Explainable Artificial Intelligence for Smart Cities

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The emergence of Explainable Artificial Intelligence (XAI) has enhanced the lives of humans and envisioned the concept of smart cities using informed actions, enhanced user interpretations and explanations, and firm decision-making processes. The XAI systems can unbox the potential of black-box AI models and describe them explicitly.

Explainable Artificial Intelligence (XAI) | smart cities | artificial intelligence | Survey | machine learning | future cities | Internet of Things (IoT) | data mining | smart health | real-time systems | Black Box | White Box

1. Introduction

Information and communication technologies (ICT) and the Internet of Things (IoT) are essential components of smart cities, which may boost operational efficiency and improve services while helping residents lead sustainable lives [1][2]. Viably, the administration of accessible resources benefits from information and communication advances. There is a critical purpose for developing smart technologies to enable people to experience new and better things in their everyday lives [3][4]. In addition to making these technologies more efficient, increasing their efficiency may make them eco-friendly, more productive, and more flexible. While the digital revolution was important in many ways, it was also crucial for businesses to think about how easy and efficient it would be to run their businesses.

ICT is essential to the smart cities idea. It is not only crucial in policy formulation, decision-making, implementation and the provision of valuable services, but it is also essential in all other stages of the strategy. Artificial intelligence (AI) can help make cities more efficient in many areas of life, including their use in energy management, temperature management, education, health and human services, water management, air quality management, traffic management, payments and finance, smart parking, and trash management [5][6][7]. A smart, AI-powered city will use energy and resources more efficiently, protect the environment, improve its citizens' lives, and enable them to adopt current ICT more quickly. Specifically, (i) technology and data availability and reliability, the dependency on third parties and the lack of skills are limiting factors; (ii) ethical issues when using AI are complicated; and (iii) regulatory issues when attempting to interconnect infrastructures and data are complex.

Explainable AI (XAI) in smart city development plays a crucial part. Recent applications based on deep learning, big data, and IoT architectures need intensive use of complicated computational solutions. Since these systems are closed to users, they are called “black boxes.” People will fear that their tools may be untrustworthy if this is true. In the last few years, attempts have been made to solve this problem using XAI methodologies to make things more transparent.

1.1. Clinical Decision Support Systems

Clinical decision support systems (CDSS) are computerized systems that help healthcare providers use information more intelligently, helping to improve both patient health and the healthcare process. In order to accomplish many goals, CDSSs are developed with the following capabilities: diagnosis, prediction of treatment response, the suggestion of treatments (personalization), prognosis and the prioritizing of patient care based on risk [8]. In addition, CDSS can be beneficial in areas with limited resources, such as the number of healthcare facilities, equipment and physicians. CDSS may be categorized as knowledge-based or non-knowledge-based. While non-knowledge-based CDSS are usually based on AI, knowledge-based CDSS rely on medical guidelines and knowledge (https://www.limswiki.org/index.php/Clinical_decision_support_system accessed date: 14 December 2022)). The AI-based CDSS examines past clinical data to produce prediction models to assess new input variables. When these results are used as guidance for doctors, these recommendations can aid them in their practices. There is tremendous promise for AI-based CDSS in clinical practice. Using a CDSS increases clinical choices while reducing medical mistakes since it is objective and relies only on input data and decision-making logic.

Nonetheless, their use of data depends on the amount and quality. Bias in training data results in skewed or inaccurate predictions for AI models. Biased or erroneous human decisions are likely to occur if this practice is widespread [9][10][11].

1.2. The Need for XAI: Fair and Ethical Decision-Making

Understanding the mathematical underpinnings of existing machine learning architectures may only provide insights into how and why a result was obtained, not into the inner workings of the models. One must use explicit modeling and reasoning techniques to answer questions like “How did that happen?” One also knows that contextual adaptation, e.g., systems that aid in developing explanatory models for tackling real-world issues, will be a crucial difficulty for future AI. Human expertise should not be excluded, but AI should supplement it. When classification findings may lead to dangerous incidents for people, it is necessary to comprehend the mechanism that is at work behind such outcomes. Complex machine learning models are an essential focus of XAI research. Machine learning models may be classified according to their interpretability or opacity.

2. Definitions and Key Technologies of XAI

XAI is a method that helps humans understand how the output is created by the machine/deep learning algorithm. It contributes to quantifying model correctness, fairness, and transparency and results in AI-assisted decision-making. XAI is critical for organizations' trust and confidence when using AI models. Additionally, AI explainability enables organizations to take a responsible approach to AI development [12].

