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CIoT-Net: a scalable cognitive IoT based smart city network architecture

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Abstract

In the recent era, artificial intelligence (AI) is being used to support numerous solutions for human beings, such as healthcare, autonomous transportation, and so on. Cognitive computing is represented as a next-generation application AI-based solutions which provide human–machine interaction with personalized interactions and services that imitate human behavior. On the other hand, a large volume of data is generated from smart city applications such as healthcare, smart transportation, retail industry, and firefighting. There is always a concern on how to efficiently manage the large volume of generated data. Recently many existing researches discussed the analysis of the large quantity of data using cognitive computing; however, these researches are failed to handle the certain problems, namely scalability, and flexibility of data gathered in a smart city environment. Data captured from millions of sensors can be cross implemented across various cognitive computing applications to ensure real-time responses. In this paper, we study the cognitive internet of things (CIoT) and propose a CIoT-based smart city network (CIoT-Net) architecture which describes how data gathered from smart city applications can be analyzed using cognitive computing and handle the scalability and flexibility problems. We discuss various technologies such as AI and big data analysis to implement the proposed architecture. Finally, we describe the possible research challenges and opportunities while implementing the proposed architecture.

Keywords: Cognitive computing, Internet of things, Smart city

Introduction

Smart cities are witnessing significant growth in data produced by IoT based sensors. These devices are connected and provide insights on how humans use them in conjunction with one another and individually, and how they can be further optimized to serve better. Traditional methods have failed to provide personalized solutions to users with a human touch. artificial intelligence (AI) fused with Cognitive science has sparked interest from both the research community and the industry. Cognitive computing relies on the approach to training AI to function with human brain-like thinking. It learns from people their psychology, environment, voice, and social media to provide reasoning abilities like a human using IoT sensors such as headbands, wearables and phones. A cognitive computing system developed by IBM, known as Watson, demonstrated the ability of machines to think like humans. Watson learns data from documents with no human intervention and supervision and expresses itself like humans using natural language processing. Without internet access, Watson was ranked champion against human competitors in the show titled "Jeopardy!" in 2011.

The growth of unstructured data gathered from IoT devices exceeds that of structured data. Cognitive computing-based AI benefits from being able to learn using both structured and unstructured big-data to train itself, and continually improve the algorithm. There are existing applications using cognitive science and AI such as Welltok in the healthcare industry and Vantage software in the Finance industry. However, many of the existing applications do not benefit from the possibility of flexibility of data gathered from different sensors, i.e. multiple common data streams which benefit a single application can benefit multiple applications. As data grows, the issue of scalability is a growing concern and by implementing common data streams to train and implement different applications instead of a single solution, it will reduce the data from being left unexploited. AI-based algorithms Deep learning and Reinforcement learning have particularly witnessed much success due to their ability in replicating brain-like-thinking better than traditional machine learning methods.

We discuss existing research literature on cognitive computing-based implementation. Min Chen et al. [1] described how human and machines interact with one other enabling the machine to learn from data stored in cyberspace. Different smart-city based applications and scientific experiments are trained by applying cognitive data with artificial intelligence. Their study provides a basic overview, applications and benefits of the use of human data in providing more personalized solutions via cognitive computing based artificial intelligence. Alhussein et al. [2] proposed a cognitive IoT-cloud based smart healthcare framework. Using data received from medical device sensors including EEG devices, they developed an EEG seizure detection method in epileptic patients. The detection model provided an accuracy of 99.2% using artificial intelligence based deep learning algorithm. Their research presents a single, smart city based smart healthcare domain application using cognitive computing data. It is possible that data type gathered from a sensor can be used to train different smart city-based domain applications using cognitive computing. Gupta et al. [3] discussed the benefits of cognitive computing for quicker analysis of big data. Using human brain like computing powered by artificial intelligence, it is possible to draw human-like contextual meaning from big data and provide solutions. Cognitive computing powered artificial intelligence solutions offer better, quicker and accurate decisions. Their research allows us to understand cognitive computing based artificial intelligence solutions are ideal for using big data. Data emerging from millions of sensors in a smart city are enormous, and data will only grow with time. Existing research present individual benefits that can be obtained using cognitive computing based on artificial intelligence. However, there are issues that are not addressed which are as follows:

- There is a need to understand how a cognitive computing-based system will be implemented on a large-scale smart city environment where data is growing, and scalability is a concern.

- There is a lack of research addressing the flexibility of cognitive data to provide not only single cognitive computing AI-based solutions but multiple solutions using the same data.
- Current cognitive systems are not flexible enough to provide solutions for multiple smart city-based applications. They lack scalability and flexibility which makes them unable to offer multiple real-time solutions.

The motivation of this paper is to address the issue of scalability and flexibility of data in implementing cognitive computing-based solutions in a smart city environment. Cognitive computing is the next evolution that is growing fast in the industry and many organizations recognize the potential of services that are beyond conventional AI based solutions. Smart cities produce large amounts of data streams which helps transform existing cognitive computing-based solutions into more efficient and effective results. Therefore, it is important that an architecture for a smart city environment allows multiple and common streams of human and environment collective contextual data to benefit multiple cognitive computing-based applications. The main contribution and significance of this paper are listed below:

- This paper presents the related work done to identify the necessary foundations of an IoT, cognitive IoT and smart city architecture in the context of IoT.
- The proposed CIoT-Net architecture is the first architecture which demonstrates different domains of a smart city network such as smart home, buildings, energy and transportation share similar sets of cognitive data used to build multiple cognitive computing-based applications.
- The technologies that enable the proposed CIoT-Net architecture to function, which include cognitive enabled artificial intelligence and big data in cognitive computing.
- The opportunities and challenges that arise in implementing the CIoT-Net architecture. We discuss the requirement of scalability in big data analytics, the concerns of data security and privacy and the role of artificial intelligence in addressing security concerns.

