

INVESTIGATION OF HOW VARIABLES IMPACT INDUSTRY MODEL IN SMART CITY: EXPLANATION WITH SHAP VALUES

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ABSTRACT

In the present era, the implementation of smart cities involves the utilization of various smart sensors to gather data. These sensors transmit their collected data to servers for analysis. However, this process requires additional available channels for data transmission. With the increased usage of Internet of Things (IoT) devices, the frequency band becomes overcrowded. To address this issue, one possible solution is to employ opportunistic access methods like cognitive radio. This article focuses on the utilization of Machine Learning (ML) to forecast the performance of IoT cognitive radio (IoT-CR) sensors. The decisions made by the ML model are explained using Explainable Artificial Intelligence (XAI) techniques such as the Shapley value (SHAP). The significance of SHAP lies in its ability to clarify the outcomes of ML models, which is crucial for ensuring their quality. To demonstrate the effectiveness of XAI, the article presents a case study in the industrial sector where ML quality is improved through its implementation.

Keywords—Smart sensor, XAI, Machine learning, IOT, Cognitive Radio, Smart City

1. INTRODUCTION

In last years, smart city is a used for every field in a city. In healthcare, education, environment, industry to offering different services to any smart government. Others use are presented in Fig.1.

Due to Smart city, the number of devices connected to the internet is increasing and IOT (Internet of things) sectors are growing [11] see Fig.16 . This IOT equipment need more and more sensors and they transmit huge data by making the concept of big data see Fig.14. The transmitted data to base station need more frequency to operate.

As we know frequency band is limited and we need optimization in their use.

Here comes the idea of using a cognitive radio (CR) concept in IOT [12,13,14], they use the frequency band in a smart way by adopting the opportunistic access without disturbing the Network Provider (NP).



Fig. 1. Smart city fields

Several papers discuss the concept of CR used in IoT objects in order to exploit the available spectrum and increase productivity in order to connect more devices with high speed to send and receive data [1,4].

In this paper, we called users in smart city using the concept of cognitive radio in IOT objects as

IOTCR (Internet of things Cognitive Radio). Those Objects can be cameras, smart radar or smart sensors in the industry field etc.. Every IOTCR user has battery, need energy and internet to be connected all the time. Due this functionality, IOTCR needs energy efficiency and speed to deliver data.

The idea of this paper is that IOTCR pass through a negotiation phase with other IOTCR to acquire the underutilized channels and avoid interference caused to the NP. In our article, all the privilege is for the NP which paid for the channel so no interference is accepted with. The paper [1] tolerate a delta interference with NP which is not allowed because the provider paid for the channel and has 100% access .

Our model uses XAI (explainable Artificial intelligence) or called also XML (explainable Machine Learning), [9] which is an artificial intelligence (AI) where humans can understand the decisions or predictions made by the IA. In our case we use the XIA to explain the result of an industrial manufactory in a smart city. This result is to trust or no the IOTCR.

For XIA Many methods exist, we choose SHAP because it is the only reel mathematical model and also because it's simple to implement [10].

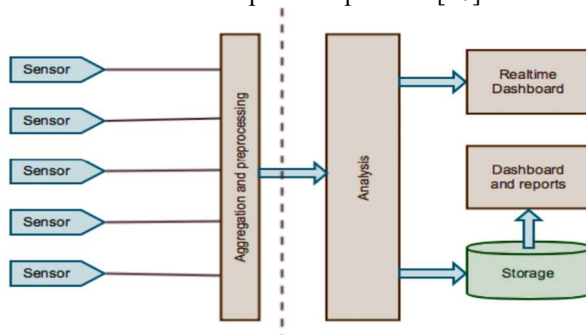


Fig.2: Sensors Network [15]

Several papers explain the ML output without explaining how SHAP works.

SHAP methods are game-based. Without a game between variables (features), we cannot implement SHAP.