Figure 1 shows the difference between the working methodology of AI and XAI. As AI becomes more sophisticated, humans face difficulty comprehending and retracing the algorithm's steps. The entire calculating process is transformed into what is often referred to as a "black box" that is impenetrable. These black-box models are constructed using the data directly, and not even the algorithm's developers or data scientists understand or can describe what is occurring inside them or how the AI algorithm arrived at a particular conclusion [13]. As machine learning models improve performance, explainable and interpretable predictions become increasingly hard to create. Black-box models may be defined as deep learning [14] or ensembles [15][16][17]. On the other hand, white-box or glass-box models are known as open-source models because it is straightforward to create understandable results using explainable examples, like the reference [18] and decision tree models. It is possible to make the new models more understandable and interpretable. However, these models still need state-of-the-art performance compared to the earlier models. It boils down to their frugal design; when they perform poorly or are well-interpreted and quickly explained, it is due to them having a frugal design [19]. Interpretability, as mentors remark, is beneficial for accomplishing other model goals, which may include establishing user confidence, recognizing the effect of certain factors, comprehending how a model would behave given inputs and ensuring that models are fair and impartial [20].

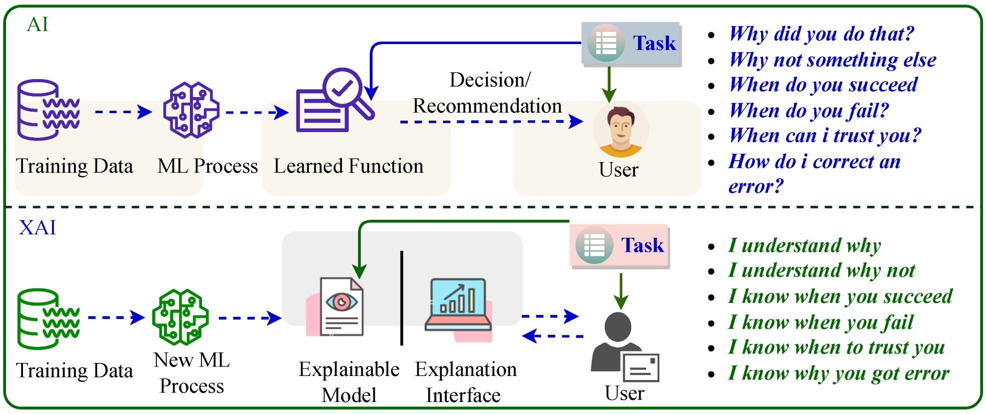

Figure 1. Difference between the working methodology of AI and XAI.

- **Understandability:** It denotes that the goal of a model is to allow a human to comprehend how the model works, and a model is considered to be excellent if the model allows a human to gain understanding without being dependent on understanding the model's internal structure or algorithmic techniques by which the model processes data [21]. Descriptions should be composed of little pieces of information, which humans and computer algorithms can interpret and should connect quantitative and qualitative ideas [22].

- **Comprehensibility:** The capacity of a learning system to express its learned information in a human-comprehensible manner is known as comprehensibility [23]. Computability is typically related to model complexity when comprehensibility is considered [24].

- **Explainability:** As an interface between people and a decision-maker, an explainability is understandable to humans while also providing a close approximation of the decision-maker [24].

- **Transparency:** For a model to be transparent, it must be comprehensible by itself. Simulatable, decomposable and algorithmically transparent models are all types of transparent models [25].

2.1. Ante Hoc Methods

Predictive models and explainability techniques have two fundamental connections between them. An illustration of ante hoc is using the same model to predict and explain, such as using feature weights to predict a linear regression. It is critical to point out that there are assumptions associated with these approaches and they must be met if the explanation is to operate as expected [26][27]. Clear indications about the underlying prediction algorithm and data, whether transparent or opaque, should be used to have an explainable approach. Can someone describe the workings of a predictive model without knowing how it works? When explaining data or forecasts, is it necessary to make data characteristics intelligible to humans first? For example, while describing a forecast, think of how it may be stated in terms of the temperature in a room compared to calculating a squared sum of the room temperature and the height. Sometimes the system designer wants to provide a list of data transformations or an example-based explanation in instances when the input domain is not intelligible to humans [25][28].

2.2. Trade-Off between Performance and Interpretability

As with any other bold statement, the issue of interpretability versus performance becomes bogged down in myths and misconceptions. It might be true that the more complicated the model is, the better it is for predictions, but it is only sometimes true [29]. In such circumstances, the prediction is wrong. This phenomenon is quite prevalent in several industries. For example, because features must be tested in confined physical settings where all of the characteristics are closely linked and no wide range of potential values is represented in the data, many issues have just a limited subset of features [30]. More predictive models allow for more complex functions to make a prediction. Predictability involves having specific complexity and the data is widely distributed across the world of suitable values for each variable. There is also sufficient data available to use a complex model. Therefore, “more complex models are more accurate” appears correct. The trade-off between performance and interpretability may be seen in this circumstance. Also, it is essential to remember that, while attempting to resolve problems that do not follow the abovementioned principles, an organization will risk fixing too simplistic (variance) problems. A key difference between a complicated model and a sophisticated one is that a complicated one makes the prediction process more complicated, whereas a sophisticated one keeps the model simple but accurate. The performance brings complexity with it and as a result, interpretability confronts itself on a downhill slope. However, when these newer techniques of explainability arise, this would flip or nullify the increase in explainability [31].

