret-ability across various algorithms while maintaining explanatory power.

B. Scope of Explanations

i) Local Interpret-ability

- Focuses on explaining individual predictions or small data clusters
- Particularly effective when decisions rely on limited, clearly-defined features
- Provides case-specific insights into model behavior

ii) Global Interpret-ability

- Characterizes overall model behavior across the complete input space
- Identifies system-wide patterns and dominant feature relationships
- Delivers comprehensive understanding of decision-making mechanisms

The differentiation between the local and the global perspectives enables researchers to choose appropriate explanatory process based on their particular analysis requirements, from detailed case examinations to broad model assessments.

C. Explainable Artificial intelligence Methodologies

As XAI becoming famous in AI, various types of this methodologies are developing. In this literature, there are various XAI methodologies to assist inform and execute the explanation of black-box models in XAI. These methodologies follow different plans and furnish various interpretations [15]. Here, we categorize them into 5 different groups. Visible Explanation: Visible explanations consist of a set of methodologies to analyse the association among end results like input and output, which let users to realize the part of every input to the output. In this scenario the characteristics set are small, explaining these correlations is convenient for end-users. Local level and global level explanations are assisted visibly. However, as the characteristic is large, visible explanations can let down to imagine correlations accurately, causing users to misunderstand them. Partial Dependence Plot (PDP) [16] facilitates global explanations and uncovers the dependency among the input characteristic and output. Individual conditional explanation (ICE) [17] scheme is a much recent methodology that's related to PDP. PDP manages and calculates the mean value over the marginal level distribution, whereas ICE keeps the complete distribution. Accumulated Local Effects (ALE) [18] scheme take averages variations in prediction level and accumulates them on local level grid. Also, Ceteris Paribus (CP) [19] plots and Breakdown plots [20] are also employed to visualize the causal factor of property on the models' predictions for a particular data case.

i) Feature-based Explanation-

Feature-based schemes, like visible explanation methodology, purpose to assess the share of properties to the model's prediction. Moreover, they considered some sections like type, comprehensibility and robustness. Statements can be global or local. Likewise, it can be model-agnostic or model-specific. SHapely values is a game-theoretic moves to find out the feature value of the model. Then, SHapley Additive explanations (SHAP) [21] methods use Shapely values and it is planned for global and local explanations. Besides, KernelSHAP [21] designed to defeat the conditioned expectations solutions of SHAP and approximates the management and calculation of SHAP. Also, global and local level surrogate models seek to explain model's prediction. Whereas local surrogate models are just like Local Interpret-able Model-Agnostic Explanations (LIME) [22] focusing on explaining the several data instances, the global surrogate models focusing on the entire model. Anchors [23] have also the quality of the local explanations by extracting a set of the if-then rules. Feature Interaction [24] is used for identifying the interaction effects of different methodologies of the set of featured-output or featured-feature. Permutation Feature Importance (PFI) [25] is a globular explanation formulation which bases on shuffled the values of non-important attributes does not happen the prediction error. Also, Leave-One-Covariate-Out (LOCO) [26] is another methodology that refers dropping every variable equally and one at a time, developing the model, and analyses the following model's error to a criterion model that belongs of all features of this model.

ii) Examples-based Explanations

Examples-based approaches are like model-agnostic methodologies that justify either global or local activity by analyzes specific case from data. Unlike features values or visual processes, these methods aim to assist users creates an easy mental model that how decision process flows and works. Counterfactual statements [27], a widely used methodology, diagnoses how input occurrences could track to various outputs—answering in the "what if" sense. Contrastive Explanation Method (CEM) [**Error! Reference source not found.**] make attentions that why a particular prediction was carried out rather than other by specifying required and enough conditions for the decision making. Prototypes and criticisms [29] pay attention to choose symbolical or unrepresentative examples from the datasets. In addition, different algorithms like k-Nearest Neighbors (KNN) [30] and Trust Score [31] may also provide local interpret-ability.

iii) Perturbations-based Explanations

These methodologies involve systematically altering the input to observe changes in model predictions, providing insights into model behavior. Modifications can include masking, blurring, or substituting input features—either at individual feature levels or through grouped segments like super pixels [32]. Occlusion [33] is a basic technique where features are replaced (often with zeros) to determine their influence on the output. Random Input Sampling for Explanations (RISE) [34] generalizes this concept by randomly masks parts of the input. Predictions Difference Analysis (PDA) [35] evaluates each feature's importance by measuring prediction variation when uncertainty is introduced. Meaningful Perturbation (MP) [36] involves training meta-predictors to estimate whether the inputted features are active, with their predictions error serving just like a measure of explanation quality.