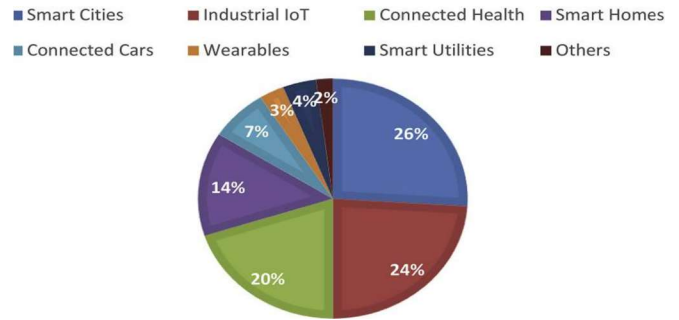


Fig .3. Distribution Of IOT Sectors [11]

In this groundbreaking study, we embark on a pioneering endeavor within the realm of IoT Cognitive Radio (IoT-CR). Our primary objective is to introduce a groundbreaking model that draws upon the principles of game theory as a foundation. By harnessing the power of game theory, we aim to implement the SHAP (Shapley Additive Explanations) framework, thus revolutionizing the field of eXplainable Artificial Intelligence (XAI) in the domain of IoT-CR.

The remainder of this paper is organized as follows. In section 2 we discuss the concept of game theory, ML and XIA. In section 3 we present the proposed work and in section 4 the numerical result is presented. Finally, a conclusion and future work in section 5.

2. GAME THEORY, ML AND XIA

2.1 Game Theory Concept

What is this Game Theory?

Game theory is a part of mathematics that analyses the behavior of the gamer: users choose between different strategies taking into account conflict and cooperation.

The idea of game theory has its concept from economic science, which is the study of how human make decisions when they have important goods (like time or money) between competing goals (like waking up early) or cooperative behavior (like cooperation between countries for economic gains). Game theory was introduced within economics with the publication of The Theory of Games and Economic Behavior by John Von Neumann (Brilliant Mathematician) and Oskar Morgenstern (Economist) [3].

In game theory, we have four component such fig.7

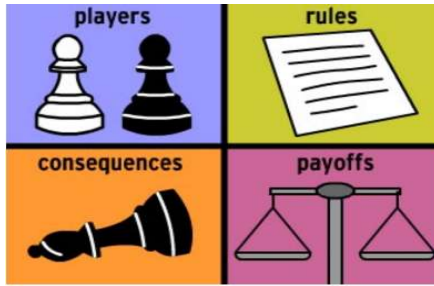


Fig.4: Component Of Game Theory

Game theory is an essential field for research, and it helps to choose the suitable strategy of the players in a game. It has multiple applications in various domains [5].

There are different types of game theory such in Fig.8.

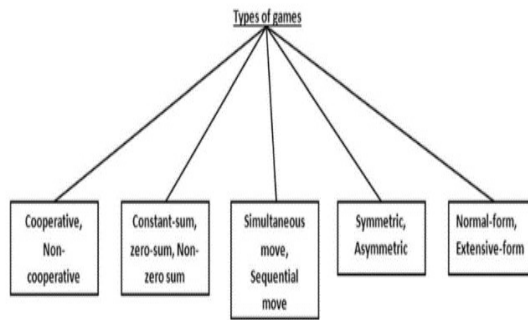


Fig.5.Types Of Game Theory

2.2 ML and XIA

Machine learning (ML) models are often black boxes that are evaluated according to their performance on a set of data, without knowing exactly why and how decisions are made.

However, if obtaining the best performance possible may suffice in some cases, we realize that understanding decisions is increasingly important. An example: a ML model recommends refusing to grant a loan to an individual. If this individual asks for an explanation, his adviser must be able to provide them to him.

