Selecting Explanation Methods for Intelligent IoT Systems: a Case-Based Reasoning Approach

Humberto Parejas-Llanovarced, Jesus M. Darias,
Marta Caro-Martínez[0000-0001-5239-8207], and
Juan A. Recio-Garcia[0000-0001-8731-6195]

Department of Software Engineering and Artificial Intelligence
Instituto de Tecnologías del Conocimiento
Universidad Complutense de Madrid, Spain
{hparejas,jdarias,martcaro,jareciog}@ucm.es

Abstract. The increasing complexity of intelligent systems in the Internet of Things (IoT) domain makes it essential to explain their behavior and decision-making processes to users. However, selecting an appropriate explanation method for a particular intelligent system in this domain can be challenging, given the diverse range of available XAI (eXplainable Artificial Intelligence) methods and the heterogeneity of IoT applications. This paper first presents a novel case base generated from an exhaustive literature review on existing explanation solutions for AIoT (Artificial Intelligence of the Things) systems. Then, a Case-Based Reasoning (CBR) approach is proposed to address the challenge of selecting the most suitable XAI method for a given IoT domain, AI task, and model. Both the case base and the CBR process are evaluated, showing their effectiveness in selecting appropriate explanation methods for different AIoT systems. The paper concludes by discussing the potential benefits and limitations of the proposed approach and suggesting avenues for future research.

Keywords: eXplainable Artificial Intelligence, Artificial Intelligence of the Things, Internet of Things, Case-Based Reasoning

1 Introduction

Recently, eXplainable Artificial Intelligence (XAI) has appeared intending to make users understand Artificial Intelligence (AI) models. The need to include explanations in AI models is crucial nowadays due to the application of AI in many domains, like medicine or security [27, 20, 4]. However, XAI is not only important in those domains, but in every domain where we are using black-box AI models, i.e. AI models not interpretable and understandable by their users, and, in consequence, not trustworthy [16]. Then XAI is an AI subfield whose main goal is to explain the underlying behavior of black-box AI systems to the final users, especially in critical domains [10]. The Internet of Things (IoT) encompasses some of these domains. IoT appeared recently with the objective of exploiting the potential of connected devices. Moreover, these devices can complete intelligent tasks by integrating AI models. Like any other AI system, these AIoT (Artificial Intelligence of the Things) [21] systems must also include explanations to improve the users' trust, especially when the results obtained with this kind of system are crucial in decisive situations. This way, we can coin the term XAIoT to refer eXplainable IA models applied to IoT solutions.

XAI is a field in continuous change, and consequently, there is a wide range of explainers (XAI methods) that can be applied to explain AI models [5]. However, the amount of XAI methods available is so huge that it is often difficult to know which method best applies to a concrete intelligent system. Every XAI method has its own features and can be more suitable for different explanation needs [5]. Therefore, picking the XAI method for a given AIoT system is a very complex and challenging decision-making task.

The *iSee project*[1] aims to build a platform based on a complex Case-Based Reasoning (CBR) system, where users could reuse explanation experiences for their intelligent systems. Previous results of this project [8] proposed a CBR approach that reuses knowledge about specific explanation needs and decides which XAI method is most appropriate. By extending this work to the IoT domain, in this paper we aim to build a CBR system that helps to decide which XAI method is the most suitable to explain an AIoT system. The contribution of this paper is two-fold: first, we have generated a novel case base of explanation solutions for the AIoT domain, and second, a CBR system able to identify the best explanation method for a given XAIoT need.

The paper is structured as follows. In Section 2, we study the related work about XAIoT and CBR systems. Section 3 describes the case base, its elicitation process, and formalization. We detail the CBR process in Section 4. Finally, we explain the evaluation performed (Section 5) and present the conclusions in Section 6.

2 Literature review

To understand the existing works in XAI for case-based reasoning systems in the IoT domain, we have conducted an exhaustive literature review[2] creating and employing different search queries in a systematic way, which is described below. First, we focused our search on the existing works on Case-Based Reasoning and Explainability during the last five years. As a result, we got 143[3] articles, 76% of them published in the last two years. This publication increment shows the CBR community's interest in the XAI field. Then, we extended our search to publications concerning CBR and XAI applied to IoT systems. The outcome

[1] http://isee4xai.com

[2] The database used for the review is Google Scholar https://scholar.google.com/

[3] Terms used in the query: *"Explainability", "Case-Based Reasoning"*. We delimited the search retrieving papers dated between: *2018 -2023*. We also filtered the search using only *review articles*.