The paper is organized as follows, "Related work" section we discuss the related work to the IoT and Cognitive IoT architecture which includes its features and key components related to Cognitive IoT architecture. We discuss the smart city architecture concerning IoT. In "CIoT based smart city network architechture" section, we propose the CIoT-Net architecture. We discuss in detail each layer involved. In "Enabling technologies in cognitive computing" section, we discuss the technologies which enable the successful implementation of Cognitive computing-based systems. In "New opportunities and challenges" section, we discuss new opportunities, challenges faced in implementing Cognitive based IoT architecture and its benefits. Finally, in "Conclusions" section, we conclude the paper.

Related work

In this section, we provide a brief overview of the Internet of Things, some aspects related to IoT architecture, cognitive IoT architecture and smart city architecture in the context of IoT common to the development of interoperable IoT systems.

IoT architecture

IoT, known as a network paradigm, is a critical research challenge in which physical devices such as actuators, sensors, smart industry, and other smart technologies are connected to communicate with data centers and exchange information [4]. Based on several existing related IoT architectures that have been developed. Min Chen et al. and Hwang et al.'s research [1] evaluated that collecting various valuable information in the IoT real-time concerns of objects in the objective world via the internet forms a gigantic network and Sheth et al.'s research [5] described that IoT performs the interconnection between massive sensory devices to do the fusion between the physical world and the data world.

It is considered that IoT architectures accommodate the large and fast data processing requirements for extracting deep insights from data using cognitive computing capabilities in IoT architectures. A. Fernández et a.sl research [6] presented that with the steady increase in information and the constant improvement in machine computing power are irreversible in the new era of the big data. As shown in Fig. 1 a differentiator for the IoT architectures is the location of the analyzes in the IoT system. Below we will discuss each subsection of the IoT architecture.

- Application layer: One of the major objectives in this layer of IoT is the creation of an intelligent environment such as smart buildings, smart home, smart health, smart, and smart industry and also this layer of application guarantees data integrity, authenticity, and confidentiality.
- Network layer: Network layer consists of a set of interconnected devices sharing resources, information, and services, according to Badra, research [7] and Wu M, Ling F-Y research [8] proposed this layer which responsible to connect the IoT infrastructure, it collects data from the lower layer known as the perception layer also helps to transmit the communication to the upper layer IoT architecture. Cui A, Stolfo SJ research [9] and Mattern, Floerkemeier research [10] proposed that the communication medium in which is considered as wireless or wired, their different

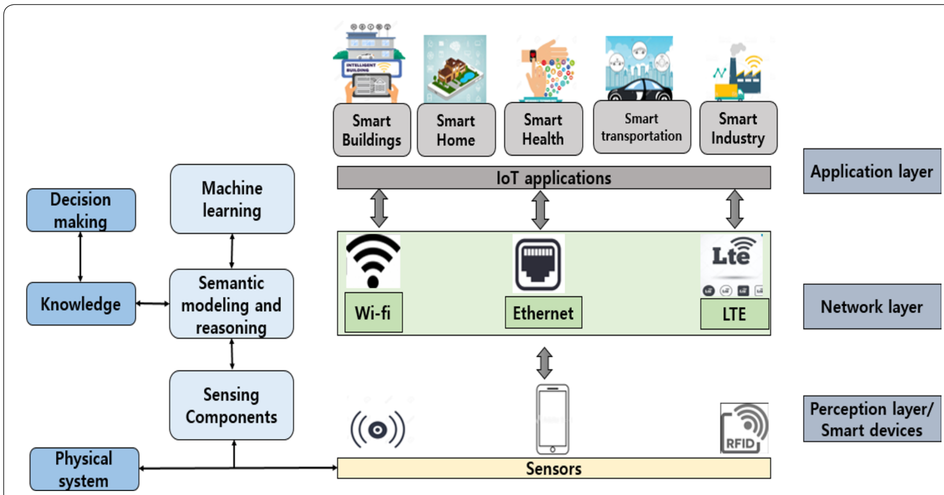

Fig. 1 CIoT architecture based on related work

technologies used which can be Zigbee, wi-fi, wi-fi and LTE, Bluetooth low energy (BLE).
- Perception layer: The perception layer considered one of the closest levels to the environment, known as the sensor layer in the IoT in which it is responsible for collecting packets and converting this information into a digital signal and identifying objects.

According to Vlacheas et al.'s research [11] which suggested a cognitive management framework for the smart city and the main objective to improve the sustainability of cities, thus operating IoT systems with great cognitive abilities. Your cognitive approach identifies and connects the objects that are relevant to the application in question. Based on Zhang research work [12] developed concepts and examples of applications related to IoT in which they propose a cognitive system that allows the cooperation between several devices. IoT architecture requires identifying structure where it coordinates and controls the process for being managed by various elements and application on the IoT [13]. The architecture is known as the core element of the integrated information center, which is operated by an IoT service provided.