3. XAI for Smart City Enabling Technologies

In general, smart cities are defined as technology-enabled, socially intensive and environmentally friendly urban areas. This section discusses key enabling technologies of smart cities such as blockchain, IoT, big data, 5G and beyond technologies, digital twins, AR/VR, and computer vision. Researchers have recently attempted to address smart city problems using predictive and advanced analytics, smart environmental monitoring and smart mobility. Still, the design and development of smart cities have remained an open research problem [32]. With the advancements in technologies such as computer vision, IoT, and big data and AI, it has become feasible to address smart cities-related challenges [33][34][35]. Recently, numerous machine learning and deep learning methodologies have been applied to applications related to smart cities. For instance, fine k-nearest neighbors (KNN) [36], decision tree [37], medium KNN [38], You only look once (YOLO) v4 and YOLOv5 [39] and mass region-based convolutional neural networks (R-CNN) methodologies are applied for image classification, traffic congestion, and autonomous driving vehicle-related problems [40][41]. However, most machine learning models depend highly on training data sets, pre-processing data methodologies, and fine-tuning non-transparent machine learning models. The current data-driven methodologies cannot understand, interpret, and explain complex decision-making-related tasks [42]. Such black box-like methodologies cannot identify and explain decision-making in smart cities. XAI algorithms can be applied to computer vision problems, traffic congestion, self-driving cars, intrusion detection systems (IDS) [43][44][45], etc., to address the above issues. It is also essential to monitor and validate the behavior of the smart city application before deploying advanced machine and deep learning models.

3.1. XAI for Blockchain

Blockchain is an immutable ledger that can process various transactions and carry out asset management and tracking. Blockchain is widely known for tracking and trading physical assets, such as houses, cars, and real estate properties and virtual assets such as patents, copyrights, and many more [42]. Furthermore, blockchain technology is suitable for providing real-time information in a completely transparent and secure environment. Blockchain technology can be implemented using smart contracts. Smart contracts are predetermined constraint-based programs that are executed on a blockchain network. It enables the automation of agreements without any interruptions.

Blockchain technology is one of the essential solutions to drive cloud-based data centers. Moreover, blockchain technology brings reliability and trustworthiness aspects in designing and developing secure engineering solutions [46]. However, the merits of blockchain technology also bring two critical challenges: (i) cross-layer implementation of blockchain technology in cloud computing environments and (ii) the need for a control mechanism due to the automation of tasks in most blockchain-based solutions. Blockchain technology systematically organizes data to prevent intruders from manipulating or hacking the system. The increasing complexity of data-driven AI methodologies and their non-transparent behavior presents numerous security challenges to smart city problems [47]. XAI methodologies have extended and improved the explainability of AI models. Especially in decentralized AI applications, integrating blockchain with AI models guarantees data privacy and security. It also provides data accessibility and traceability. Integrating AI and blockchain architecture can implement a secure decentralized framework for storing and retrieving data generated with AI models.

As every coin has two sides, combining blockchain with XAI methodologies will also bring numerous future challenges which need to be tackled smartly. Firstly, the validation of explanations given by XAI methodologies is a huge challenge due to the minimization of humans in the loop. Secondly, achieving the real-timeliness of applications is a big concern, which requires an immediate resolution [48].

Applications of XAI for Blockchain

Integrating XAI with blockchain can support diverse trusted, non-transparent, secure, decentralized and undisputed systems and application domains.

a. Customer Profile Assessment: Integrating XAI with blockchain will massively affect banking and finance operations. The banking and finance applications are jointly integrated with blockchain technology (BCT) and XAI-based multi-agent systems (MAS). The XAI and blockchain-based multi-agent systems comprise various intelligent expert agents. The expert agents analyze bank customers' profiles, credit history, demographic information and health history. The blockchain-based multi-agent systems also enable effective decision-making and minimize risk probabilities in investments by fostering trust and transparency [48]. Furthermore, the integration of XAI with blockchain also assists in identifying creditworthy customers and decision-making about load allotment, providing business finance, or empowering start-ups.

b. Medical Imaging: Integrating XAI with blockchain technology can implement a secure decentralized medical diagnosis framework for medical image-based diagnosis. The XAI and blockchain-based medical diagnosis framework uses block-wise encryption and histogram shifting methodology to ensure secure transmission of historical patient data and provide trustable information about patient history, such as how, who, when, and where the patient profile data is created. This methodology can also assist radiologists in making decisions by explaining critical patient conditions. The combination of medical imaging technology, XAI and blockchain can assist doctors in making transparent, trustable, unbiased and effective decisions for critical patients [49].