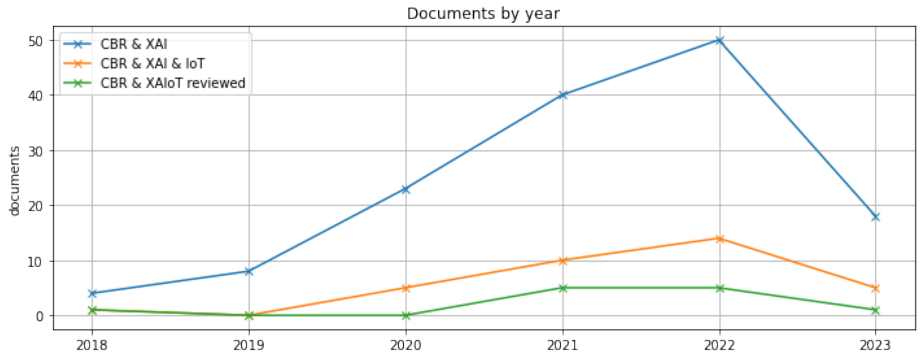

Fig. 1: Quantitative analysis of the review on explainable CBR, XAI, and IoT.

was 35[4] documents, 83% of which have been published since 2021. In Figure 1, we depict this quantitative information.

To understand the impact of XAI applied to IoT, we analyzed eighty-two (82) publications[5] obtaining a total number of one-hundred (100) different XAIoT approaches. In Figure 2, we can observe the distribution of XAI solutions according to the AI task and the IoT domain. The most prevalent task in the XAIoT literature is *Decision Support* with a prevalence of 42%, the next is *Image Processing* with 11%, and *Predictive maintenance* with 9%. Concerning the XAI methods applied to each IoT domain, most existing works are in the *Healthcare* domain. The three most applied XAI methods are *SHAP* with 18%, *LIME* with 13%, and *Grad-CAM* with 9%.

After the quantitative analysis of the existing works in XAIoT, we describe next the most relevant works and their association with CBR. Abioye et al. [1] examined several AI techniques identifying opportunities and challenges for AI applications in the construction industry. CBR systems were depicted as part of knowledge-based systems as a branch of AI. Atakishiyev et al. [6] in their study sheds comprehensive light on the development of explainable artificial intelligence (XAI) approaches for autonomous vehicles, pointing out potential applications of CBR. Islam et al. [12] consider CBR as a model for pattern recognition, validation, and contextualization. They highlight Weber et al.'s work [28], who proposed textual CBR (TCBR) utilizing patterns of input-to-output relations in order to recommend citations for academic researchers through textual explanations (mainly generated at the local scope, i.e., for an individual decision). Caruana et al.[7] demonstrated how case-based reasoning could be used to generate explanations for a neural network by using the latter to compute

[4] Terms used in the query: *"Explainability", "Case-Based Reasoning", "Internet of Things"*. We delimited the search retrieving papers dated between: *2018 -2023*. Again, filtered the search using only *review articles*.

[5] Forty-six works proposed by [12], twenty-eight papers recommended by [15], two articles presented by [2], and six recently published researches [11, 22, 9, 3, 18, 14].

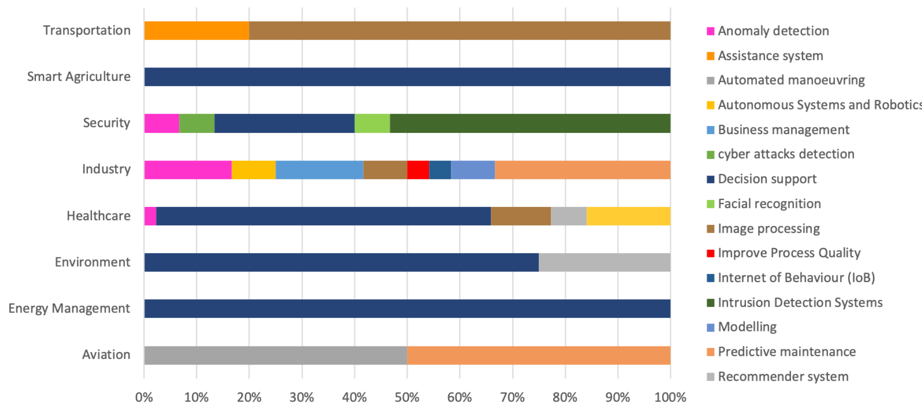

Fig. 2: Quantitative analysis of the distribution of papers on eXplainable Artificial Intelligence according to the IoT domain and AI task.

