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An Architecture for Cognitive Computing in Healthcare

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Abstract

The integrated impact of computing techniques and resources with big-data processing transforms human lifestyles by providing quality services ranging from healthcare to smart homes and effective interactions. However, many healthcare systems fail to consider patient emergencies and cannot provide a customized resource service. Cognitive computing is a requisite technology to create these intelligent systems based on artificial intelligence algorithms. This paper presents technologies for personalized healthcare services through cognitive computing. This paper investigates cognitive computing developments from discovering knowledge, cognitive science, and big-data analytics at the onset. Then, the system architecture for a cognitive computing system is given. Furthermore, this paper presents the technologies for cognitive computing healthcare improvement opportunities and their challenges. Finally, this paper discusses the representative intelligent systems of cognitive computing, including medical, robotic, and cognitive-communication systems.

Keywords: *cognitive computing, big-data, healthcare, machine learning, pervasive computing, ubiquitous systems*

1. Introduction

Cisco estimates that 500 billion machines will connect to the internet by 2030. Every device comprises sensors to gather data, interact with the environment, and communicate via IoT, the network connecting the devices. Internet technologies are rapidly advancing [1], and the new information communication technologies (ICTs) are converging with various application fields adding new features to them continuously. These are the driving force of the successive industrial revolutions through utilizing intelligent machines, building connectivity between them, and enabling them to collaborate with humans effectively [2].

Innovative integration of sensor machines with IoTs through automation can yield systems that enhance human-machine collaboration experiences.

Economic growth and climate changes have raised the morbidity of chronic diseases in human society, so human health is under threat [3]. The conventional healthcare systems are categorized into three layers, i.e., the accumulation layer, the communication layer, and the analytics layer [4]. In the accumulation layer, body area sensors gather the sensing data and transmit it to the base station via intelligent ends or smartphones[5] [6]. Then, the base station transmits it to the analytics layer (such as a cloud computing data center) via the internet, where the data is kept and analyzed in the cloud computing data center using machine learning algorithms. Eventually, the cognitive computing system gets the users' health status and makes the appropriate clinical treatment actions [7]. Even though the healthcare system gives benefits to patients, the following problems arise:

- Because of the multi-modal nature of the medical data, the Conventional data mining and machine learning methods fail to accurately uncover the hidden patterns in the data[7]. Therefore, intelligent methods will help in extensive disease discovery for the different varieties of data.
- Body sensors transmit user health data to the cloud platforms for processing, thus increasing the communication latency and failing to give timely medical analysis and services during emergency periods [8] [9].
- The rigidity of network resource deployment can result in a waste of resources [4].

Over the past few years, cognitive computing is receiving much recognition in academia and industry with the pace of

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development in computer hardware and software technologies, artificial intelligence (AI), and big data. Cognitive computing is an interdisciplinary research field that applies techniques from "psychology, signal processing, biology, mathematics, physics, information theory and statistics" in attempting to develop "machines with the abilities of reasoning similar to the human brains" [10]. Cognitive computing applications are emerging in the industry. For instance, the Waston System by IBM [11] reasons and processes natural language by learning from documents. Conventional computational intelligence techniques, which include (robotic technology, emotional communication, and medical cognition) utilize traditional intelligent data processing, analysis and visualization, deep learning, pattern recognition, and generic algorithms for developing smart applications in healthcare [4] [12]. Solving challenging problems in healthcare requires understanding situations or key patterns rather than simply processing, interpreting, and classifying. Consequently, systems models that can process data through understanding and solving problems like the human brain need to be developed. This requires building artificial intelligence (AI) and computational intelligence models to process the big data generated from physical-cyberspace systems on matters of human healthcare. Medical Big data analytics [13] entails mining the hidden patterns from the data and visualizing resultant information using analytical methods to gain insights from the results. Medical big data processing is a challenging task in the form of presentation, storage, timely information retrieval, and cost efficiency in terms of access to healthcare provision. Effective decision-making in healthcare has massive potential for reducing the cost of care, improving the quality of care services, and minimizing error. Current cognitive computing systems in healthcare [13] are yet to reach human-like intelligence. This work presents trends in developments of cognitive computing. It gives further insights into developing intelligent systems that will co-fuse humans and machines' capabilities for richer human experiences in the healthcare sector.