Cognitive IoT architecture

The Cognitive internet of things is known as a network or an environment in which everyone and everything is connected, also nowadays is considered that the Internet of Things is growing rapidly, with more devices connected every day [14]. Based on the LIDA research [15] and SOAR research [16] mentioned it is also considered in the existence of different types of structures based on prominent agents and architectures in cognitive systems. According to Zucker et al.'s research [17] suggested a cognitive architecture is outlined for buildings that use these structures.

The concept of cognitive IoT can integrate, improve performance, and achieve intelligence. CIoT is used to analyze the perceived information based on prior knowledge, make intelligent decisions, and perform adaptively and control actions. Based on Chen et al.'s research [18], IoT collects real-time important information objects of the objective world which form an extensive network through the internet. IoT realizes interconnection among massive sensing devices to make co-fusion between the physical world and the data world [5].

Based on Lin research [19] proposed decision making which has semantic information and cognition are introduced in IoT applications to improve intelligence, such as smart community system, Kawsar et al.'s research [20], proposed the health and safety system and another system [21]. In the proposed CIoT architecture based the Smart City Network, there are three key components of CIoT architecture, sensor components, machine learning and semantic modeling which we discuss below:

- Sensor: In sensor components there are several types of sensors and basically, it is a device that has the function of detecting and efficiently responding to some stimulus and are used to collect the environment data in the IoT, acquire all critical information regarding the context of physical systems and allow the elaboration of the semantic goal model of the physical world. Networks of wireless sensors play an essential role in directing collected data to a central server. Sensors are used to allow data collection from the Internet environment of Things. Sensing share decision requires spectrum usage characterization and prediction to achieve channel selection [22].

- Machine learning: Known as advanced algorithm optimization, has the ability to improve performance based on existing semantic models to provide the system with self-learning capabilities. Based on Bhattacharya et al.'s [23] showed that in machine learning Various Analytics applications in building.
- Semantic modeling: The cognitive processes involved in the modeling, transformation, It uses the perceived information to construct semantic models, that later facilitates and automates for the elaboration of the physical and semantic reasoning.

Smart city architecture in the context of IoT

Implementing Smart city architecture in the context of IoT should allow to increase the quality of life of the citizens and providing more security [24]. The extension for this is given according to G. Fierro research [25], where presented more system includes an extensible architecture is provided. Sharma et al. proposed similar architecture [26], where an XMPP message bus is also used as the transport layer. Although these architectures facilitate a hardware abstraction, they do not consider cognitive elements or new IoT concepts. For the construction industry, the modern IoT architectures have not yet been established. Some of the recent developments are aimed at facilitating the creation of open platforms that simplify data processing and integration.

CIoT based smart city network architecture

In this section, we describe in detail a cognitive computing framework that is in nature both scalable and flexible. In this paper, we utilize multiple sources of data collected from various sensors to serve different cognitive computing-based applications. Our proposed architecture requires the least amount of formulating separate configurations intended for different applications. The proposed architecture is depicted in Fig. 2. We can provide quicker and real-time based solutions to serve the dynamicity of data produced by smart cities efficiently.

The proposed CIoT-Net architecture is based on five layers, the Smart City platform, IoT layer, Data layer, Cognitive computing layer, and the Service layer. We will discuss each segment in detail below:

Smart city platform

The Smart City platform consists of many sub-layers which include but are not limited to, smart buildings, home, energy, transportation, agriculture and industry. Big data generated here is in the form of both structured and unstructured data. Smart homes and buildings provide data collected from sensors which include multiple human aspects such as emotions, voice, brain activity, etc.

- Smart buildings: Smart buildings contain many sensors which enable to collect data from different sources to help optimizing services in light, elevators and

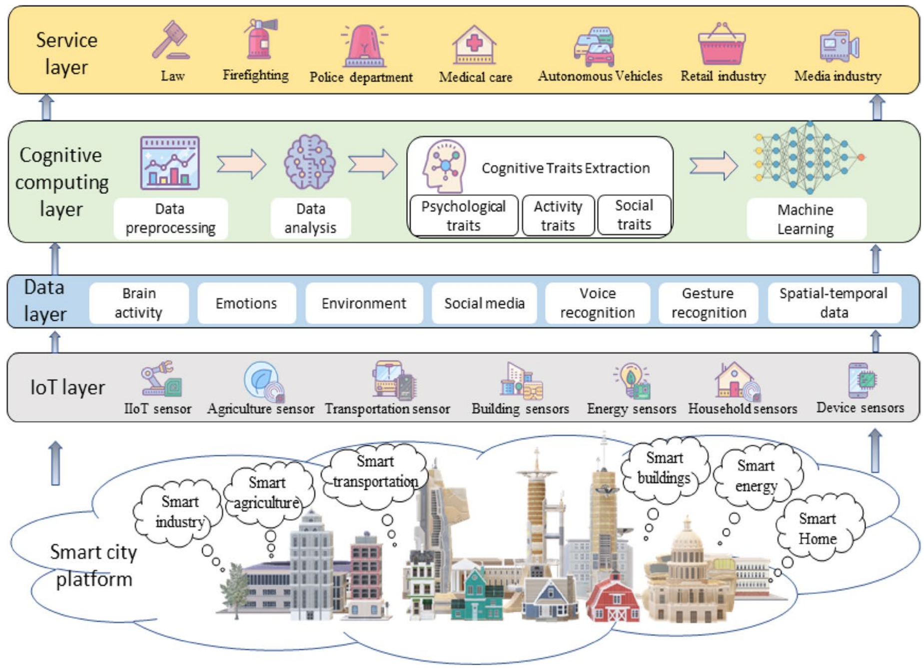

Fig. 2 CIoT-Net architecture

HVAC systems, etc. Buildings collect data such as emotions, environment, etc. which collectively provide multiple solutions such as optimizing of energy consumption using thermal analysis and control over lighting, air quality control, elevators, etc. based on user preferences for maximizing their comfort.