Explainable AI (XAI) is a set of tools and frameworks to understand and interpret the predictions made by your machine learning models. You can debug and improve the performance of your models, and help others to understand their behaviour (see fig.10)

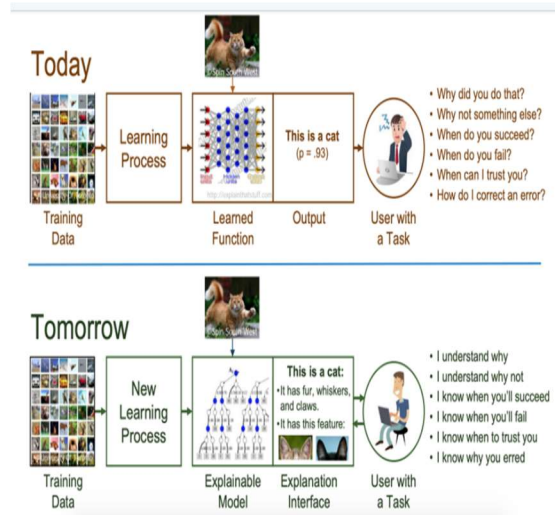


Fig.6: XIA To Explain ML Prediction

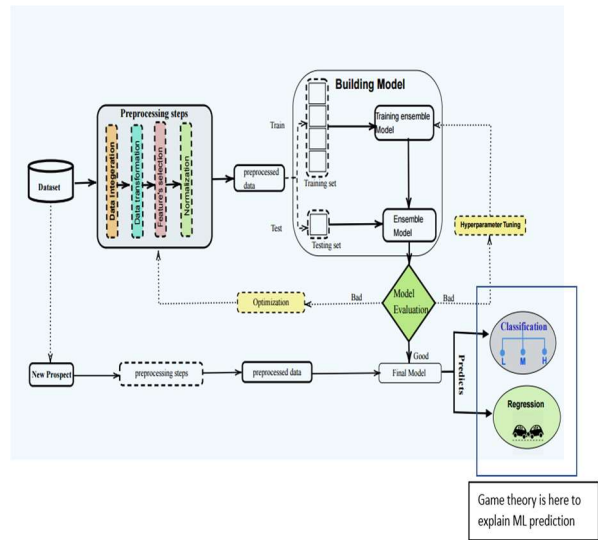


Fig7. ML Model And Game Theory

3. PROPOSED WORK

3.1 IOTCR Spectrum Access

Keep in mind that the principal functions of CR are: spectrum sensing, spectrum sharing and spectrum managements [2] as in Fig. 4. The same phases are between CR and IOT.

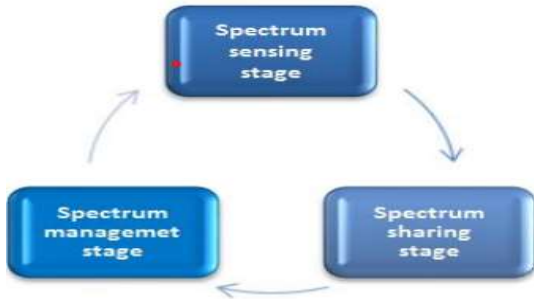


Fig.8. Shared Phases Between CR And IOT

In our framework , in spectrum sensing phase the IOTCRs sense the channel to decide if the channel is idle or occupied by an NPs as in Fig.5.

In Spectrum sharing there are two types (see fig.6):

1. Underlay Spectrum sharing: IOTCRs start sharing Connection with the NP with transmission power which the NP considers like noise.
2. Overlay spectrum sharing: In the spectrum sharing method, only idle channel not utilized by NPs is used by IOTCR .

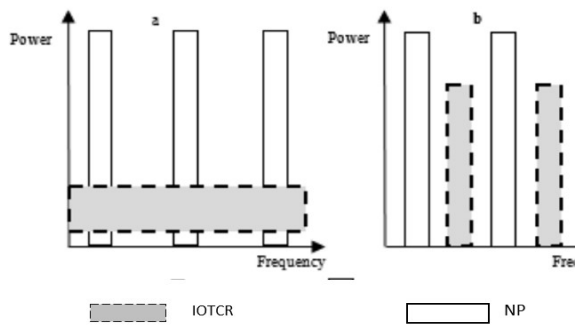


Fig.9 Underlay Spectrum Sharing, B) Overlay Spectrum Sharing

In spectrum management

We suppose that an IOTCR is using the overlay mode in phase of spectrum sharing, it means that if the NP is detected the IOTCR must quit the channel (fig.3).