2. The Development of Cognitive Computing

In psychology, behaviorism [14] is a character trait assumed by subjects based on cultural beliefs and practices. The trends of behaviorism have been on a gradual decline since the mid of 20th century. The fast development in information theory, linguistics, and data science and the adoption and usage of emerging computer technologies has resulted in magnificent and mind-boggling cognitive revolutions. Cognitive Science [10] is an emerging interdisciplinary field that studies the transmission and handling of information in humans' brains. Psychologists and cognitive scientists investigate human mental abilities by observing various features, which include: emotion and reasoning, attention, memory, perception, and language usage [15]. Chen et al. [10] groups the cognitive process into two phases: i) discovery of the physical phenomenon through perceptive sense organs such as nose, eyes, skin, and ears as means of input information from external environments. ii.) These inputs communicate to the brain via nerves for action, analysis, storage, and learning. The processing of results is relayed to other body parts for stimuli controlled by the nervous system. Hence a complete loop is established for sensing the environment to the action taking, also referred to as decision-making. Thus, a newborn baby recognizes the world through constant communication with the external environment from which information is acquired and processed in a complete-loop manner. Meanwhile, the baby progressively establishes her or his cognitive system through these communications and feedback from the environment.

The human cognitive system is very sophisticated, requiring methods and tools from different disciplines to undertake in-depth multi-dimensional [16] studies to understand it well. This implies that cognitive science cuts across different subjects such as AI, neuroscience, psychology, linguistics, and anthropology. Up to date most research [10] [16] in cognitive computing show that it has different capabilities which are interdisciplinary in nature. Table 1 summarizes the capabilities of Cognitive Computing.

Fig. 1 depicts the developments in cognitive computing. Cognitive computing and big-data analytics are divergent technologies acquired from data science. Big-Data emphasizes processing the data characterized by "4V" features: variety, volume, velocity, and value. [22]. Whereas the data processed in cognitive computing might not automatically be big-data. Similar to the human brain, limited memory does not affect information cognition. The human brain is very efficient in image processing. Therefore, cognitive computing algorithms utilize cognitive science theories, providing machines with capabilities to attain some degree of human-like intelligence [23]. Human-like cognitive computing aspires to facilitate machines in understanding and recognizing the world from an objective human thinking perspective. Understanding the needs of humans necessitates strong machine cognition through sensor computing [24]. Hence the collective intelligence abilities of machines require improvements for better decision-making. Embedding cognitive computing into the Internet of Things (IoT) smart apps can aid humans with important suggestions in decision making [25]. Further, the integration of ICTs with cognitive sensors provides powerful networks [26].

3. Cognitive Computing System Architecture

Fig. 2 shows an architecture of the cognitive computing system. With the technological, and infrastructural support such as the internet of things (IoT), 5G networks, advances in machine learning, activities entailing human-machine interaction, computer vision, and voice recognition systems will be deployable on a large scale. Intelligent applications can be health supervision, smart farming, intelligent cities, and cognitive healthcare. Each of these applications will require unique system architectures. However, machine learning frameworks can apply universally to various cognitive computing architectures.

3.1. Internet of things and cognitive computing

From Fig. 2, cognitive computing depends on the information gathered. The communication field focuses on transmission of information using various networks e.g. 5G, while the computing domain focuses on utilizing information. In cognitive computing applications, data is supplied or generated via interactions from environment. The internet of things(IoT) [27] gathers variety and timely rich information of world objects creates a huge network via the internet. It achieves interconnection between many sensing devices, thus making co-fusion among the data and physical world [28]. Currently, [29] data fusion techniques apply to IoT in enabling digital platforms to monitor the patient's movements and the status during rehabilitation activities using remote supervision