iv) Gradient/Back propagation-based Explanations

In contrast to perturbation methods that manipulate inputs, gradient-based methods utilize the model's internal information flow—especially during back-propagation—to assess input-output dependencies. These methods frequently generate heatmaps or attribution scores to visualize influential features. Activation Maximization [37] is one such technique that visualizes neuron responses. Saliency Maps [38], DeepLift [39], and DeepSHAP [**Error! Reference source not found.**] (an efficient extension of KernelSHAP for deep networks) offer localized explanations. CNN-specific methods include Deconvolution [41] and Guided Backpropagation [42], which trace contributions from the output back to the input. Class Activation Maps (CAM) [43] are designed to interpret CNN predictions by highlighting class-relevant regions in input images, and this is further extended by Grad-CAM [44] to support a broader set of CNN architectures.

II. ROLE OF XAI IN DISTRIBUTED SYSTEM

The Integration of XAI into Distributed Systems systems continues to spark discussion in academic and practical domains. According to Doshi-Velez [45], there are scenarios where offering explanations may not be essential. Trust in an AI system might still be justified when the effort or cost to implement explain-ability exceeds its value, when errors have minimal impact on the system's outcomes, or when the application is well-established and thoroughly validated through real-world usage. On the other hand, many researchers and practitioners assert that XAI becomes critical when users need to interpret, rely on, or control AI decisions—especially for business justification, ethical obligations, or compliance with regulations [11].

Implementing XAI in Distributed Systems systems offers numerous advantages. In complex and sensitive machine learning applications, realizing the reasons for decision can be very important for the result. XAI techniques help clarify how and why a particular decision was made. For example, consider a drone powered by AI for use in high-risk operations.

If it wrongly aims to unidentified object then this raises significant concern. In Black-box model, it is almost impossible to trace out these types of errors. However, XAI facilitates with a tool that break down and predicts the process of decision making and makes it possible to withdraw the cause of failure and also betters the systems accountability. It also uses to monitors the behaviour of machines learning models, particularly when it works with distributed systems sensors data, which is sometimes inconsistent and contains noise. These element leads the system failure but XAI helps to identify and correct this error and solves the issue and assist with more accurate and well-structured decision making. The XAI always provide localized explanations instead of only giving general insights of the system. It can explain the decision process for individuals as well. It provides high benefits for the domains like healthcare, as it is very important to rationale for a specific patient's diagnosis is more important as analyze and visualize general trends in a patient's data. XAI also make opportunity to uncover hidden insights and unrecognized relations within the data. When the machine learning algorithms are transparent. It may uncover the information and useful patterns that otherwise would be unidentified, that offers new opportunities for problem solving. And lastly, ML model's behaviour can be distorted due to errors and biases in the training data. XAI methodologies and processes help in detecting flaws at the initial development stage, helping to prevent unexpected outcomes. This makes the base of more balanced dependable and ethical systems for development of distributed applications.

A. Autonomous Systems and Robotics

In this field, AI enabled machines have the power of performing task that are difficult for human with high accuracy. These tasks may include industrial operations like welding, ironing, pressing, painting and handling different heavy machines. These tasks always performed with care as it required care and force with speed [46]. while these types of systems offer up to the mark efficiency, integration XAI which enhances their usability by assisting their decision-making process transparent and according to the understanding of humans. This increases trust and belief in accountability and dependability in autonomous systems. Wang et al. [47] uses Partially Observable Markov Decision Processes (POMDPs) approach for robots to explain their decision-making power and this framework was tested in simulated environment that reflects humans plus robotics team collaboration. This shows that by providing explanation it not only betters the performance but also ensures trust and transparency, Iyer et al. [48] provides an explainable deep reinforcement learning (DRL) scenario for the object's detection classification. This scheme emphasis object silency maps, which opens significant areas in an image. Kampik et al. [49] explains the behavioural values of autonomous agents in a human robot interaction context using a text-based scheme, through an experiment which involves ultimate game scenerio and then the researcher demonstrates that how explain-ability influences user perception and interaction with robots. Meanwhile Guo [50] designed a Double Dueling Deep Q-learning Neural Network (DDDQN) for optimizing Quality of Experience (QoE), Quality of Service (QoS) and energy efficiency in UAV-assist 5G networks. Although complete interpret-ability was not the main destination. This theory creates some portion of a explain-ability for the systems.