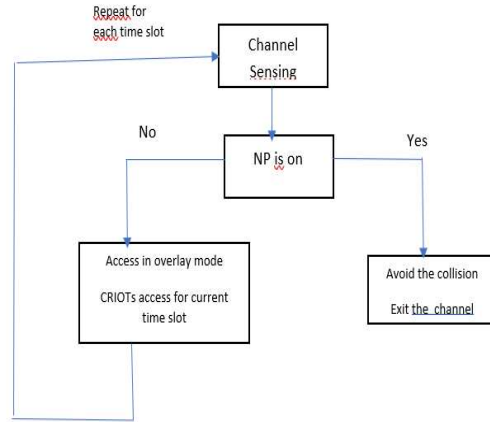


Fig.10 CRIOTs Access In Overlay Mode

3.2: SHAP: Cooperative Game Theoretic Model

SHAP is to explain the ML output, this concept used Cooperative game theory.

Game theory is a theoretical modeling of conflict situations between competing actors and allowing to analyze the behavior of different actors.

This game G is a static game, because all participants must choose their strategy simultaneously. The Game G is a tuple (P, S, U) , where P is the set of players, S is the set of strategies and U is the set of payoff values.

- Players (P): The set of players

P corresponds to the set of features.

- Strategy (S): game G has one strategy S_i (i) Cooperative CP , $S=CP$

- Payoff (V): In CP game G , each player's goal is to maximize their payoff. Our work does not present any malicious side of players.

During the coalition formation process, every player sends the same proposal that contains a comprehensive offer for all QoS

parameters. In our industrial model (section 3.2), $V_i(C_i)$ should be an increasing quality detection of gas $DZ_i(C_i)$, a decreasing function of the consuming bandwidth $CB_i(C_i)$ and a decreasing function of energy consumption $E_i(C_i)$ and Error detection of channel $ED_i(C_i)$.

as follows:

$$V_i(C_i) = DZ_i(C_i) - CB_i(C_i) - \beta E_i(C_i) - \gamma ED(C_i) \quad (1)$$

With ERZ_i defined as error detection of gaz, the formulation of detection of gaz $DZ_i(C_i)$ is:

$$DZ_i(C_i) = (1 - ERZ_i(C_i)) \quad (2)$$

with the throughput described below:

$$F_i(C_i, G_i, Q_i) = (1 - R_f(C_i, G_i, Q_i)) \quad (3)$$

We have an IOT sensors using cognitive radio to access the channel, we assume that all nodes have the same initial battery capacity.

The power consumed by sensors belongs to:

- Power of sensing the channel and sensing the gas W_s and W_z
- Power for waiting for the next opportunity W_w

Total energy consumption of each sensor i:

$$E_i = E_{S,i} + E_{T,i} + E_{N,i} + E_{z,i} \quad (4)$$

$E_{S,i}$: energy of sensing the channel

$$E_s = w_s * t_s \quad (5)$$

$E_{T,i}$: energy of transmitting data to a server (the data are the level of gas in the air)

$$E_T = w_T * t_T \quad (6)$$

$E_{N,i}$: energy negotiation of the channel

$E_{z,i}$: energy of sensing the gas

$$E_{N,j,k}(C_i, G) = w_T.T_{RTS} + w_w.T_{SIFS} + \left(\sum_{i=1}^m q(b_i + w_w.T_{DIFS} + w_T.T_{RTS} + w_w.T_{SIFS}) \right) + w_w.T_{CTS} + w_{rx}.T_{SIFS} \quad (7)$$

The Shapley value is calculated by computing a weighted average payoff gain that player i provides when included in all coalitions that exclude i.