Table 1. Capabilities of Cognitive Computing

Feature	Description (*t*) (*t*)
Interaction [17]	Using the sensors, cognitive computing can gather information from its surrounding environment and respond just like humans can hear, see, and talk
Learning [18]	Based on the information gathered from the surrounding environment, cognitive computing systems update their states continuously and thus respond to the environment accordingly
Reasoning [19] [11]	The cognitive computing systems have the capability to make inferences based on the data gathered and the built-in AI intelligence
Understanding [20] [21]	Cognitive systems can be utilize to understand the human behavior, and illnesses

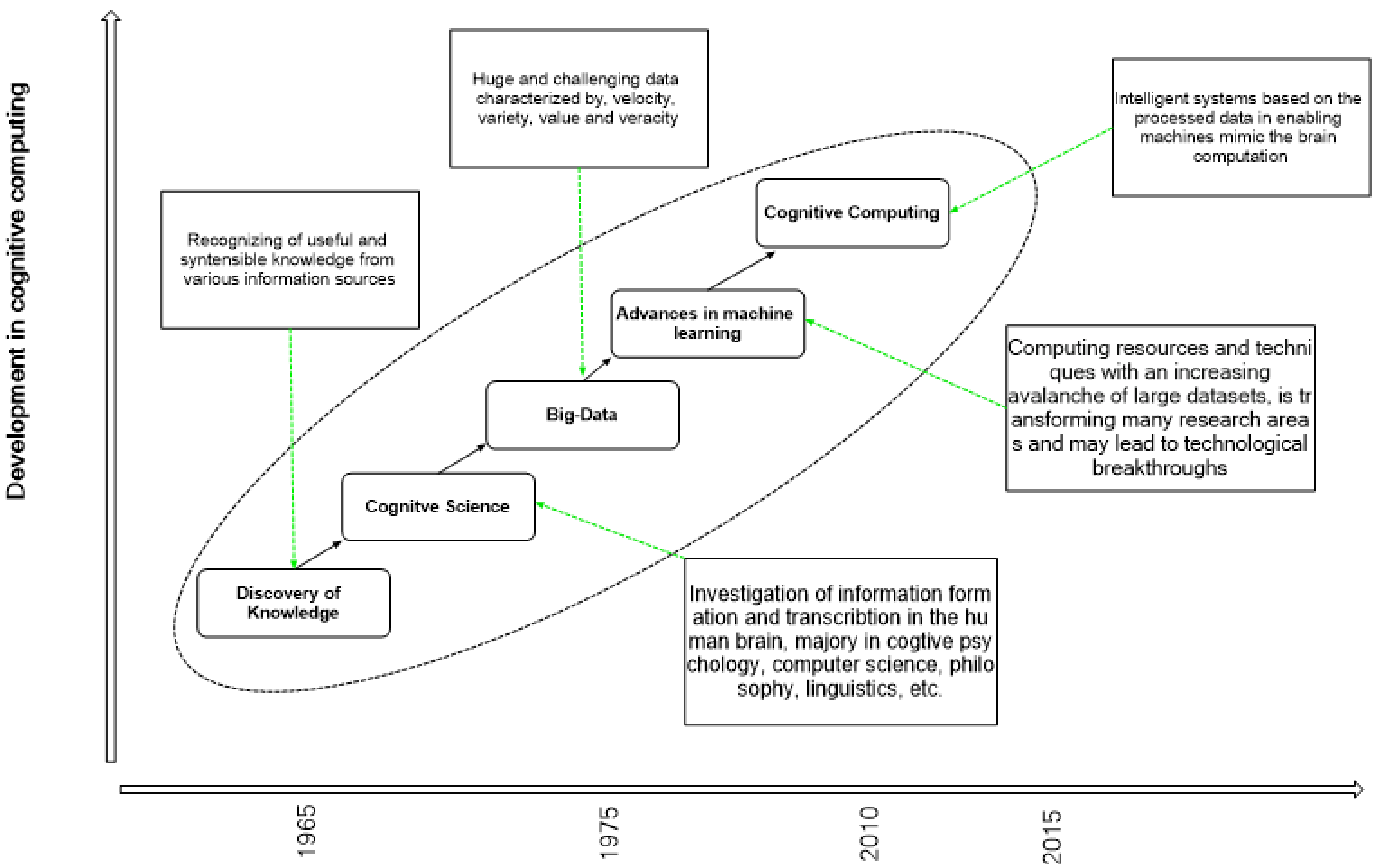

Fig. 1. The developments of cognitive computing

by doctors. The IoT first gets information about objects monitored via perception technologies such as wireless sensors, RFID, and satellite positioning WiFi. It then transmits and shares the information efficiently to network devices. Eventually, IoT analyzes and processes data utilizing intelligent computing techniques such as data mining, machine learning, and cloud computing to achieve intelligent decision-making and control through the fusion of information with physical systems. The IoT acquires perception and sharing of information. The extensive usage of IoT will generate big data, giving crucial information sources for cognitive computing.

3.2. Machine learning technologies for cognitive computing

Several frameworks and libraries [30] provide artificial intelligence and advanced machine learning capabilities to implement deep learning. The following are popular deep learning frameworks and libraries in literature.

3.2.1. TensorFlow

Tensorflow [31] is an advanced machine learning system that works in heterogeneous environments and on large scales. Tensorflow provides dataflow graphs that apply to computation