the distance metric for case retrieval. Sado et al. [25] review approaches on explainable goal-driven intelligent agents and robots, focusing on techniques for explaining and communicating agents' perceptual functions and cognitive reasoning. CBR is presented as a technique in eXplainable Goal-driven artificial intelligence (XGDAI) that enable continual learning of explanatory knowledge, domain knowledge, domain models, or policies (e.g., sets of environment states) for explanation generation. Senevirathna et al. [26] explore the potential of Explainable AI (XAI) methods, which would allow the next generation beyond 5G (B5G) stakeholders to inspect intelligent black-box systems used to secure B5G networks. Vilone and Longo [27] present a systematic review aimed at organizing XAI methods into a hierarchical classification system that builds upon and extends existing taxonomies by adding a significant dimension—the output formats. Among the XAI methods, a combination of a Neural Network and Case Base Reasoning (CBR) Twin-systems [13] maps the features' weights from the Deep Neural Network (DNN) to the CBR system to find similar cases from a training dataset that explains the prediction of the network of a new instance. Finally, we can cite *CBR-LIME* [24] as an XAI method where a CBR approach is used to find the optimal setup of the LIME explanation method. Regarding similar approaches for selecting the most suitable explanation method using CBR, in Darias et al. [8], the authors proposed capturing the user preferences about explanation results into a case base. Then, they defined the corresponding CBR process to help retrieve a suitable explainer from a catalog of existing XAI libraries.

3 The XAIoT Case Base

From the previous literature review, we can conclude that there is a wide variety of XAI methods for explaining intelligent systems in the IoT domain. All these experiences can be compiled into a case base to guide the selection of the proper explanation method for a new AIoT scenario. This is the first contribution of this paper: the elicitation of a case base of explanation solutions for the AIoT domain[6].

In this section, we describe how we formalize these cases and analyze the resulting case base.

3.1 Case formalization

The formalization of this case base is rooted in the previous analysis of existing literature on XAI solutions in the IoT domain. From this analysis, we have inferred the different features required to describe a XAIoT experience. In our formalization, the case description defines the XAIoT problem, while the solution determines the method applied to explain that situation. In the description D of a XAIoT case C, we have defined the following attributes:

- **Domain (DO).** The domain is the area of expertise or application to which the problem described in this case belongs to. The domains we find in the IoT field are *Aviation, Energy Management, Environment, Healthcare, Industry, Security, Smart Agriculture*, and *Transportation*.
- **AI model (AIM)**. The AI model is the algorithm or technique applied to solve the problem. It is the model to be explained to the user. In the IoT field, we can find the following AI models: *Case-Based Reasoning, Ensemble Model, Fuzzy Model, Neuro-Fuzzy Model, Neural Network, Nearest Neighbors Model, Tree-Based Model*, and *Unsorted Model*.
- **AI task (AIT)**. The AI task is the challenge that the AI model aims to solve. We can identify the following AI tasks in the IoT domains: *Anomaly detection, Assistance, Automated maneuvering, Autonomous processes and robotics, Business Management, Cyber attacks detection, Decision support, Facial recognition, Image processing, Process quality improvement., Internet of Behaviour, Intrusion detection, Modelling, Predictive maintenance, Recommendation*, and *Risk prediction*.
- **AI problem (AIP)**. This is the problem that the AI task implements. We can have *classification* or *regression* problems in a XAIoT case. We have considered other AI problems, but they do not apply to the IoT field.
- **XAI method input format (IF)**. The input format is the type of data the XAI method can accept and process to produce the explanations. Allowed values are: *images, time series, text*, or *tabular data*.
- **XAI method Concurrentness (CO)**. Determines if the XAI method is independent (or not) of the AI model that is explaining. If the user needs an explanation method that depends on some knowledge from the AI model, then this model is *ante-hoc*. On the contrary, if the user needs an explainable method fully independent of the AI model, then she needs a *post-hoc* XAI method.

[6] Available at: https://dx.doi.org/10.21227/4nb2-q910 [23]

- **XAI method Scope (SC)**. The scope can be *local* if the XAI method only explains a prediction or an instance of data, whereas it is *global* if the method explains the whole AI model or dataset.
- **XAI method Portability (P)**. This is another property of the XAI methods that is very well-known in the literature and that we consider in the description of each case. The portability feature points out if the XAI method is only applicable to explain a specific AI model (then the portability is *model-specific*) or applicable to explain any AI model (*model-agnostic*).