$$\Phi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(N-|S|-1)!}{N!} (v(S \cup \{i\}) - v(S)) \quad (8)$$

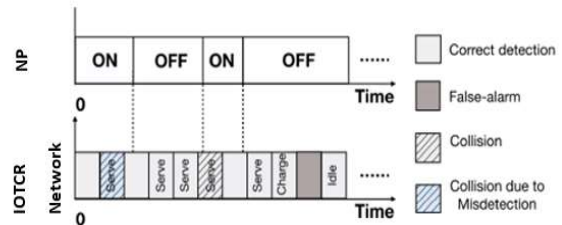


Fig.11 IOTCR Spectrum Sensing

3.3. The Shapley Value to explain ML Model

Model interpretability is an element that can make or to undo a machine learning project in the industry and helps us get closer to the intelligence explainable artificial intelligence (XAI). Interpretability is the degree to which a human can understand the cause of a decision. The interpretation of a model attempts to understand and explain the decisions made by the model, i.e. the “what?”, the “why?” and the “how?”. There are many methods for model interpretability [16-18].

The only interpretability method based on a reel mathematical theory with a simple interpretability is the Shapley (fig.12).

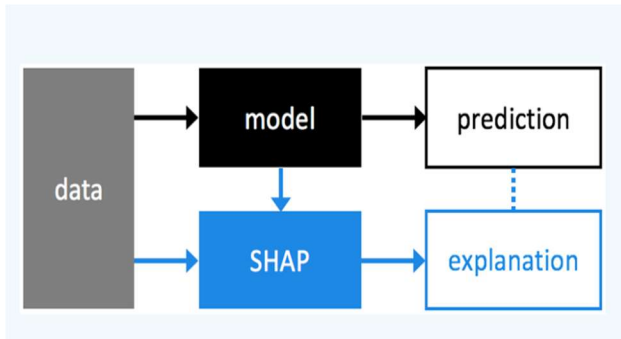


Fig.12: Shapley Value To Explain ML

Shapley value is a solution concept in cooperative game theory. It was named in honor of Lloyd Shapley, who introduced it in 1951. [7] [8] To each cooperative game it assigns a unique distribution (among the players) of a total surplus generated by the coalition of all players. The Shapley value is characterized by a collection of desirable properties. Shapley value is a powerful for ML explicability. The Shapley value approach attempts to explain why an ML model reports the output that it does in an output.

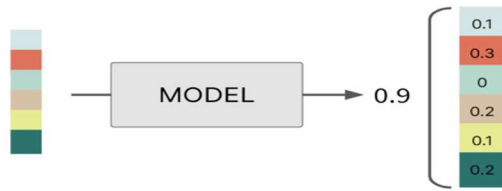


Image by Author: An example of how individual features can contribute to a model's score.

Fig 13: Shapley Value And ML

In Fig.9 the model gives 0.9 as a result, with Shapley value we can analyze, contribute weight to each feature(different colors) to explain result.

Shapley's values calculate the importance of a feature by comparing what a model predicts with and without this attribute (feature). However, as the order in which attributes a model sees can affect its predictions, this comparison is made in all possible ways, so that the attributes are compared fairly. This approach is inspired by game theory.

In summary, Shapley values borrowed from game theory, capture the marginal contribution of each player to the result.

3.4: IOTCR in Smart City: Case Of Industrial Field (Gas Manufactory)

As seen in Fig.16 there are different applications of IOT in different field, the industry occupied 25%. This is why we have chosen an example in industrial field.

In our model Fig.2, there are different types of sensors (IOTCRs), case when gas manufactory detects bad air and starts the purifying air. Sensors send their data to a central server. With ML in our industrial field we can predict the reliability (*trust*) of those sensors.

Table1: Trust Of IOTCR Based On ML Output

ML output	Trust
< threshold	No
= threshold	Yes
> threshold	Yes

In Table1, the trust of IOTCR is ML output based in a threshold.