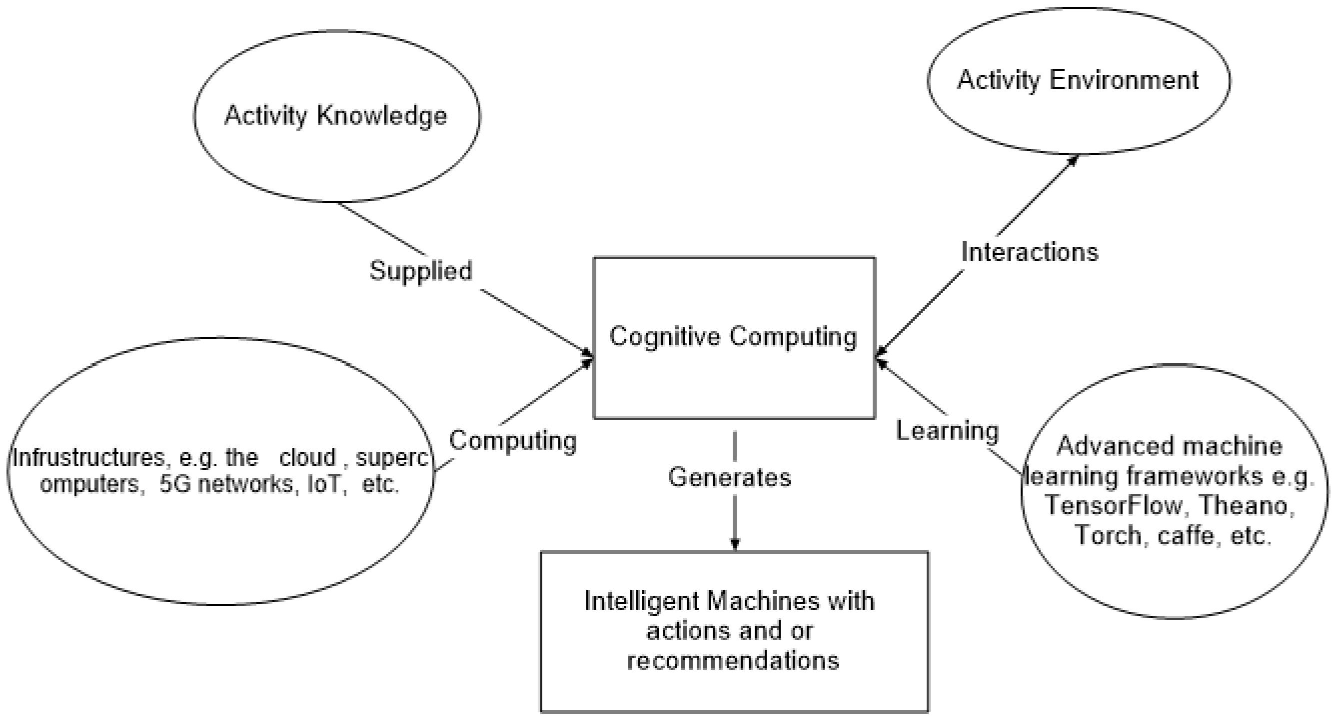

Fig. 2. Cognitive System Architecture

operations and shared states. The nodes of dataflows map to different machines across clusters, including GPUs, multicore CPUs, and Tensor processing units. This framework gives application developers the flexibility to experiment with training algorithms. TensorFlow is released under an open source license in 2015. The API of TensorFlow includes Python and C++. TensorFlow supports image, speech, handwriting recognition, natural language processing, and forecasting.

3.2.2. Caffe

Caffe [32] is a popular deep learning framework for the computer vision community. In 2014, It won an ImageNet Challenge. The Caffe framework offers deep learning toolkits for model training and deployment. [33] attains state-of-the-art remote sensing scene classification results with the Caffe implementation framework. Caffe is C++ based and can be compiled on heterogeneous devices. Caffe supports Matlab, C++, and Python programming interfaces. The Caffe framework has a vast user community that contributes to the "Model Zoo" deep net repository." GoogleNet and AlexNet are two standard user-made networks available to the public.

3.2.3. Deeplearning4J

The Deeplearning4J [**?**] framework has built-in GPU support, an essential feature for the training process, and supports Hadoop's distributed YARN application framework. Deeplearning4J has a rich set of deep network architecture support: Recurrent Neural Networks (RNN), RBM, Long Short-Term Memory (LTSM) network, DBN, Convolutional Neural Networks (CNN), and RNTN. Deeplearning4J further provides support for a vectorization library known as Canova, and it is Java implemented which is faster than Python. This framework provides natural language processing, image recognition, and fraud detection capabilities.

3.2.4. Keras

Keras [30] library provides bindings to deep learning frameworks such as Tensorflow, Deeplearning4J, Theano, Torch, etc. It enables experimentation with Python on CPUs and GPUs. Keras follows critical principles in its implementation, including modularity, extensibility, and friendliness. Further, Keras is open-source and has rich documentation.

4. Smart devices in Healthcare: Taxonomies and Ontologies

The fundamental taxonomies in healthcare systems encompass data organization (history, reminders, and alerts), data sharing, data mining, and decision support. Innovative device features can be enhanced by integrating digital patient health records into intelligent devices. Four core areas of a healthcare system are essential in enabling successful clinical decision support applications through cognitive computing. These areas are: Structured clinical information (encompassing standards and structured patient data) Exchange of cross-platform information by devices Data mining that interprets data into a meaningful information Decision support to help patients/clinicians make informed decisions effectively and efficiently.