- Smart home: IoT sensors provide data concerning the occupant's movement patterns, the schedule for managing home activities, preferences set for indoor temperatures. Application of cognitive computing can provide humans with better control to enhance their safety and well-being.
- Smart energy: A cognitive visualization tool is formed by combining and using data collected from both perceptual and logical part of the brain. Connecting the cognitive tool with imagery and weather analysis, energy companies provide advanced safety solutions to power plants such as in detecting operational risks in machinery while maximizing uptime.
- Smart transportation: Using data collected from human brain activity, emotions and environment, a cognitive computing-based tool is used with voice analysis to provide real-time data on optimum speed and directions to follow for transportation to reach their destinations on time. Railway services and automobiles have managed to provide solutions for more reliable and on-time services to their users.
- Smart agriculture: Sensors in smart agriculture can collect sensor data which includes perceptual and logical activity from the brain sensors and combine it with imagery analysis to efficiently detect where the harvested fruits and vegetables are located and pick them. Labor gaps are filled with robotic technology-based harvesting equipment which learns from data collected from these sensors.

- Smart industry: Combining data collected from environment sensors and brain sensors to include human information such as workflow process and contextual knowledge, industry performance can be optimized, productive decisions in real-time can be made and raw resources in industries can be better managed.

IoT layer

The IoT layer describes the data that is being from sensors placed in numerous devices. These sensors not only provide initial data for the cognitive computing algorithm to be designed but also provide an ongoing real-time view of how adequately the equipment is performing. These are included in Industrial Internet of Things (IIoT), Agriculture, transportation, buildings, energy, households and various other devices. Type of data collected from these sensors is used to optimize multiple smart city services mentioned in the Smart city platform.

Data layer

The data layer specifies the type of data collected from sensors concerning human activity. These are requisite for the design of the cognitive computing powered artificial intelligence system. Data layer includes the following,

- Brain activity: The human brain consists of two parts. The left portion and the right portion of the brain. The left side is responsible for the logical reasoning which helps humans in presenting a scientific approach to a problem. The right side of the brain is concerned with the perceptual view of the brain which aids in providing intuition, visualization and a creative approach to issues. Combined with these two parts of the brain, cognitive computing offers a human brain-like approach and analysis towards any challenge.
- Emotions: Emotions are used to detect a range of feelings human beings express such as surprise, doubt, anger, distress, stress, etc. These range of emotions are learned by detecting facial impressions such as tensing of facial expressions, muscle stress, pupil dilation, etc. These range of emotions can be taught and used in domains such as healthcare and robotic technology.
- Environment: Environment data is observed based on human interaction with the surrounding environment. Our decisions vary based on the different contextual environment with their associated situation such as position, time, goals, tasks and conditions. Learning rational thoughts and feelings is insufficient for the cognitive computing algorithm without the proper contextual knowledge of the environment.
- Social media: Human beings have a natural understanding of detecting sentiments being expressed. Whether it is a happy, sad or even a sarcastic sentiment, we can quickly identify the difference. However, machines are not as good at this. Training human analysis of opinions posted on social media with cognitive-based artificial intelligence, we can derive more in-depth analytics of emotions expressed towards organizations.
- Voice recognition: Extracting and training cognitive based AI based on voice has many applications especially in customer service. Human voice-tones, expression of

urgency and stress levels can be recorded and used in training AI to help provide personalized support to customers.
- Gesture recognition: Gesture recognition relies on learning the user's hand movement coupled with brain activity. Combining this with AI, there are multiple uses such as gesture-controlled systems and aid to physically challenged people, patients with stroke, etc.
- Spatial–temporal data: Spatial–temporal data is applied to train robots for navigation purposes and to develop awareness of time and space. This skill in humans is often used for puzzle solving and organizational skills by first visualizing the problem in front of them and then approaching it with the solution.

Cognitive computing layer

This layer defines the process following which the cognitive computing algorithm is designed. We highlight the steps which involve data preprocessing, data analysis, cognitive traits extraction and machine learning. This layer produces an algorithm based on chosen feature selection which enables us to provide more personalized solutions in smart cities. Merging both cognitive traits and machine learning models we deliver Cognitive computing based artificial intelligence model.

- Data preprocessing: Raw data collected from sources may contain noisy data or incomplete data. Including this data will result in inefficient cognitive computing based artificial intelligence-based models. The missing data is removed if it is inconsequential to the outcome, or it can be replaced to avoid losing any vital information.
- Data analysis: Data analysis refers to the selection of cognitive traits that are essential to the training of our model. Multiple traits are selected which serve various use cases instead of building a separate cognitive model for each different use case in the smart city. For example, brain activity involving both rational and perceptual understanding can be used for solutions for both smart energy and agriculture systems. User contextual environment data and emotions can be used to serve optimization purposes in both smart home and transportation.
- Cognitive traits extraction: We extract the required data using sensors placed in different facets of the smart city allowing the collection of user data in real-time to train the machine learning model. Psychological data is gathered by collecting user emotions, voice, spatial–temporal data and brain activity data. Activity traits are collected from the user context-based environment and gestures. Social traits are extracted from brain activity, emotions and social media.
- Machine learning: Machine learning allows training systems to provide analytics or prediction based on the training received. Machine learning has evolved to think intelligently with which it can develop its learning patterns on its own and provide better analysis. This evolution is called artificial intelligence. Cognitive computing has taken it one more step forward by merging the way how humans think and trained machines to think with a much more natural approach. Deep learning and Reinforcement learning are commonly used to develop algorithms

from large data sources such as IoT devices which actively learn and improve themselves with no intervention needed. We discuss this in detail in Sect. 4.