c. Auditing: The XAI with blockchain applications can protect organizations from money laundering, bank transaction fraud, and income and sales tax fraud. The integration of BCT and MAS uses a widely known consensus algorithm with the SHA-256 secure hashing algorithm to ensure the safety of banking and financial transactions. In addition, a joint integration of BCT and XAI-based multi-agent systems can analyze biased and disputed decisions, explain them, and assist government officials, judges, and lawyers in identifying and detecting various frauds. Furthermore, the integration of XAI with blockchain can also detect election-related frauds, such as manipulating votes and election results. [50].

d. Real-time Decisions: Based on the intelligent sensing units connected to smart vehicles, XAI with blockchain solutions can assist in making real-time decisions such as fatal accidents and traffic congestions [51]. The XAI and blockchain-integrated systems contain deterministic and non-deterministic predictors. The deterministic predictors assist in making accurate decisions based on the inputs and data of the XAI methodology. For inexact decisions, the non-deterministic predictors produce inexact decisions. The deterministic or probabilistic predictors can make all types of AI-related decisions, such as frequent pattern mining, optimization-related decisions, clustering, classification-related decisions, and many more [48]. In non-real-time situations, XAI with blockchain solutions can be a blessing in identifying fatal accidents and handling traffic congestion solutions by diverting vehicles in the right direction. **Figure 2** demonstrates a use case of XAI with blockchain for smart cities. As shown in **Figure 2**, XAI-based multi-agent systems integrated with blockchain methodology in applications, such as banking and finance, medical imaging and accounting, assist in identifying credit-worthy customers, and making decisions about their loans and finance. The blockchain methodology contains block-wise encryption, histogram shifting methodology, and SHA-256 cryptography. The XAI-based multi-agent systems integrated with blockchain methodology can explain the reasons for customers' credit and health history, banking, and finance transactions to make critical real-time decisions.

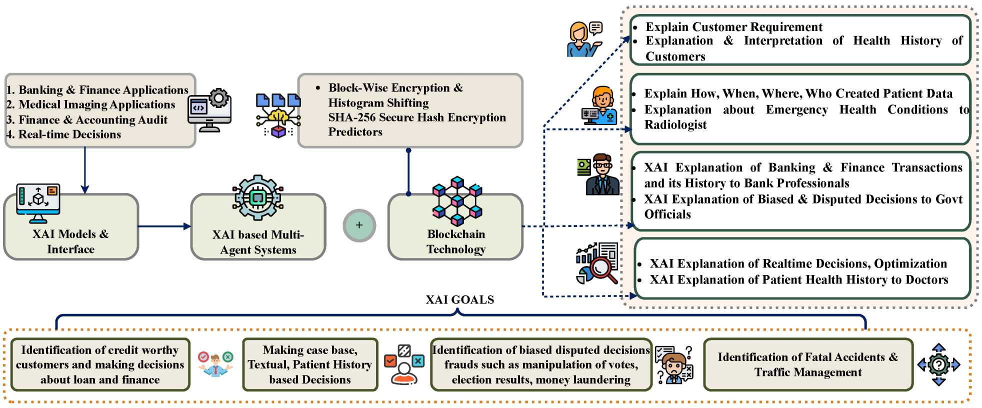

Figure 2. A Usecase of XAI with Blockchain for Smart Cities.

3.2. XAI for IoT

In the development of innovative smart city solutions, Internet of things (IoT) technologies has played a vital role in shaping the life of citizens by addressing issues such as traffic congestion, theft detection, geospatial farming, telemedicine, remote healthcare monitoring, and many more [52][53]. In recent times, smart city problems have been addressed using various data sensed via smart sensing devices. Furthermore, the introduction of intelligent edge computing and edge-AI-enabled devices and their integration with IoT technologies have envisioned the future directions of smart city concepts [54][55]. Edge-AI-enabled devices have been integrated with powerful machine and deep learning methodologies to analyze and predict smart city-related issues, such as the air quality index (AQI), weather prediction, accident prevention, and traffic monitoring.

However, Edge-AI-enabled devices and robust machine learning methodologies can not assist in real-time or near-real-time decision-making. To achieve this objective, XAI methodologies can be integrated with intelligent IoT, the Internet of medical things (IoMT), the AI of medical things (AIoMT), and edge AI-enabled smart devices to identify, interpret, and explain a particular situation which helps in making critical decisions. **Figure 3** represents a use case of integrated XAI and IoT-enabled architecture for smart cities. As shown in **Figure 3**, edge-level XAI is responsible for collecting sensing information from Edge-AI-enabled smart devices and sending it to the application servers for processing via a cloud gateway [56][57]. Furthermore, the application server also notifies individuals of emergency alerts via network operators. The XAI-enabled IoT systems use methodologies such as QARMA, CDSS, LIME, etc. Thus, for example, XAI and IoT-integrated devices can notify the family members and explain the whole situation to them after a fatal accident, make critical decisions based on the critical health condition of patients, provide real-time notification and explain traffic congestion situations.