B. Financial Systems

Financial services are transformed by the use of Artificial intelligence as it provides less cost and enhance efficiency for different sectors, it also provides assets management, investment advisories, customer support and risk analysis [51]. because it is a high-risk domain the use of AI it introduces the significant consequences. Therefore, integrating XAI into financial applications is need of the day as it ensures safety and trust. Bussmann et al. [52] proposed an explainable artificial intelligence driven model which is designed to assess high risk factor in loan acquiring by providing factual and transparent insights into credit scores and forecast borrower behaviour using a method called TreeSHAP scheme, which consist of Shapley values for interpret-ability. Sachan et al. [53] elaborated a belief-rule-based (BRB) explainable decision support system for automatically approving loan approval system. Gite et al. [54] uses Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) for prediction of stock price. This is very helpful the investors to understand the dynamics of stock prices, the fluctuations in the price and support informed decision-making process and this model's interpretability was achieved by LIME that offers local explanations of the model. Meanwhile, Gramegna and Giudici [55] design a model that is based on technology that explains consumer attitude in terms of policy buyer or policy cancellation. XGBoost algorithm is used to analyze different structural and behavioral shapes and patterns.

C. Energy Managementc

Different decision-making systems capable with AI are being increasingly integrated into large scale distributed systems such as smart cities, interconnected smart home environments and distributed energy grids. These can be use to forecast energy consumption and emissions. Kim and Cho [56] introduced a novel energy demand prediction model that is specifically created for distributed smart environment. This scheme uses and auto-encoder based deep learning model for predict or forecast energy consumption over several intervals of 15, 30 and 45 minutes under different unusual varying environment conditions tested on 5 years household dataset of electricity usage and this model encountered 8 key features containing global power, date, potential, global strength and sub metering quality to produce predictions. this model outperformed the conventional machine learning models like MLP, Decision Trees and LSTMs in predictive accuracy terms. Amiri et al. [57] formed a model which is base on distributed AI transportation's energy predictive model using ANN. Their scheme, aimed at urban transportation networks, leveraged Local Interpret-able Model-Agnostic Explanations (LIME) to guarantee model's transparencies and support reliance in system recommendations. Sirmacek and Riverio [58] projected two explainable algorithms—1 machine learning-based and the other computer vision-based—for estimation of real-time tenancy in smart office environments by using low-resolutions thermal sensors data. To understand the decision process, SHapley Additive Explanations (SHAP) were apply, providing perception into both the impact of individual features and the importance of every pixel in spatial analysis. These scheme holds promise for improving automation and space utilization across distributed infrastructures like office buildings and smart campuses.

D. Smart Agriculture

The mix-up of AI-powered decision assisted systems in agriculture has set up the way for much sustainable and economical farming activities. These intelligent schemes facilitate better management in decisions making, but challenges stay regarding user belongings and adoption. Therefore, it is very important that all AI applications in agricultural domain are clear and approachable to end-users. Viana et al. [59] presented a machine learning theory for land management which pay attention on crops like wheat, olives and maize. The model's outcomes are various environmental and socio-economic attributes like slope, soil type and drainage densities. A Random Forest (RF) algorithm was used along with explain-ability tools like as Partial Dependence Plots (PDPs), LIME and Permutation Feature Importance (PFI) to make the model's doings interpret-able. Tsakiridis et al. [60] presented a decision support tool named *Vital*, planned to automatize irrigation in open-field farming. By integrated explainable AI processes, the system aids to optimize water usage and ensures economical irrigation management while conserving resources. In other study, Garrido et al. [61] presented a multivariate and interpret-able AI model using Artificial Neural Networks (ANN) to predict evaporated water loss in irrigation systems. The model, driven by climate and soil variables (e.g., temperature, pressure, solar radiation), incorporated decision tree-based rule inference for clearness in predictions. Kenny et al. [62] developed a case-based reasoning model called *PBI-CBR* to forecast grass growth for dairy farming. By using historical data from the same region and farms, the system provides accurate predictions with built-in post-decision explanations to support user understanding. Kundu et al. [63] proposed an IoT-driven framework for plant disease detection that automates data collection and classification. Their model, *Custom-Net*, integrates elements from ResNet, Inception, and VGG architectures and employs GradCAM to enhance explain-ability. Gandhi et al. [64] proposed a fuzzy logic-based framework aimed at automating field irrigation, mechanizing water systems, and enabling precision agriculture. Their model, based on a Mamdani-type rule system, utilizes sensor inputs like soil moisture, temperature, nutrient levels and humidity to make on-spot decisions. Tested across various crops (e.g., cotton, barley, groundnut and millets) and soil types (e.g., red, sandy, clayey), it aims to create optimal conditions for crop growth and yield maximization.