Service layer

The service layer discusses the various applications of cognitive computing in the use case of a smart city. These include in the areas of Law, firefighting, police department, medical care, autonomous vehicles, retail industry and media industry. Cognitive computing uses unstructured data and this greatly boosts its analytical ability compared to previous structured data based machine learning models or databases.

- Law: Most law firms require their legal team to keep up with the latest legal rulings, law changes and all historical data on their clients and their legal entanglements. Cognitive computing leverages past and future legal documents with voice recognition and spatial–temporal information to assist legal teams in arriving on more effective solutions. It aids legal organizations with suggestions on how to proceed with a case and is seen as a supportive member of the legal team rather than as a replacement.
- Firefighting: Firefighting is a dangerous job and requires the firefighters to be always alert at all times. Cognitive-based applications are now able to provide support to firefighters based on system trained with image analysis, historical missions and cognitive-based contextual environment, gesture recognition and brain activity to provide real-time analysis of the emergency. The system can detect and alert the level of risk involved, the scenario they will face once they enter the building and provide real-time analysis should the risk factor increase. Cognitive-based applications can help save lives of both firefighters and all else involved.
- Police department: Cognitive computing applications can retain all past criminal records and the city database of every individual's address and the registration of each building and home. Combining this data with brain data, environment, emotions and social media, police officers can locate where the perpetrator may be located. If the person is in a building, it will provide a more context-aware situational awareness of what they may face upon entering the building. Police officers can be assisted with historical and contextual information of a crime scene they are actively investigating.
- Medical care: Healthcare industry leverages cognitive applications for enhanced patient care, identifying symptoms and providing an effective patient diagnosis. Combining patient medical history, illness symptoms with cognitive data such as environment, brain activity, emotions, gesture and voice recognition, the system will suggest diagnosis based on a study of symptoms which may have been overlooked by human error. Cognitive systems excel at pattern recognition which can be ignored by human error. Patient needs can be better understood, and medicine directly administered without any doctor/nurse delay. While the discussed use case involves hospital care, it can be used in smart homes to regulate medical care, especially for children and seniors.

- Autonomous vehicles: Humans driving automobile require logical thinking and perceptual thinking as part of brain activity to detect and avoid any physical obstacle in their path. Humans can detect and respond immediately to such obstructions, and such with the growth of autonomous vehicles, cognitive computing plays a significant role in improving driver safety. Cognitive data such as brain activity, environment and spatial–temporal data is used to provide real-time analysis of the road and enhance human safety.
- Retail industry: Human emotions and environment offer an active role in identifying individual shopping behavior. Retail outlets are now able to identify customer shopping patterns which help in better management of store inventory during their highest footfall. It suggests which items are more likely to be in demand based on a user preference based on the environment. Environment data includes weather conditions and geo data.
- Media industry: Media advertisements have grown more customer preference aware base on enhanced customer insights enriched from cognitive computing applications. Sources such as social media, emotions, and user tone obtained from brain activity and voice provide businesses to present advertisements which provide higher customer engagement. With the addition of environment data, advertisers can provide more personalized content which exhibits higher user interest.

Enabling technologies in cognitive computing

We discuss the technologies which are essential to the successful implementation of cognitive computing-based systems. We discuss about Machine learning using Deep Learning and Reinforcement Learning and how they are similar to human brain-like thinking.

Cognitive enabled artificial intelligence

Traditional machine learning methods rely on training systems running supervised and unsupervised algorithms based on fixed format data. This method produces a limited set of benefits as it cannot learn new information on its own and is restricted to the input data received [27]. While machine learning has served many applications in the past such as in image processing, pattern recognition and cybersecurity, they, however, are not suitable for modern cognitive computing based artificial intelligence systems [28]. They are unable to provide the level of intelligence and personalization which a cognitive computing solution offers.

Deep learning and Reinforcement learning have shown results which makes them suitable for the successful implementation of our CIoT-Net architecture-based applications. Reinforcement learning can learn from its surrounding environment and improve its algorithm while deep learning can learn many high-level features [29, 30].

- Deep Learning: Systems can be trained to behave with human brain-like thinking using Deep Learning algorithms. A human brain is divided into two parts, the left and the right portion which serve two different purposes. The left portion of the brain is responsible for logical and rational thinking whereas the right portion of the brain is responsible for visual thinking and emotion recognition and expression [31, 32]. This individual application of both the logical and perceptive side of their minds is simulated via data analysis in cognitive computing systems. Logical and rational thinking such as measurements of an object can be defined. Perceptual reasoning will require the mapping of features to help correlate between the input and output. A cognitive system is capable of perceiving objects the way humans do where it identifies unknown objects which it has not been previously trained to recognize as done in traditional machine learning methods [33].