Finally, the solution S in each case denotes the XAI method to be applied to explain the XAIoT problem represented by the description D. We can use many XAI methods as a solution for a XAIoT problem. Some are very well-known in the literature, like *LIME, XRAI, Integrated Gradients*, or *SHAP*, but others are less common, like *FFT, LORE*, or *SIDU*. The solution also includes the explanation technique that the XAI method belongs to. It will enable the reuse of alternative methods from other similar cases. This way, the solution is defined by the following features:

- **XAI method (XM)**. The XAI method to explain a XAIoT system. We have collected 47 different explainers from the literature review.
- **Explanation technique (ET)**. We can classify each XAI method regarding the explanation technique that the method belongs to. We have extracted this classification from the work by [8]: *Activation Clusters, Architecture Modification, Composite, Data-drive, Feature Relevance, Filter, Knowledge Extraction, Optimisation Based, Probabilistic, Simplification*, and *Statistics*.

Consequently, we can formalize the case base as follows:

$$case = \langle D, S \rangle \tag{1}$$

where

$$D = \langle DO, AIT, AIM, AIP, IF, CO, SC, P \rangle$$
$$S = \langle XM, ET \rangle.$$

3.2 Case base analysis

The resulting case base includes a total of 513 cases from the literature review of 100 papers of XAIoT solutions described in Section 2.

Figure 3, shows the distribution of the XAI Methods regarding the IoT domains. As we can observe the 45% of the cases are applied to the *Healthcare* domain, the 26% to the *Industry* domain, 11% to de *Security* domain, 9% to the *Aviation* domain, and 2% to each of the *Energy Management*, *Environment Smart Agriculture*, and *Transportation* domains. Regarding the distribution of the XAI Methods according to the AI Models, Figure 4 illustrates that the AI model with more cases is *Neuronal Network* with 43%, followed by *Agnostic Models* with 18%, *Ensemble Models* with 12% and *Tree-Based Models* with 9%. Figure 5 shows the distribution of the XAI Methods w.r.t. Concurrentness. As

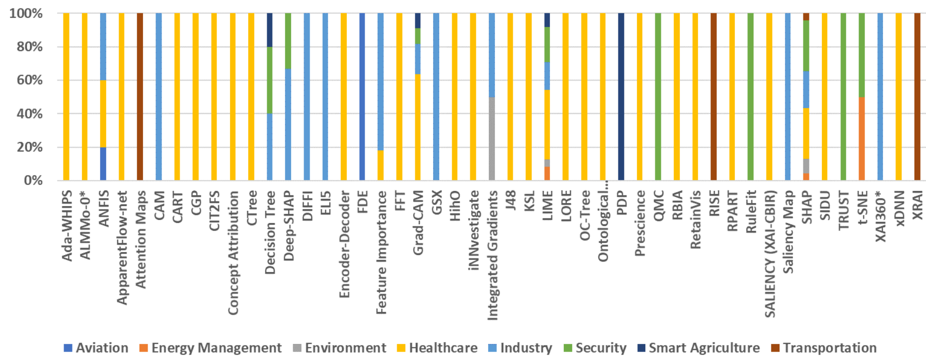

Fig. 3: Case base analysis: explanation methods per domain.

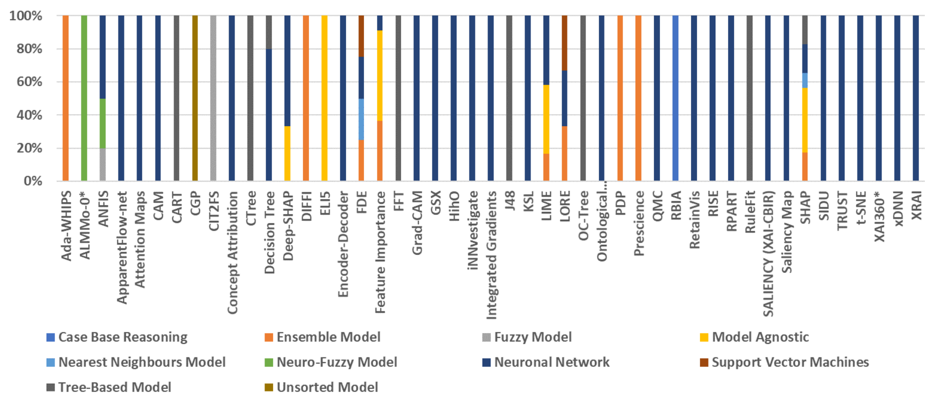

Fig. 4: Case base analysis: explanation methods per models.

we can note, 86% of the cases refer to *Post-hoc* and the remaining ones to *Ante-hoc* methods. The distribution of XAI Methods according to Scope is shown in Figure 6, wherein 60% of the cases are *Local* and 40% *Global*. Figure 7 represents the distribution of the XAI Methods according to the Input Format, in which the 53% of the cases are *Numeric*, 24% *Text*, 22% *Visual* and 1% Rule. Finally, in Figure 8 we can see the distribution of the XAI Methods according to the Portability, where 56% of the cases are *Model Specific* and 44% *Model Agnostic*.