E. Healthcare in Distributed Systems

AI has direct impact on human lives by making reliability, transparency, and explain-ability essential especially in distributed and federated environments like IoT-based healthcare systems. These systems are contained interconnected layers such as edge devices, sensors and different cloud platforms required for these models that are not only trust able but also explainable at each level of decision making. Chittajallu et al. [65] designed XAI-CBIR, a human-in-the-loop explainable Artificial Intelligence system made up for surgical training. It works on a CNN-based model to acquire content from medical videos and utilizes visible saliency maps for interpret-ability, enabling feedback-based refinement in a distributed edge-cloud situation. Hatwell et al. [66] improved explain-ability in computer-assisted diagnostics by introducing the Ada-WHIPS model, which explains the decision rules in AdaBoost, making it suitable for edge-level deployments where quick and interpret-able feedback is necessary. Pnevmatikakis et al. [68] developed a risk prediction and virtual coaching platform for health insurance, utilizing Random Forest and DNN models in a distributed data processing setup. SHAP was used to explain predictions regarding user lifestyles. Gozzi et al.[69] addressed the explain-ability of distributed AI systems classifying hand movements using EMG signals, which are crucial for controlling prosthetics. They used models like SVM, LDA, XRT, and CNN across distributed platforms, and applied SHAP and GradCAM for explain-ability, with the goal of improving user experience for amputees relying on smart prosthetics. Dave et al. [70] investigated various feature-and example-based XAI methods (SHAP, LIME, Anchors, Counterfactuals, etc.) on heart disease datasets to interpret decisions made by complex models deployed in distributed health monitoring systems.Similarly, Monroe et al. [71] proposed the HihO (Hierarchical Occlusion) model, a CNN-based method that enhances the speed and interpret-ability of medical imaging analysis in Distributed Systems healthcare applications, outperforming GradCAM and RISE in efficiency on the PPMI datasets.

Table 1: Summary of XAI Studies by Distributed System's Application Domain

Domain	Reference	Year	ML/DL Models	XAI Model Name	XAI Texonomy		
					Ante-hoc/ Post-Hoc	Model Spesific / Model Agnostic	Local / Global
Autonomous Systems and Robotics	Iyer et al.[48]	2018	DRLN	SILENCY-MAP	Post-hoc	Agnostic	Local
	Guo et al. [50]	2020	DRL	-	Post-hoc	Specific	Local
Energy Management	Kim et al. [45]	2019	Autoencoder	t-SNE	Post-hoc	Agnostic	-
	Sirmacek et al. [58]	2020	CatBoost	SHAP	Ante-hoc	Agnostic	Local
	Amiri et al. [57]	2021	NN	LIME	Post-hoc	Agnostic	Local
Finance	Sachan et al. [53]	2019	-	Belief-Rule-Base	-	-	Local
	Bussman et al. [52]	2020	XGBoost	Shapley Values	Post-hoc	Agnostic	Local
	Gramegna et al. [55]	2021	XGBoost	SHAP	Post-hoc	Agnostic	Local
	Gite et al. [54]	2019	LSTM-CNN	LIME	Post-hoc	Agnostic	Local
Healthcare	Chittajallu et al. [65]	2019	ResNet50	XAI-CBIR	Post-hoc	Agnostic	Local
	Hossain et al. [67]	2020	ResNet50, Deep tree, Inception v3	LIME, GradCAM	Post-hoc	Agnostic	Local
	Monroe et al. [71]	2020	CNN	HihO	Post-hoc	Agnostic	Global
	Pnevmatikakis et al. [68]	2020	RF, DNN	SHAP	Post-hoc	Agnostic	Local
	Hatwell et al. [66]	2020	AdaBoost	Ada-WHIPS	Post-hoc	Agnostic	Local
	Dave et al. [70]	2020	XGBoost	LIME, SHAP	Post-hoc	Agnostic	Global
	Gozzi et al. [69]	2022	CNN	GradCAM, SHAP	Post-hoc	Specific	Global
Smart Agriculture	Kundu et al.[63]	2021	Garridoetal.[90]	Grad-CAM	Post-hoc	Agnostic	Local
	Viana et al .[64]	2021	RF	LIME, PDP	Post-hoc	Agnostic	Local, Global
	Garrido et al. [61]	2022	ANN	DT	Ante-hoc	Specific	Global