- Perceptual thinking or feature mapping in case of cognitive computing is essential to train systems to think as humans do. Rational thought or analytic thinking is insufficient on its own. A system may be trained to recognize a human face by learning features such as the shape of ears, nose and mouth. However, with the addition of factors such as facial hair, distinctive expressions, spectacles and photographic angle, it becomes difficult for the system to recognize the face [34]. The mapping relation between the image of the person and the result is obtained using intuition as humans do. In deep learning, image classification obtained using deep learning mimics human perceptual thinking. A large amount of image features is required for training the deep learning model, and the mapping data is used in cognitive systems to provide personalized solutions.
- Reinforcement learning: Reinforcement learning behaves in the same way often how a human learns. Based on an incentive or reward-based learning, reinforcement learning learns from the environment and improves its behavior. The system is rewarded if from among multiple paths the chosen action is an optimal solution towards reaching the desired objective [35]. The initial approach opted might be good for the system, but it may not be the optimal one. Constant learning and improving the approach results in refining the approach.

Similarly, a parent teaches a child repeatedly to pronounce words and how to spell them. The child makes errors in the beginning, but upon corrections, the child learns the correct answer and associates the sound with the correct spelling. The child is rewarded by the parent with each successful attempt towards the right solution and is corrected when straying away from the correct response. The final solution is the aggregation of the maximum count of rewards. Reward and failure both count as experience for the algorithm to learn from its mistakes and arrive at the desired optimal solution [36].

Role of big data in cognitive computing

The large volume of data generated from IoT based sensor devices, digital devices and software applications in the form of both structured and unstructured data is increasing. Kambatla et al.'s research [37] described that in big data, a huge amount of data is generated.

The cognitive system is influenced by a various number of factors such as smart city platform, IoT layer, and data layer. Based on Ogiela et al.'s research [38] proposed cognitive system can examine a range of different type of data and interpretation which generates insights. Several tools and techniques are understood by cognitive computing such as IoT, natural language processing, deep learning, machine learning, big data, and Data processing.

Interestingly cognitive systems possess the ability to analyze, learn, and remember a problem that may be contextually relevant to the firm. The main features of the cognitive system are knowledge and learning ability of improvement without reprogramming; develop and analyze hypotheses based on the current knowledge base of the system.

A large volume of data which is useful for machine learning such as Deep learning and Reinforcement learning methods in conjunction with Cognitive computing can provide solutions. We can consider these solutions as a significant symbiosis between cognitive computing and big data. Three main aspects are considered by applying cognitive computing with big data are scalability, natural interaction and dynamism.

The scalability process would save effort and time because of the number of redundant calculations involved that is reduced. The model adjustment is done manually in the big data analysis, whereas in cognitive computing, the system allows incorporating changes alone. This system in which the system can incorporate such dynamic changes alone shows the dynamism of cognitive computing over big data analysis. Natural interaction can be consider that the synthesis of natural language is a significant implication, which makes the cognitive system highly desirable. The ability to process between natural language and unstructured data in less time, compared with big data, brings a natural aspect of interaction.

Based Bedeley et al.'s research [39] suggested that on the use of big data analytics consists of 5v categories such as value, velocity, volume, veracity, and variety. While in cognitive consist of 4 categories such as observation, decision, interpretation, and evaluation.

Observation based on Chen et al.'s research [40] mentioned that is a basic requirements for the cognitive system where data analysis takes place, integration and aggregation. These observations to be made by a cognitive system must have access to the volume of data. A volume that is known as the amount of data that is generated and stored. Based on Santos et al.'s research [41] mentioned that when there is a variety of information sources, the interpretation of the data set will enable better understanding and resolution of a complex set of problems. These data can be considered as unstructured, structured, multimedia and texts. Variety which consist of various sources and types of data, based on Huang et al.'s research [42] mentioned that these data can be IoT devices, social Medias, global positioning system and much more. Its consider that in cognitive system the capabilities of making decision based on data. In the big data its consider Value as a feature that suggests worthless data volume until the data is converted for information source.

New opportunities and challenges

In this section, we are going to provide brief overview about some opportunities and challenges when applying CIoT-Net architecture in smart city environment. The internet of things in which it creates and can offer huge benefits but also faces several key challenges [43]. Promises to provide a lot of automation in all things exchanging information as for example in industries including energy, health and many other sectors connected through the internet of things.

Scalable big data analytics

Big data is a significant data volume, but in addition to this large volume of data, other important variables make the composition of the big data by velocity, variance, veracity, and value and volume. Based on the proposed CIoT-Net architecture in Smart City platform, it offers new opportunities and challenges that we are going to discuss each section in detail below:

- Big data management: Is one of the biggest challenges, considered the management and storage current technologies are not suitable for Big Data; Algorithms are not efficient to work with data heterogeneity; the storage capacity grows more slowly than the amount of data; a big amount of data that cannot be analyzed will take the Internet of Things with current manual approaches, was presented evaluate some big data platforms and technically advanced analyzes to analyze data are available [44].
- Big data aggregation: Big data aggregation is another great challenge that allows you to synchronize distributed Big Data forms and external data sources such as repositories, applications, sensor networks, etc. with the internal infrastructures of an organization.
- Big data analytics: It brings potential transformer to multiple sectors and great opportunities; but otherwise, it also presents unprecedented challenges for tapping large volumes of data. Based on the Wang et al. research [45] suggested, for many reasons the big data analysis is still challenging, since the complex nature of big data is based on 5Vs, the performance to analyze and the need for scalability such heterogeneous data sets with real-time response.