Once we have defined and analyzed the structure of the case base, the following section describes the proposed CBR system for selecting the most suitable explanation method for a XAIoT system.

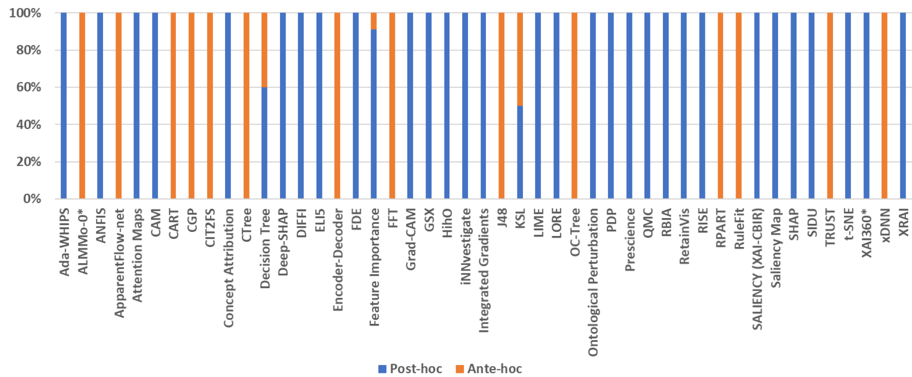

Fig. 5: Case base analysis: explanation methods per concurrentness.

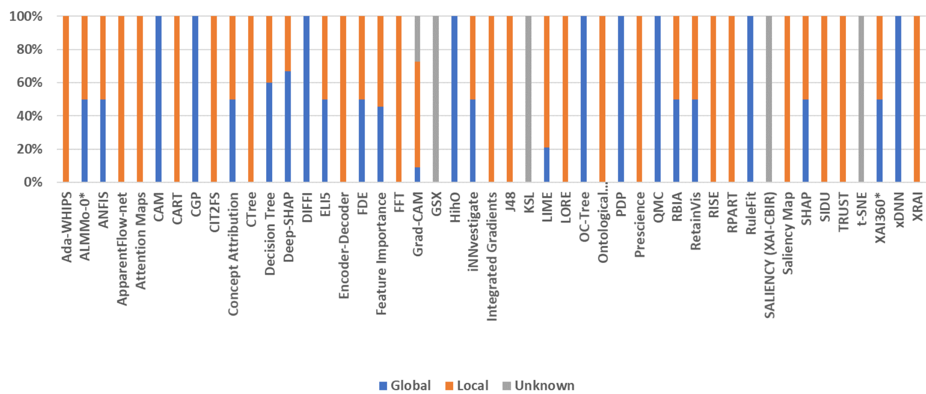

Fig. 6: Case base analysis: explanation methods per scope.

4 CBR process

The second contribution of this paper is the definition of a CBR system able to identify the best explanation method for a given XAIoT problem[7]. Next, we present both the retrieval and reuse stages of the proposed CBR system.

4.1 Retrieval

We propose a CBR retrieval process following the MAC/FAC (many-are-called, few-are-chosen) schema [19].

The *filtering step* (MAC) is necessary to discard the XAI methods unsuitable for a query q and to guarantee that all the retrieved explainers are valid solutions. Therefore, this step filters the compatible XAI methods according to hard

[7] Available at https://github.com/UCM-GAIA/XAIoT.

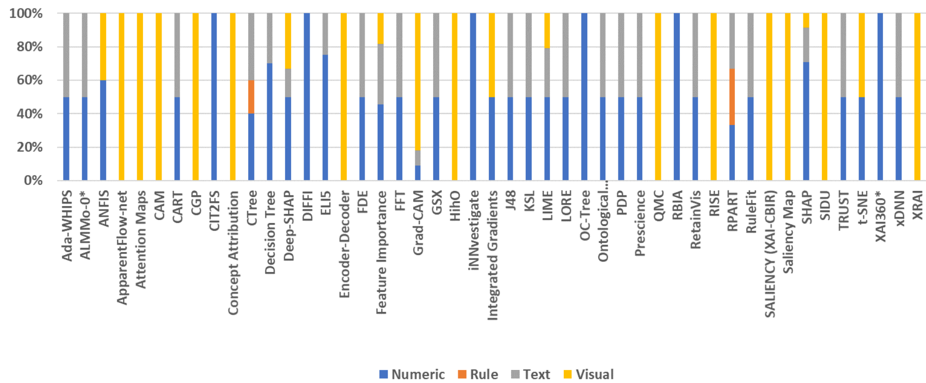

Fig. 7: Case base analysis: explanation methods per input format.