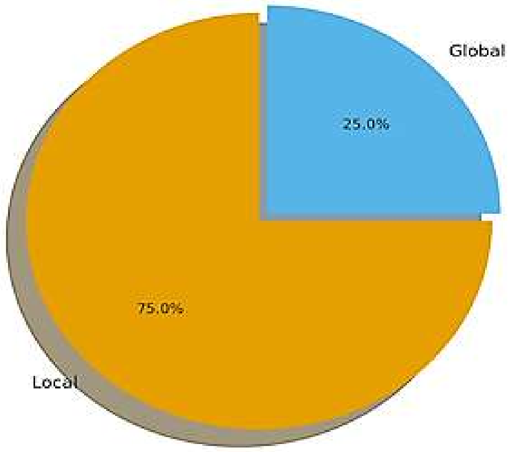

Figure 3: Proportion of Local vs Global Explain-ability in XAI Studies

We describe a proportion of Local vs global explain ability in XAI studies in Figure 3. we do studies of different domains like autonomous systems, energy management systems, finance related domain and most of the domains about 75% of overall mentioned methodologies uses local explain-ability while remaining uses global explain-ability.

Despite the progress offered by XAI in supporting complex decision-making systems, there remains fundamental hesitation in fully trusting AI technologies, as evidenced by past instances of human over-reliance on them [72]. Alongside its potential, XAI also presents a set of challenges and limitations that merit consideration [11], [35], [73], including the following: Some foundational concepts in XAI remain ambiguous or conflicting. The field lacks standardized terminology, leading to conceptual confusion. For instance, while there is general consensus that explanations should be “faithful,” there is disagreement over whether this fidelity must be model's internal workings or to the data development process itself. Such inconsistencies hinder constructive discourse and cause misinterpretation [73]. Many current XAI techniques fail to quantify expected error rates. This absence makes it difficult to evaluate explanations rigorously under scientific scrutiny, limiting the reliability of interpret-ability claims [73]. A major gap exists in defining objective, quantitative metrics to assess the completeness and accuracy of interpret-ability methods. The choice of explanations should not rely on the individual observer's domain area. Therefore, there is a pressing need for universal and consistent evaluation standards [35]. Increased transparency in model behavior, while beneficial for interpret-ability, can be exploited by malicious actors. When attackers learn which input features influence predictions, they may craft adversarial inputs with subtle changes to manipulate the model’s output [11]. Several popular XAI approaches must be assailable to adversarial s attack. This raises critical interests about their reliability, as manipulated explanations could mislead users rather than clarify model decisions [74]. The current XAI landscape lacks a cohesive framework to integrate multiple methods in order to produce more robust and comprehensive explanations. For non-expert users, generated explanations can often be unclear or misleading. These may emphasize important features but fail to explain the relationships among them or why they matter. Deeper collaboration with domain experts or advanced analytical methods is needed to uncover the meaningful connections between the attribute’s properties and their implications on the basis of decision-making power.