To trust sensor IOTCRi:

- Gives the good result of gas detection (low error detection of gas)
- Good detection of idle channel to transmit its data (low error detection channel)
- Good consuming of energy (optimization of using energy)
- Good utilization of bandwidth to transmit its data (optimization of using bandwidth)

Our ML model depends on:

Feature 1= Consuming bandwidth CB
Feature 2= Energy consumption E
Feature3= Error detection ED of channel
Feature 4= detection DZ of gas

With XAI , we can explain the result of ML and thus find a logical solution to the problems. In

XAI with SHAP (Fig.13) each feature is assigned a weight score/importance (positive or negative)

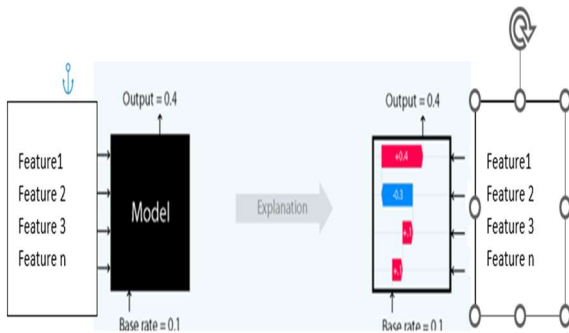


Fig.14: Shapley Value (SHAP) Attributes Scores To Each Feature

with XAI: SHAP we can explain why some sensors are trusted and why others are not.

Table2 : Example of Feature weight attributed by SHAP

ML output	Trust	Feature weight
< threshold	No	ED (+0.9), T(+0.1), E(+0.0), L(+0.1), DZ(+0.1)
= threshold	Yes	ED (+0.5), T(+0.1), E(+0.0), L(+0.0), DZ(+0.2)
> threshold	Yes	ED(+0.1), T(+0.1), E(+0.1), L(+0.1), DZ(+0.8)

In Table 2, with SHAP as XAI we can explain why some IOTCR are trusted and why others are not based on weighted attributed to each feature.

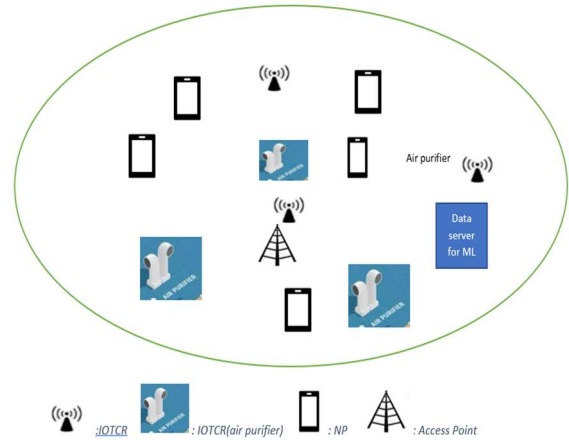


Fig. 15: IOTCR In Smart City Example Of Industrial Field

3.5 Algorithm Of proposed Work

Algorithm1 : XAI using SHAP to explain ML output for IOTCR sensors

Input: N sensors sense every time slot t (t=10s)
D: data send to a server for collecting
d: dataset for ML prediction
F: features of sensors ?

Output: ML (trust or no the sensor i (IOTCRi))

Weight of feature $F_i = \{DZ_i, ED_i, CB_i, E_i\}$ of sensor i
for i=1 to N **do**
Use XAI: SHAP to explain the output of ML:

- SHAP uses cooperative game theory
 - Players are features F_i
 - For every F_i compute U_i of coalition S
 - attribute weight to features of IOTCRi

end for

4. NUMERICAL RESULT

Machine learning methods, such as neural network (fig.19) from a dataset, can attain good result (fig.17, fig.19).

This result is difficult to interpret by humans. This difficulty is due to black box model. By introducing the SHAP values, these models can be explained.