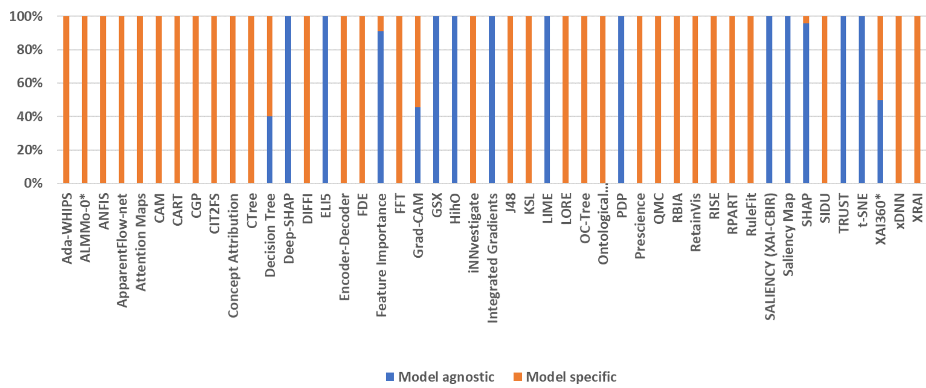

Fig. 8: Case base analysis: explanation methods per portability.

restrictions such as the input format, target AI model, or type of AI problem. These filtering attributes are $\mathcal{FA} = \{IF, AIM, AIP\}$, and the corresponding MAC function is defined as:

$$filter(q, C) = \{c \in C : q.a \neq null \wedge q.a = c.a, \forall a \in \mathcal{FA}\} \tag{2}$$

The *sorting step* (FAC) obtains the most similar cases to q using a similarity metric that compares the remaining attributes in the description, denoted as $\mathcal{SA}$. We have defined the following similarity metric:

$$sim(q, c) = \frac{1}{W} \sum_{a \in \mathcal{SA}} w_a \cdot equal(q.a, c.a) \tag{3}$$

where c is a case within the case base and $\mathcal{SA} = \{DO, AIT, CO, SP, P\}$ is the set of attributes from D that we consider to obtain the most similar cases to q

(domain, AI task, concurrentness, scope, and portability). The values w_a are the weights assigned to each property, so $w_a \in [0..1]$ and $W = \sum w_a$. We calculated these values using a greedy optimization method to minimize the error.

As a result, the *sorting step* returns a list containing the most similar cases to the query (its nearest neighbors). Each case with its corresponding similarity value $sim(c)$.

4.2 Reuse

After the MAC/FAC retrieval process, the CBR process includes a *reuse step*. In this step, the solution and similarity values of the nearest neighbors are used to build a final solution for the query. We propose two different reuse strategies:

Simple voting. The simple voting strategy returns the majoritarian XAI method in the nearest neighbors. We can define it as the explanation method xm with maximal multiplicity $M(xm)$ in the multiset $\mathcal{S}$ that aggregates all the explanation methods in the retrieved solutions:

$$\begin{aligned} sv(s_1, \ldots, s_k) &= \arg\max_{xm} \; M(xm) \\ \text{where} & \\ M(xm) &= \sum_{m \in \mathcal{S}} 1_{\{xm=m\}} \\ \mathcal{S} &= \bigcup_{i \in \{1,\ldots,k\}} s_i.xm \end{aligned} \tag{4}$$

Weighted voting. The weighted voting strategy calculates the solution for q as a weighted addition of our nearest neighbor solutions. This method returns the explanation method xm with maximal weighted multiplicity $WM(xm)$ that takes into account the similarity of the case $sim(c)$.

$$\begin{aligned} wv(s_1, \ldots, s_k) &= \arg\max_{xm} \; WM(xm) \\ \text{where} & \\ WM(xm) &= \sum_{m \in \mathcal{S}} sim(c)_{\{c.xm=m\}} \\ \mathcal{S} &= \bigcup_{i \in \{1,\ldots,k\}} s_i.xm \end{aligned} \tag{5}$$

5 Evaluation

To demonstrate the benefits of our case-based approach to finding the most suitable explanation method for a given XAIoT problem, we performed an evaluation using cross-validation. The main goal is to evaluate and compare the accuracy of the reuse strategies presented in the previous section.