Large scale, diversified instrumentation

The smarter city plays a very important role, not only because of the impact on reuse and reuse of the required technology (the number of deployment sensors) but also because of the growing demand for new services (by citizens). Below we are going to describe discuss more about large scale.

- Scalable data processing: Data-centered CIoT services are expected to provide noisy data cleansing, support for reduced data redundancy, and real-time data processing and delivery. In particular, an efficient service design model is required to scale with the large number of IoT services shared between multiple applications with different processing requirements.
- CIoT Challenge: In environment, various IoT sensors and devices such as cellular, multi-sensors and wearable would have led to a substantial increase and expected to exceed largest connected devices. For different practical applications of large-scale CIoT, it is much more challenging to process massive sensing data and which may be mixed characteristics, which includes high dimensionality, heterogeneity, and others. Bhattacharya and D. Culler evaluated that, it would lead to great challenges related to the integration of devices into infrastructures as well as analyzes of backend systems [46]. Approaches are needed to address these challenges, allowing heterogeneous devices to be automatically integrated into analytical infrastructures.

Preserving security and privacy

The privacy and security of the proposed CIoT-Net architecture are important to maintain, and it's a primary concern. For the CIoT-Net architecture to function as intended, the data collected from the IoT layer and transmitted to the cognitive computing layer must not be compromised or altered. The cognitive computing layer requires that it continually learns and improves its understanding of the environment of the user, both internal and external to the user, to provide accurate and personalized services. We discuss concerns about unsecured IoT devices, the impact of data loss from IoT devices and the type of exploitation possible using stolen user data below:

- Unsecured IoT devices: Many services such as medical care, autonomous vehicle, and firefighting require a continuous stream of data from sensors to provide critical services which directly affect human health. Sensors implemented in medical care, transportation, building, and household are computationally low powered IoT devices. Cyber-attacks are frequent on IoT devices which allow an attacker to seize control of them to steal user data and disable the machine. Disabling of the sensors will adversely affect the security and performance of the proposed CIoT-Net architecture.
- Impact of data loss: An example of the impact of disabling the sensors on the security of the CIoT-Net architecture is in the case of firefighting. Data such as gesture recognition and brain activity in the context of the surrounding environment directly affects a firefighter's ability to approach the incident with full awareness. Each firefighting incident requires new data accumulated from the sensors capturing the surrounding environment and user's health and stress level to approach the disaster incident tactfully. Without the flow of data from sensors, a firefighter's job and the victim's health are both at an increased risk.
- Data exploitation: Data theft from sensors will affect privacy concerns of the user and compromise the architecture. An example of privacy concern is with data comprising of human emotions linked with gesture and voice recognition patterns which are collectively used in medical care services. A malicious attacker can use this collected data to expose private medical information to the public or place ransom requests to the user for financial compensation in exchange for the data. The data can be further exploited by selling it off to other organizations who may use it for advertising fraudulent medical services to users.

There are security and privacy challenges in implementing the CIoT-Net architecture, and for the proposed architecture to function in its optimum state, defense solutions must be considered. We identified that data manipulation and data theft are the primary concerns for the cognitive computing layer to function optimally. We discuss below why artificial intelligence is ideal for managing big data and how alternative solutions for data security such as blockchain technology are not ideal for the CIoT-Net architecture:

- Artificial Intelligence: We require a solution that caters to the growing need of big data security. AI can help resolve both privacy and security concerns in the CIoT-

Net architecture. AI-based models are not only trained using data but perform better as the size of the data grows, i.e. the model's accuracy improves as it learns from a larger volume of data. AI-based models operate on two phases. Firstly, they require a collection of data to train the model, which is its initial training, the foundation upon which the model is built. Secondly, they need a continuous stream of data to improve the model and provide better security solutions. AI-based solutions do not cease developing and improving their models, and they continuously require new information or data to ensure security against unknown or ground-zero attacks. AI and Big data go hand in hand whether it is to provide human-like personalized services to users or provide security solutions against cyber-attacks.

- Blockchain technology: Considering that there is a vast stream of data collected from sensors which power cognitive computing, solutions such as blockchain technology are not ideal. Though a blockchain based network ensures sensor data security by storing data as transactions in blocks, data in blockchain based systems are immutable, i.e. it cannot be altered. However, as the size of data grows, there are concerns about scalability issues that emerge in blockchain based systems.

Nowadays with the development of technologies cities are becoming smarter and based on Zhang et al.'s research [47] mentioned that these applications used in smart cities bring several concerns and challenges in terms of security and privacy. To support the treatment and restriction of personal information, there is a requirement due to a lot of information on a cognitive internet of things system in which it may be personal data.

Security is known as an older concept tries to protect data and devices from attack, spyware, and subversion. While privacy is a related term to people and their data, especially personal or confidential data, which emphasizes the need to protect data that should not be exploited, accessed without permission or used in a way that the owner does not expect.

Issues related to privacy and security are increasingly becoming major challenges in the implementation and emergence of this same technology in various smart systems areas. Based on Li et al.'s research [48, 49] proposed on smart cities, even if the above developments can contribute to the improvements of society, it's considered all smart applications are vulnerable to hackers through update attacks such as Sybil attacks, collision attacks, knowledge, espionage, and spam attacks. Basic requirements for good privacy and security are known to include confidentiality, integrity, access control, availability, non-repudiation, and privacy, since this unique privacy and security challenges are becoming a problem, preventing smart cities from being tempting enough to encourage more use.