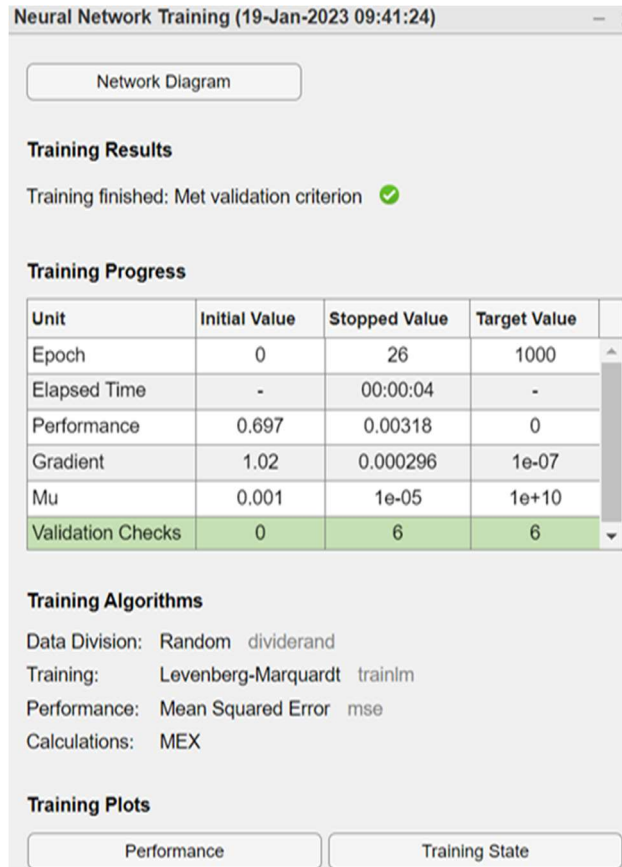


Fig.16: Neural Network Training

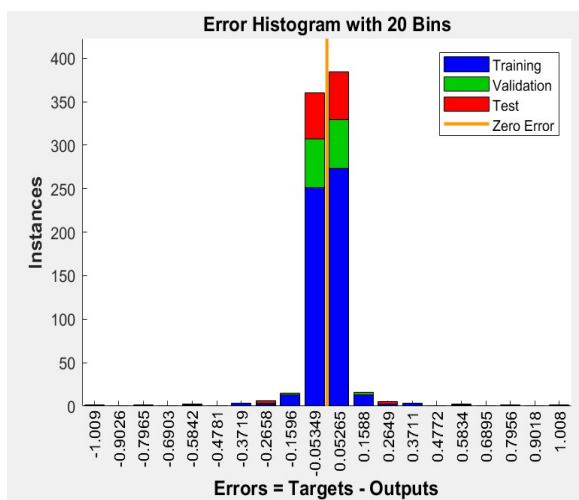


Fig.17 : Histogram On Neural Network Training

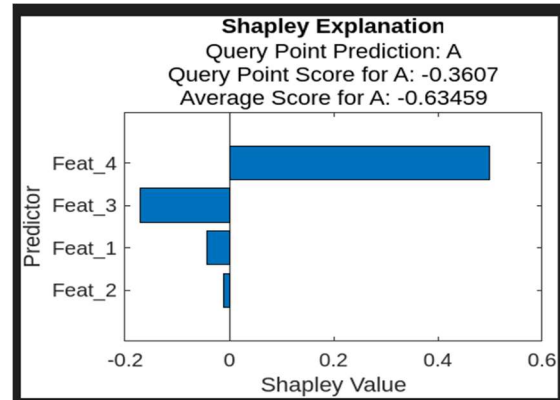


Fig.18. Feature Importance Plot For Class A Of Sensors

As a good method to explain the model, the SHAP framework gives interpretation. Global on Fig.15, feature 4 for sensors class A has a higher effect than other features, indicating that the change of this feature can have a more noticeable influence than others. For class AA Fig.16 feature 3 has more impact than the others. We conclude that the impact of features is depending on the type of the sensors.