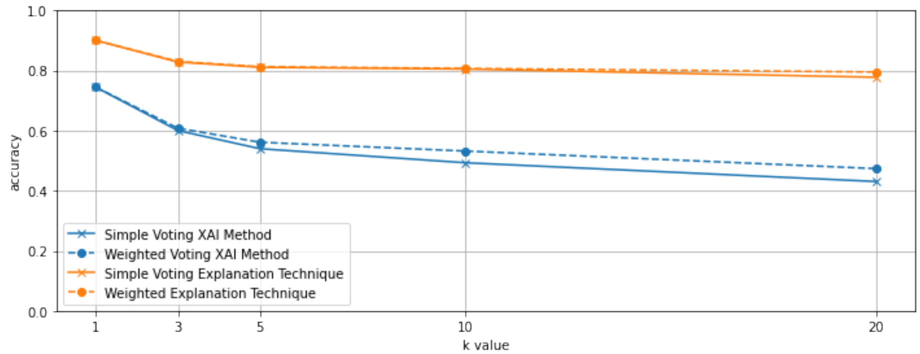

Fig. 9: Evaluation result for several values of k using the Simple Voting and Weighted Voting reuse strategies.

Results, using a 20-times leave-one-out evaluation, are summarized in Figure 9. We can observe the accuracy of the prediction of the two variables in the solution of the cases: *XAI method* and *Explanation Technique*. The accuracy of *XAI Method* and *Explanation Technique* obtain the highest values of 0.74 and 0.9, for $k = 1$ in *simple* and *weighted* voting, respectively. From a baseline of a random choice between 47 XAI methods (2% random probability) and 11 explanation techniques (9% random probability), these are very significant results. Thus, we can conclude that the CBR process is able to achieve a remarkable performance when predicting the best explanation technique and concrete explanation method for a given XAIoT problem. Here, it is worth noting that this performance is based on the quality of the cases elicitated from the literature review.

Regarding the comparison of the reuse strategies, the accuracy of *weighted voting* is almost similar to the accuracy reached by the *simple voting* strategy for different values of k. The analysis of the k parameter shows that, independently of the reuse strategy, the second-best accuracy is obtained when the number of nearest neighbors is $k = 3$. When increasing this value, most of the configurations of the CBR system achieve an accuracy close to 0.83 for *the Explanation technique* and 0.60 for the *XAI Method*.

We have also studied the impact of the case base size on the performance. Being CBR a lazy-learning process where cases are incrementally included in the case base, it is necessary to analyze its behavior to find the required minimum number of cases. This analysis is presented in Figure 10, where the number of cases in the case base increases from 5% to 100% of the total dataset. This Figure shows that performance stabilizes approximately when 85% of the cases have been included in the case base. This tendency led us to conclude that the proposed CBR system will increase its performance as other new cases are included in the case base.

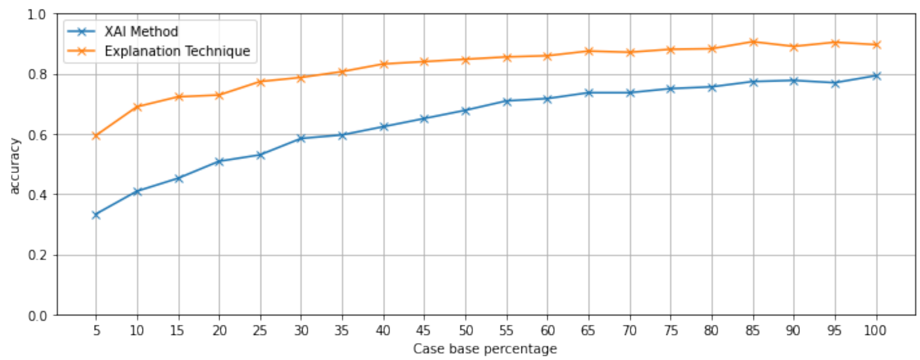

Fig. 10: Learning process of the CBR system showing performance as the case base grows

Finally, we have analyzed the competence of the case base. Competence is the ability of a system's case base to support the solution of potential target problems [17]. It is usually estimated as the coverage of the cases that can be computed as all the possible combinations of attribute values in the case description. To illustrate this analysis, we have generated scatter plots for the most relevant pairs of attributes. Figure 11 shows the coverage for all the possible combinations of AI Tasks and XAI Methods. Although there are empty areas in this plot, it is essential to note that many XAI methods are not applicable to solve several tasks. Therefore, we can conclude that the case base provides quite good coverage. A complementary view is provided by Figure 12. This figure contains two scatter plots illustrating the case base coverage regarding the AI Movel Vs. Domain and AI Task Vs. Explanation Technique. Here we can also observe a satisfactory coverage of all the potential problems with respect to these attributes.