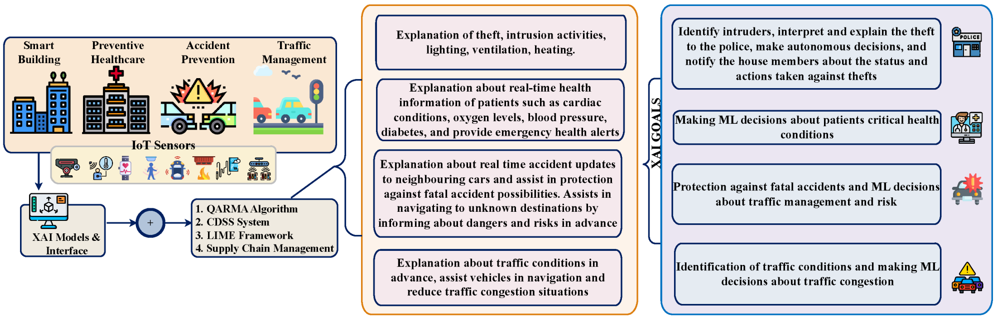

Figure 3. A use case of XAI with IoT for Smart Cities.

Combining XAI with blockchain and IoT infrastructure brings economic and scalability challenges. The scalability issue comes from the overall size of each block and its adaptability with the increase in the number of transactions. Along with the increase in the number of transactions, the handling and maintenance costs will also increase due to increased traffic. Furthermore, the increase in the number of users and transactions will also increase the latency time for processing. Still, the challenges of combining XAI with blockchain and IoT have remained open research issues [58]. Researchers have introduced methodologies such as Segwit, Sharding, Plasma, etc.

Applications of XAI for IoT

Integrating XAI with IoT can support various critical, trusted, decentralized and undisputed systems and application domains.

a. Preventive Healthcare: The XAI integrated clinical decision support systems (CDSS) explain the relevance of XAI methodologies from various perspectives: (i) medical, (ii) technological, (iii) legal, and (iv) end-user (patient) perspectives. The XAI-integrated CDSS system uses the analysis findings to conduct a detailed ethical assessment of patients' profiles with appropriate explanations [59]. Integrating XAI, CDSS and edge, and edge AI-enabled smart devices can provide real-time information about patients, such as cardiac conditions, oxygen levels, blood pressure, diabetes, and many more; it also assists caretakers and healthcare experts and family members in making critical healthcare decisions. In addition, XAI and IoT-enabled frameworks can also be applied to advanced analytics on patients' vital health information and can predict health diseases in advance [60].

b.

Smart Building Management: XAI and IoT-enabled smart building/home architectures can autonomously control building operations [61][62]. The XAI systems integrated with QARMA algorithms and models monitor smart building operations. The QARMA methodologies can formulate quantitative rules for creating, updating, and managing smart building operations such as protection against thefts and intrusion activities, lighting, ventilation, heating, etc. Furthermore, XAI-integrated QARMA methodologies can also identify intruders, interpret, and explain the theft to the police, make autonomous decisions, and notify the house members about the status and actions taken against thefts [63].

c. Accident Prevention: The XAI and IoT integrated frameworks, such as the local interpretable model-agnostic explanations (LIME) framework, can easily be integrated with LoRA and the LIME framework can explain the classification results generated by XAI algorithms. For example, The LIME integrated XAI and IoT-based systems can provide real-time accident updates to neighboring cars and protect against fatal accident possibilities. It also assists in navigating to unknown destinations by informing about dangers and risks in advance [64].

d. Traffic Management: Based on the intelligent sensing units connected to smart vehicles, XAI with IoT solutions can assist in smart vehicle management [65]. The XAI, supply chain management (SCM) and blockchain-integrated heuristic search methodology can assist in avoiding traffic congestion situations and identifying traffic conditions in advance. The XAI-enabled SCM system stores the information and time of every service provider (SP). The XAI-enabled SCM system is connected with smart networks such as vehicular ad-hoc networks (VANET). Every service provider has an open location key against the traffic information gathered by the XAI-enabled SCM system; finally, the stored information is integrated to identify traffic conditions in advance, assist vehicles in navigation, and reduce traffic congestion situations [66].