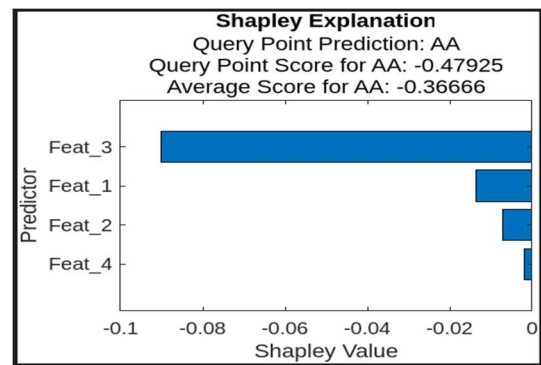


Fig.19. Feature Importance Plot For Class AA Of Sensors With Query Point Score (Q1)

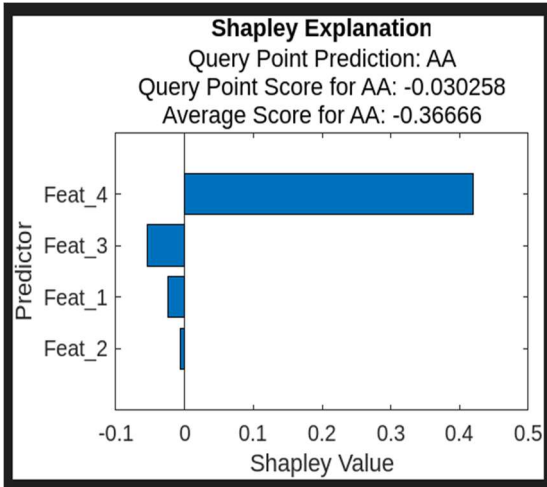


Fig.20: Feature Importance Plot For Class AA Of Sensors With Query Point Score (QR2)

With a same type of sensors AA, in Fig.16 and Fig.18 , we have different feature impact depending on query point QR1= -0.47925 and QR2=-0.030258. The Shapley value of a feature for a query point is the contribution of the feature to the deviation from the average prediction. For a query point, the sum of the Shapley values for all features corresponds to the total deviation of the prediction from the average.

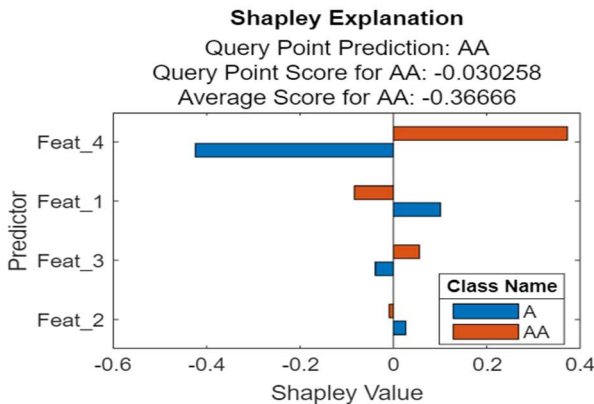


Fig.21 : Shapley Explanation For Both Class A And AA

5. CONCLUSION AND FUTURE WORK

The field of smart cities has received significant attention, and among its important domains is the industrial sector.

In this particular research paper, Machine Learning (ML) was employed to forecast the quality of IoT cognitive radio (IoTCR) sensors within the context of smart industries. The decisions made by the ML model were elucidated using Explainable Artificial Intelligence (XAI)

techniques, specifically the Shapley value (SHAP). This model offers the advantage of being analyzable without requiring knowledge of the internal workings of the blackbox model.

This paper has some constraint that must be clarified. The study relies on publicly available datasets and not on a dedicated industry dataset. In addition, the dataset was small, having only under a hundred records. Research with more specified data can give more conclusive insights. Moreover, we can improve the process of features. With limited dataset, the amount of feature is limited. For model explanation, the Shapley value uses all possible combinations of the features. In the future, we will consider utilizing other existing datasets with more features and will extend the scope of study to include some African countries. For the future work, we must explore more machine learning algorithm and compare different ML output. For example we can compare random forest [22], XGboost [20] , extra trees [21] and Decision tree[19].

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