6 Conclusions

The great amount of different XAI methods that we can find in the literature and the novelty of the AIoT systems make it necessary to support the task of deciding which XAI method is the most adequate for their explanation to users. However, the choice is challenging since designers of XAIoT systems should consider many facets to make the best decision. To address this problem, we present a CBR solution that uses a wide case base of 513 cases extracted from an exhaustive literature review [23]. We propose a formalization of such cases together with a retrieval process and two different reuse strategies.

From the experimental cross-validation evaluation, we can conclude that our approach achieves a significant performance in determining which XAI method or explainability technique is more suitable for a given XAIoT problem.

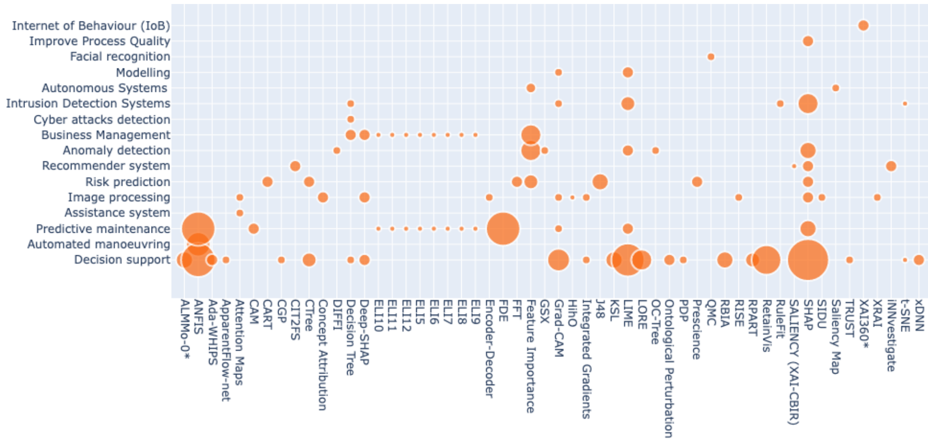

Fig. 11: Case base coverage. Scatter plot showing the number of cases (bubble size) available in the case base, w.r.t AI Task (y-axis) and XIA Method (x-axis)

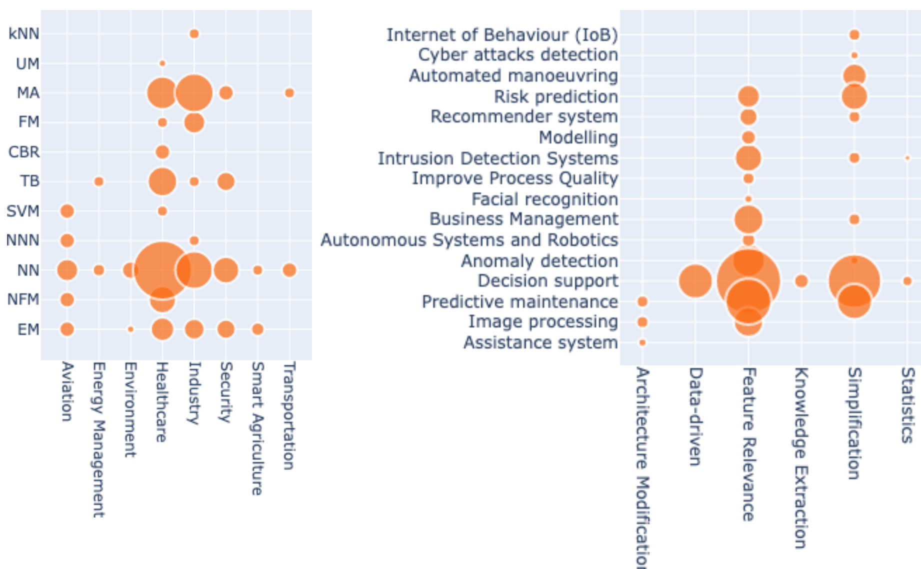

Fig. 12: Case base coverage. Scatter plot showing the number of cases (bubble size) available in the case base. (LEFT) AI Model (y-axis) and Domain (x-axis). (RIGHT) AI Task (y-axis) and Explanation Technique (x-axis).

As future work, we could evaluate our approach with users, since users' opinions are fundamental to evaluating users' satisfaction and trust in the explanations. Consequently, we would also need to incorporate knowledge about the target users in the case description, like their goals or knowledge. Finally, another line of future work could be to apply this approach and our previous approach [8] to other AI fields. The case description could be adapted to the specific field where we are going to apply our approach, but mainly our proposed approach could be used like it is now because our case description is general and could be transferred to other problems and tasks.

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