3.3. XAI for Big Data

Big data is a collection of structured, unstructured and semi-structured data, information and knowledge [67][68][69][70]. Integrating AI and big data-enabled systems collect, interpret, process and store large amounts of data. It also applies advanced analytics that can be used for predictive modeling and analytics [71]. However, due to the black box-like behavior of most AI methodologies, machine, and deep learning methodologies fail to interpret and explain large volumes of data resulting in poor decision-making. Integrating XAI algorithms with big data can assist big data systems in understanding, interpreting, and processing diverse and large volumes of data [72]. It can also assist in identifying complex patterns, categorization, dimensionality adjustments, and maintaining transparency and accountability of data [73]. The big-data-based XAI integrated decision support systems, multi-agent systems, and healthcare systems can assist organizations in explaining and making decisions about customer's geographical segmentation, health and personal history, selection and prediction of stocks, identification of anomalies in lifestyles of elderlies and planning and formulating supply chain strategies. **Figure 4** represents a use case of integrated XAI and big data applications for smart cities. Furthermore, the knowledge layer is responsible for the timely generation of processed information to assist various big data systems and tools in decision-making. For example, healthcare experts and clinicians can apply medical approaches with caution based on the inputs received from XAI-integrated big data systems, which will assist them in selecting appropriate medical practices, medical operations, and critical healthcare decisions. Finally, the service layer is responsible for notifying the real-time updates and explaining a particular event.

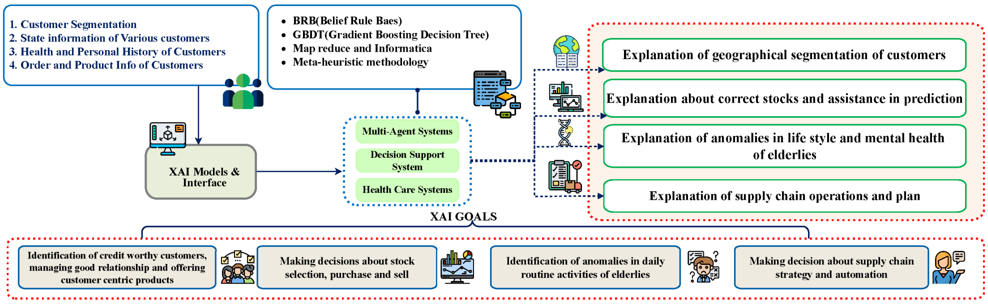

Figure 4. A Usecase of XAI with Big Data for Smart Cities.

However, integrating XAI with big data technologies also challenges future directions. For instance, in applications such as healthcare, XAI can visualize the AI model and assist healthcare experts in decision-making. However, generating accurate medical diagnosis reports, deriving conclusions from them, and validating these reports is a major concern for healthcare experts [74].

Applications of XAI for Big Data

Integrating XAI with big data can support diverse, decentralized, risk-oriented, unbiased systems and application domains.

a. Customer Segmentation and Management: The big data-based XAI integrated decision support systems can assist organizations in geographical segmentation, understanding, and interpretation of various types of customers. Such systems consist of belief-rule-base (BRB) and factual and heuristic rules. Furthermore, it can understand, analyze, extract, and interpret historical data using supervised machine learning and deep learning methodologies. The big data-based XAI integrated decision support systems also assist in managing customer relationships and offering them various customer-centric products, their explanation and benefits [75]. Furthermore, XAI methodologies can also assist in understanding the needs and requirements of regular customers in offering suitable products to customers.

b. Stock Prediction and Management: The XAI integrated multi-agent stock prediction systems can assist stakeholders in picking the right stocks concerning the current know-how. Such systems are integrated with gradient boosting decision trees methodology, which can interpret and predict stock price inclines and declines [76]. It can also assist finance portfolio managers in making the right decisions about stock selection, purchase, and selling for their esteemed customers [77]. Furthermore, the XAI integrated Big data systems can better understand customer finance history, current needs, and aspirations to gain more profits and make future stock decisions.

c. Health Analytic of the Elderly: The big data-enabled XAI integrated healthcare systems can analyze activities of daily living (ADLs) of the elderly, their daily lifestyle monitoring status and anomalies in routine activities; such systems use the concept of data-driven AI to identify the cognitive decline of activities of daily living in a smart home. It analyses cognitive decline and explains why a sudden decline has happened in routine ADLs. The data-driven big data-enabled XAI systems also identify the possibility of health diseases such as Dementia and Parkinson's [78]. Furthermore, such systems can assist healthcare experts in understanding the elderly's mental health conditions, cardiac conditions, blood pressure, and oxygen levels to predict the probability of critical health conditions and diseases in advance [79].

d. Business Analytics for Supply Chain Management: The big data-integrated-XAI supply chain systems can plan and organize supply chain operations, gain real-time insights into customer feedback and build cost-effective business strategies for finance and marketing. Such systems use a robust meta-heuristics base that can analyze customers' and vendors' histories and formulate a cost-effective business strategy [80]. Furthermore, big data-integrated-XAI supply chain systems can also provide further recommendations for improving supply chain strategies based on customer necessities and feedback using meta-heuristics [81].