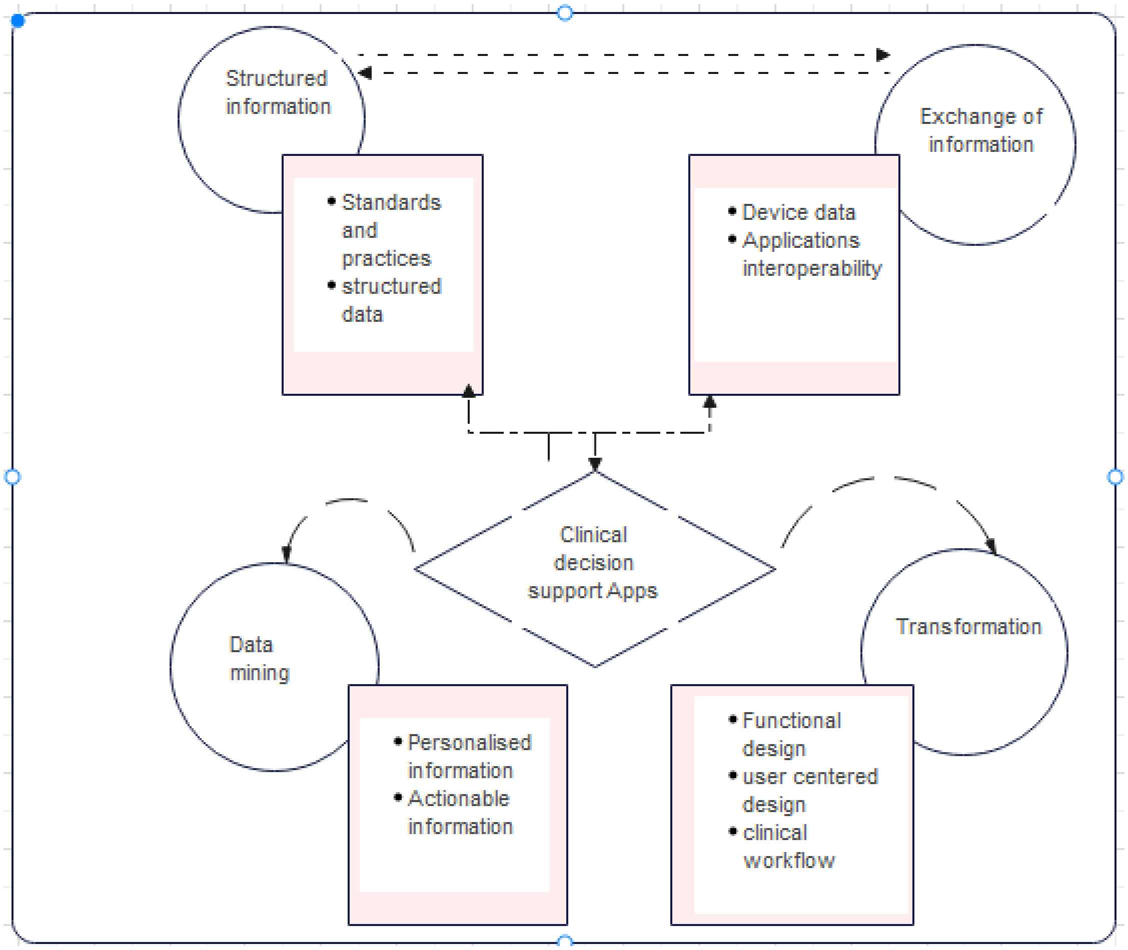

Fig. 3. The Five key focus areas for effective and efficient smart-device apps in healthcare

4.1. Structured information for healthcare applications

Digital technologies in healthcare, including e-prescribing, electronic medical records(EMRs), imaging, and the increased use of intelligent devices to monitor health that generates big data, potentially benefit researchers and medical practitioners when the data is structured and standardized.

Clinical apps use structured and standardized data to enable patients and clinicians to make informed healthcare decisions through the provision of evidence. Three processes are core to attain these benefits; EMRs value unlocking, innovative forms that enable direct control of patients, and pervasive computing of networked systems that facilitate efficient patient data access.

4.2. Digitalisation of clinical decision support

In the fourth industrial revolution era, digital technologies are ubiquitous across institutions. Wearable devices, smartphones, and tablets enable the collection of digital datasets, data mining, and knowledge production. For instance, a smartphone care app [34] replicates the paper-based healing of ulcer [35].

Future clinical decision support apps will utilize the existing feature capabilities [36] of hardware and software of the ubiquitous devices to integrate them with electronic patient healthcare records.

4.3. Data mining and analytics

The low cost of smart devices, their high processing speeds, and their capabilities for real-time metadata analytic [37] provide potential in the mHealth application adoption. Data mining techniques can be applied to give insights to clinicians. Physicians tablet-owning or computer-owning indicate that the tablet computer is a useful educational utility and endorse integration of the devices into clinical practice and medical education/decision-making [38].

5. Application Environments

In the scope of emerging intelligent systems concerning humans' cognitive abilities, this research outlines a list of human capabilities proposed by Adams et al.[39]. The human cognitive capacities include interactions, skills-building, reactions, memory, and computations. Unlike Adams [39] perspective, this work presents practical applications of intelligent systems from the literal works.