In privacy based on Arora et al.'s research [50] proposed that the data generated by IoT may present the following problems such as (a) incident management by identifying suspicious traffic patterns between legitimate and possible failure to catch unidentifiable incidents, b) protocol convergence, although IPv6 is currently compatible with the latest specifications, this protocol has not yet been fully implemented, and c) timely updates—difficulty in keeping the system up to date.

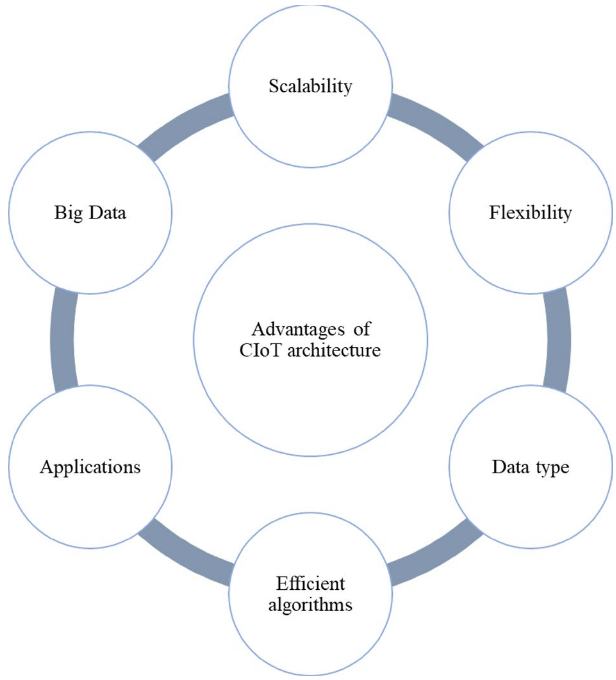

Fig. 3 Benefits of the proposed CIoT architecture

As it is known that current policies on privacy and security of internet products of things are mostly biased and perplexing. Peppet et al.'s research [51] suggested providers do not notify consumers why IoT devices are not equipped with peripherals such as personal computers. Some people believe and prefer to be anonymous and always maintain the freedom of identification and surveillance in public places [52]. Four great outstanding challenges that IoT policies are facing legal problems, such as security, privacy, discrimination and consent [53].

Context-awareness

Cognitive internet of things is seen as interconnected network devices whether physical or virtual, with minimal human intervention where the devices interact with one another following a cycle of conscious awareness. Identify the social world (with social comportment, human demand, and others) and the physical world with them together so as to form an intelligent cybernetic physical system. Enabling automatic network operation, smart service provisioning, and smart resource allocation.

As we know that the world acts are interconnected by various devices such as mobile phones and other devices through the internet. Based on Zhou et al.'s research [54] suggested that the cybernetic world next to the physical world is a perfect fusion that is becoming a trend for the development of future networks. Applying emotional cognition is an important application for smart cities since gradually human emotions become a direct reference index to the spiritual world, which allows the interaction between human and machine.

Based on the research, we identify and present six advantages from the proposed CIoT-Net architecture as shown in Fig. 3. The advantages are as follows:

- Scalability: Data gathered from sensors is not utilized to its full potential. Existing AI-powered systems use structured data to build solutions. However, cognitive computing-based AI systems benefits from their ability to learn from both unstructured and structured data.
- Flexibility: Various existing data are used to train a single cognitive computing application for a specific industry. The CIoT-Net architecture implements the same data used to power one application to be used for several other applications. A common dataset can be used to build and train multiple cognitive computing powered AI applications.
- Data type: Collecting data to benefit multiple applications requires to identify the possible different types of data and their sources from where to be obtained. In the data layer of the CIoT-Net architecture, we list the various sources from where data can be collected such as brain activity, environment and emotions and the data type such as human voice-tones, facial and vocal expressions which are essential for building cognitive computing-based AI solutions.
- Efficient algorithms: We identify that traditional machine learning methods are unable to improve themselves continuously from a flowing stream of data. Deep learning and deep reinforcement learning are the most efficient AI algorithms that can provide optimum solutions for cognitive computing applications.
- Applications: For a stream of data to build different applications, it is essential to know which type of applications can benefit from which type of shared source of data. In the service layer of the CIoT-Net architecture, we present multiple applications which utilize common data, for example, healthcare and autonomous vehicles both require brain activity and environment data to train their applications. Human emotions and environment data both help training and building applications for retail and media industries.
- Big data: Cognitive computing greatly benefits from Big data as it is a valuable and abundant source of data to train and continually improve existing AI models. Another significant benefit using cognitive computing is in its ability to use natural language processing to learn quickly from unstructured data collected from multiple sources, including social media.

Conclusions

In this paper, we presented a new architecture for Cognitive computing based IoT systems. Proposed architecture illustrates multiple cognitive traits can be implemented to not only resolve various applications but provide real-time solutions in a smart city platform. The requirement for separate configurations for diverse and dynamic smart-city based applications is reduced. The proposed CIoT-Net architecture addresses the modern problem of both complexity and scalability issues that affect smart cities when handling large IoT data. We discuss related works in the scope of IoT, CIoT and smart city architectures. We present the CIoT based smart-city network architecture. Finally, we discuss opportunities and challenges that arise with our proposed architecture.

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Authors' contributions
MMS designed and described the functionality of the CIoT based Smart City Network Architecture. JHJ and SR defined the overall organization of the manuscript. JCSS discussed how big data is used to enable cognitive computing systems. J-HP and JHP performed total supervision of this study. All authors read and approved the final manuscript.

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