3.4. XAI for 5G and Beyond

Recently, 5G technologies have faced challenges such as connection density, network access issues in basements, underwater, and space, 24×7

availability, delay in communication, quality of service (QoS), and many more. Several research works have discussed 6G technologies, benefits, and standards [82]. However, their practical usage and applications still need to be completed. Standard machine and deep learning methodologies integrated with 5G and beyond technologies can implement technologies such as remote healthcare monitoring, telemedicine, Industry 4.0 and digital twin, but fail to understand, interpret, and assist in real-time decision-making [83][84][85].

However, by integrating XAI methodologies with 5G and beyond technologies, edge-AI-enabled smart devices can facilitate humans with various intelligent applications such as connected robots, collaborative autonomous driving, smart and interpretable health, remote surgery, connected restaurants, connected cars, connected assembly, and many more [86]. However, XAI for 5G and beyond technologies also brings challenges and research directions. In applications such as precision manufacturing and autonomous vehicles, a human-computer interface-driven interface is required for smooth functioning and communication for smart city applications [87][88].

Applications of XAI for 5G and Beyond

The integration of XAI with 5G and beyond technologies can change accessing real-time updates, bringing humans and machines together on a trusted platform and automating information delivery. As a result, it can play a vital role in smart city design and development and global societal development.

a. Precision Manufacturing: The 5G and XAI-enabled manufacturing systems with human and machine participation in smart factories can increase productivity, organize production processes, automate factory operations, and increase flexibility [89][90]. Such systems consist of a gradient-boosting decision tree methodology to identify machine errors or any errors made by tools/soft-wares. Furthermore, the 5G and XAI-enabled manufacturing systems can perform focused analytics using a reliable AI-integrated prediction model for maintenance tasks. It can develop a flexible production environment for future product trends and customer needs [91].

b. Connected Robotics: The 5G-enabled explainable agents and robots can automate restaurant operations (connected restaurants), drive and control autonomous vehicles, automate and control cooking tasks and connect assembly systems [92]. The explainable agents and robots can explain their behavior to humans and carry out intra-agent explanations for a particular task [93]. Furthermore, the 5G enabled explainable agents and robots can understand, interpret and explain the allotted tasks to robots and provide real-time status to the humans [94].

c. Collaborative Autonomous Driving: The vision-based autonomous driving systems, along with 5G and beyond technologies, can enable collaborative autonomous driving, inter-vehicle, vehicle-to-infrastructure and vehicle-to-vehicle communications in near real-time using technologies such as LoRa. The combination of behavior cloning and reinforcement learning methodology can carry out imitation-based learning from human driving lessons and make safety-critical decisions [95]. Furthermore, vision-based autonomous driving systems can also provide background insights about road accidents, geographical conditions, alternative routes, smart car parking, platooning, assistance for changing and merging lanes, and managing intersections [96].

d. Targeted Healthcare: The 5G enabled EMR systems connected with clinicians and medical experts can perform feature interpretability analysis of health patients and provide essential information, quantitative and qualitative assessment of patient health history using methodologies such as local explanations, global explanations, local interpretable model-agnostic explanations (LIME), SHapley additive exPlanations (SHAP), Example-based Techniques, and Feature-based Techniques [97]. Furthermore, such intelligent methodologies, integrated with 5G-enabled smart and connected health systems, can also assist healthcare experts in combating fatal diseases such as COVID-19 [98].

3.5. XAI for Digital Twins

A virtual replica spans a physical system or object's lifecycle called a digital twin (DT). A DT is updated frequently with real-time data and uses ML simulation and reasoning for decision-making. DT is a highly complex virtual model and replica of its physical counterpart, which can be anything ranging from a car to a person to a building to a city to a bridge. The data from the physical assets are collected from the sensors connected to them and are mapped to the virtual model. The behavior of the real-world object/thing can be understood or visualized by looking at the DT. Using DT, researchers can understand how the objects are behaving presently and predict how they will behave in the future by analyzing the data from the sensors [99]. Even though DTs were originally designed to improve the manufacturing process using simulations, they are now being used in several application domains, such as healthcare and smart cities, due to the increase in big data generated from several IoT-based applications [100]. The potential applications of DT in building/designing effective smart city services are increasing every year due to the increased connectivity by IoT devices [101]. The potential applications of DTs in the smart city include planning and developing smart cities and energy saving in smart cities. The data from the utilities in smart buildings gives insights into the usage patterns and distribution of the utilities, through which decisions can be taken based on the predictions made by ML algorithms and big data analytics [102]. DTs can facilitate the growth of a smart city by creating testbeds inside a virtual twin. A smart city DT can achieve two objectives; the first thing is that DTs can act as a testbed for testing the scenarios and the other one is that DTs can analyze the changes in the collected data and learn from the environment that can be used for monitoring and data analytics [103]. For instance, DT-integrated clinical decision support systems can set a threshold for doctors using patient history and meta-heuristics. The decision thresholds can assist doctors in recommending medicines and deciding tests and treatments based on patient conditions.