5.1. Medical Cognitive Systems

With environmental changes and economic developments in society, there is a threat to human health due to increased chronic diseases. Medical cognitive systems can apply in diagnosis aid for decision making with different forms of data for suitable actions. Correct data [7] play a vital diagnosis role in medical systems. Misunderstanding or ignoring important medical information of a patient can lead to serious long-term multiple damages or even loss of life. The fusion of natural language processing, AI, and machine learning technologies can facilitate cognitive computing to establish a health disorder's frequency and relationship to the data. Multiple data points require comprehensive analysis to aid medical professionals in learning till an optimal solution is reached. Therefore, cooperation between humans and machines is essential in cognitive systems to ensure organizations get enhanced value from data in solving complex problems [11] [40].

5.2. Robotics

Robot technology greatly influences the human lifestyle. Joint efforts from multidisciplinary scientific fields [41] [42] on technology innovations endeavors to "develop human-like robots" based on cognitive architectures. The current relationship between robots and humans is not symbiotic, but rather reliance [10], which results in replacing humans with robots or using robots by humans. Developments in the social scenes suggest a generation of robotic systems that will emulate humans in the future based on different aspects such as natural language processing, computer vision, etc. Therefore, a partnership relationship between humans and robots coexisting and complementing each other is visible. Next-generation of robots will incorporate the co-fusion feature into robotic technology function designs.

5.3. Cognitive Communicating Systems

The seamless integration of the cyber and physical world is a reality with current technological devices and networks. With network developments [8], smart homes systems [43] fuse with human emotion cognition. The intelligent system [43] fuses user and house environment to generate cognitive services for viewpoints and adjustments on house users' emotions. The intelligent system perceives the user's emotions and regulates the environment appropriately.

6. Conclusions

This paper presents a cognitive computing architecture in the context of smart healthcare. The proposed architecture comprises four aspects: discovery of knowledge, the activity environment, infrastructures, and machine learning frameworks; all these work together simultaneously to make up an intelligent system. Additionally, this paper presents the popular emerging intelligent systems from three perspectives: medical cognitive systems, robotics, and cognitive-communication systems.

References

[1] Jean Bertin Nkamla Penka, Saïd Mahmoudi, and Olivier Debauche. An optimized kappa architecture for iot data management in smart farming. *International Journal of Ubiquitous Systems and Pervasive Networks*, 17(2), 2022.

[2] Zhaozong Meng, Zhipeng Wu, and John Gray. Architecting ubiquitous communication and collaborative-automation-based machine network systems for flexible manufacturing. *IEEE Systems Journal*, 14(1):113–123, 2019.

[3] Ira Tabas and Christopher K Glass. Anti-inflammatory therapy in chronic disease: challenges and opportunities. *Science*, 339(6116):166–172, 2013.

[4] Min Chen, Wei Li, Yixue Hao, Yongfeng Qian, and Iztok Humar. Edge cognitive computing based smart healthcare system. *Future Generation Computer Systems*, 86:403–411, 2018.

[5] Yong Li, Depeng Jin, Pan Hui, and Zhu Han. Optimal base station scheduling for device-to-device communication underlaying cellular networks. *IEEE Journal on Selected Areas in Communications*, 34(1):27–40, 2015.

[6] Fengli Xu, Yong Li, Huandong Wang, Pengyu Zhang, and Depeng Jin. Understanding mobile traffic patterns of large scale cellular towers in urban environment. *IEEE/ACM transactions on networking*, 25(2):1147–1161, 2016.

[7] Min Chen, Yixue Hao, Kai Hwang, Lu Wang, and Lin Wang. Disease prediction by machine learning over big data from healthcare communities. *Ieee Access*, 5:8869–8879, 2017.

[8] Liang Zhou. Qoe-driven delay announcement for cloud mobile media. *IEEE Transactions on Circuits and Systems for Video Technology*, 27(1):84–94, 2016.

[9] Liang Zhou. On data-driven delay estimation for media cloud. *IEEE Transactions on Multimedia*, 18(5):905–915, 2016.