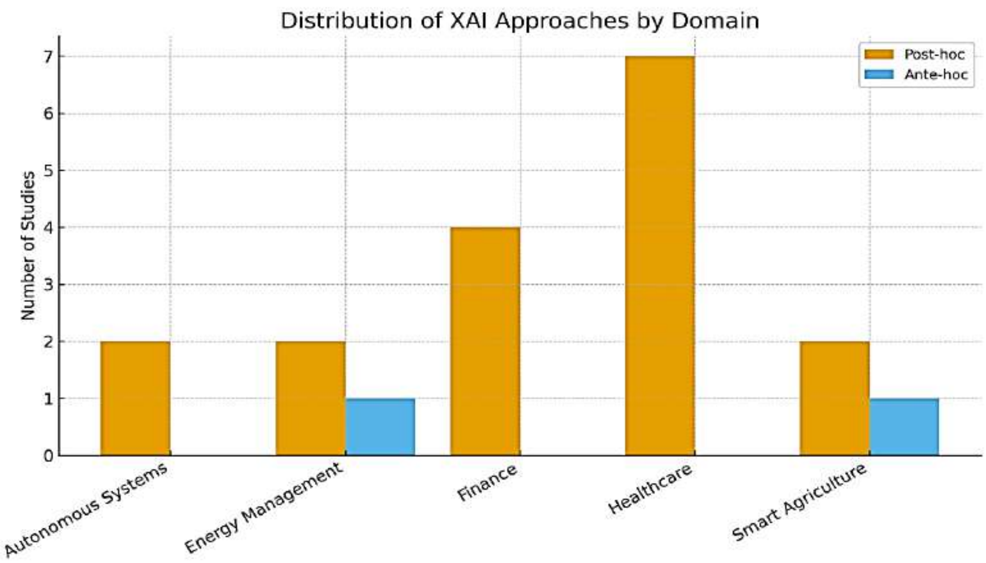

Figure 4: Distribution of XAI Approaches by Domain

Figure 4 Describe the distribution of XAI approaches by domain in which we do studies of different domains like autonomous systems, energy management systems, finance related domain, use of XAI methodologies in healthcare and smart agriculture.we compare post-hoc and ante-hoc models in these studies.

III. FUTURE DIRECTIONS FOR XAI DEVELOPMENT

Given theses challenges above, several future directions can be proposed to advance the development and reliability of XAI: Model-specific explanation methods should be prioritized, as they offer better fidelity by interpreting internal model architecture and mechanisms. In addition, integrating multiple XAI methods can address the limitations of individual approaches and lead to more complete and trustworthy explanations. Automation of XAI processes—similar to how machine learning automates tasks like feature selection and hyper-parameter tuning—can simplify explanation generation. Technological advancements in software libraries and toolkit will further enhance the capabilities of automated and interpret-able AI systems. Enhancing the safety and robustness of Explainable Artificial intelligence models is becoming increasingly crucial, especially as their use expands in areas such as Distributed Systems. Issues such as fairness, accountability, ethics, and security fall under the domain of Responsible AI and should be addressed in XAI development [11]. In Distributed networks, which may involve distributed discipline, data is produce at various layers. By providing federated learning, different fog nodes can interpret black-box models locally and offering decentralize decision-making, on the other hand the cloud server can furnish global explanation of this through summing up the insights. Given the variety of Distributed Systems frameworks and applications—from the wearable instruments to nano-IoT systems—applications-specific XAI interfaces can assist tailor explanations to the specific requirements of each area. This granularity ensures that explanations are relevant and clear for end-users.

IV. CONCLUSION

This paper emphasis a detailed review of XAI approaches as applied to distributed systems. It aims to equip researchers with a clear and thorough understanding of how XAI can enhance transparency and trust in decentralized computing environments. Initially, we outline the key motivations, requirements, and advantages of adopting XAI within distributed architectures. We then explore a deep range of XAI application across several type of distributed systems, organizing them according to system characteristics and functional domains. To ensure consistency, all discussed methods are analyzed using established XAI concepts and classifications. Lastly, we identify existing limitations and propose forward-looking research directions which can model the development of more interpretable, robust and reliable distributed AI systems.

This paper consists of a very detailed and in-depth review of different Explainable Artificial Intelligence approaches that are applied to distributed systems. The aim of this review is to equip the researcher with a transparent and through knowledge and understanding that how XAI can enhance performance, trust, transparency in decentralized computing domain. In the start we outlined the key motivations and merits of adopting the XAI within the distributed environment and architecture and then we explore more deeply and describe the range of XAI applications across several types of distributed architecture. We organize each of them with the system's characteristics and functional domains. To guarantee consistency, all the discussed methodologies are check and analyzed with the help of XAI concepts and classifications. In the end, we identified limitations and suggest forward-looking different research directions that assists and can help in modeling the improvement and development of clearer, interpret-able, robust, trustworthy distributed intelligence-based systems.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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