A smart city DT can be created by integrating building information models with the big data generated by sensors from IoT devices in a smart city. The public can walk around the city's accurate 3D model created by the DT. It can observe the proposed changes in the policies and urban planning that will pave the way for public opinion before the decisions come into practice [104][105]. AI-enabled smart city DTs can be used effectively to plan for preparation, mitigation, and response during natural disasters and calamities during floods and earthquakes [106][107]. Even though AI can help DTs simulate smart cities, through which the authorities can take necessary actions, due to the black-box nature of AI/Ml algorithms, it is challenging for the authorities to understand the reason for the predictions/classifications. In mission-critical applications such as traffic control and disaster management, wrong decisions taken by authorities can affect millions of lives and properties in urban areas. Through the transparency and justification of the predictions, XAI can alleviate these problems faced by the authorities in making decisions based on the predictions given by AI algorithms in the smart city DTs. Moreover, combining XAI methodologies with digital twins brings interface and optimization challenges [87]. The XAI-based digital twin systems are at an initial stage and cannot handle massive data processing and self-optimization in digital twin systems [108].

3.6. XAI for AR/VR

Augmented reality (AR) can use sounds, digital visual elements, sound, or other sensors to enhance the physical world. The main aim of AR is to highlight some essential features of the real world, understand those features better, and come up with smart insights that can be applied to the applications in real-world [109][110]. Virtual reality (VR) generates a virtual environment with objects and scenes, making users feel as if they are physically immersed in the virtual environment. The virtual environment created by VR can be perceived using a VR headset [111]. AR/VR coupled with AI/ML are key enablers of the smart city through the urban planners and the general public can view the virtual urban planning and simulations of events in a smart city. The AI/ML algorithms' lack of reasoning/justification by the AI/ML algorithms on predictions of some of the events, such as disasters/accidents, makes it difficult for the concerned to make decisions solely based on the predictions from the AI/ML algorithms in AR/VR applications in smart cities [110]. XAI can address these issues by providing interpretability and justification for the prediction results of the AI/ML algorithms. For instance, 5G and AR/VR-enabled recommender systems use explanation-enabled recommendation methodology (XARSSA). The XARSSA methodology can address the influence of customer demographics, extracting customer demands and choices using AR/VR-based shopping assistant applications. The XARSSA methodology uses a design science approach to attract a large customer base towards AR/VR-enabled shopping assistant applications and gain more insights about their needs [112].

Furthermore, combining XAI methodologies with AR/VR techniques will assist in smooth functioning and interfacing; however, achieving complete transparency and trust between the human brain and machine interface has remained an open research problem [113]. In addition, XAI-based AR/VR systems have to deal with massive data processing and high-performance computing challenges.

3.7. XAI for Computer Vision

Computer vision is an application of AI that enables the systems to understand meaningful information from videos, digital images and closed-circuit television (CCTV) footage and make recommendations based on the information extracted from these sources [114][115]. Computer vision has many applications in smart cities, such as object detection in autonomous vehicles that can avoid collisions/accidents, reduction in traffic, monitoring of suspected criminals [116] that will, in turn, reduce the crimes, structural monitoring, combating disasters [117][118]. The 5G and computer vision integrated multi-agent systems use reinforcement learning methodology to analyze traffic congestion situations. Such systems are integrated with interpretations techniques such as SHAP, LIME and gradient-weighted class activation mapping (Grad-CAM) for explaining various traffic situations to a driver and assisting in making driving-related decisions in dense traffic situations [119]. The applications mentioned above are very sensitive as the lives of the citizens are at stake if wrong decisions are taken. Traditional computer vision applications do not explain or justify the classification of images/videos. Hence, making real-time decisions based on the classifications given by computer vision-based applications in scenarios in smart cities, such as collision avoidance, traffic monitoring and crime prevention, may incur severe costs, such as loss of lives and ethical issues. XAI can solve the issues related to computer vision-based applications in smart cities through explainability, interpretability, and justification of classification results.

Combining XAI with computer vision methods also brings a few challenges, such as data exploration and measuring the complexity of black-box models. XAI with computer vision can easily work with text, image, and audio data [120]. However, it cannot interpret spatiotemporal quantities, matrices and vectors. Furthermore, the complexity of interpretability highly depends on black-box models, such as the depth of trees, the presence of non-zero weights in neural network models, etc.

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