[10] Min Chen, Francisco Herrera, and Kai Hwang. Cognitive computing: architecture, technologies and intelligent applications. *Ieee Access*, 6:19774–19783, 2018.

[11] Ying Chen, JD Elenee Argentinis, and Griff Weber. Ibm watson: how cognitive computing can be applied to big data challenges in life sciences research. *Clinical therapeutics*, 38(4):688–701, 2016.

[12] Rajat Kumar Behera, Pradip Kumar Bala, and Amandeep Dhir. The emerging role of cognitive computing in healthcare: a systematic literature review. *International journal of medical informatics*, 129:154–166, 2019.

[13] Shah Nazir, Sulaiman Khan, Habib Ullah Khan, Shaukat Ali, Iván García-Magariño, Rodziah Binti Atan, and Muhammad Nawaz. A comprehensive analysis of healthcare big data management, analytics and scientific programming. *IEEE Access*, 8:95714–95733, 2020.

[14] Jay Moore. Behaviorism. *The Psychological Record*, 61 (3):449–463, 2011.

[15] Victor S Johnston. *Why we feel: The science of human emotions.* Perseus Publishing, 1999.

[16] Venkat N Gudivada. Cognitive computing: concepts, architectures, systems, and applications. In *Handbook of statistics*, volume 35, pages 3–38. Elsevier, 2016.

[17] Khurram Khalil, Umer Asgher, Yasar Ayaz, Riaz Ahmad, Jose Arzola Ruiz, Noriyuki Oka, Sara Ali, and Muhammad Sajid. Cognitive computing for human-machine interaction:

An ibm watson implementation. In *International Conference on Applied Human Factors and Ergonomics*, pages 400–406. Springer, 2020.

[18] Gopi Battineni, Getu Gamo Sagaro, Nalini Chinatalapudi, and Francesco Amenta. Applications of machine learning predictive models in the chronic disease diagnosis. *Journal of personalized medicine*, 10(2):21, 2020.

[19] Youyang Qu, Shiva Raj Pokhrel, Sahil Garg, Longxiang Gao, and Yong Xiang. A blockchained federated learning framework for cognitive computing in industry 4.0 networks. *IEEE Transactions on Industrial Informatics*, 17(4): 2964–2973, 2020.

[20] Zhihan Lv, Liang Qiao, and Amit Kumar Singh. Advanced machine learning on cognitive computing for human behavior analysis. *IEEE Transactions on Computational Social Systems*, 2020.

[21] Quentin JM Huys, Michael Browning, Martin P Paulus, and Michael J Frank. Advances in the computational understanding of mental illness. *Neuropsychopharmacology*, 46(1): 3–19, 2021.

[22] M Chen, Y Liu, and S Mao. Big data: Asurvey mobile network and applications. 2014.

[23] Ana Paula Appel, Heloisa Candello, and Fábio Latuf Gandour. Cognitive computing: Where big data is driving us. In *Handbook of Big Data Technologies*, pages 807–850. Springer, 2017.

[24] Bret Hull, Vladimir Bychkovsky, Yang Zhang, Kevin Chen, Michel Goraczko, Allen Miu, Eugene Shih, Hari Balakrishnan, and Samuel Madden. Cartel: a distributed mobile sensor computing system. In *Proceedings of the 4th international conference on Embedded networked sensor systems*, pages 125–138, 2006.

[25] Kai Hwang and Min Chen. *Big-data analytics for cloud, IoT and cognitive computing*. John Wiley & Sons, 2017.

[26] Yixue Hao, Min Chen, Long Hu, Jeungeun Song, Mojca Volk, and Iztok Humar. Wireless fractal ultra-dense cellular networks. *Sensors*, 17(4):841, 2017.

[27] Min Chen, Yiming Miao, Yixue Hao, and Kai Hwang. Narrow band internet of things. *IEEE access*, 5:20557–20577, 2017.

[28] Amit Sheth. Internet of things to smart iot through semantic, cognitive, and perceptual computing. *IEEE Intelligent Systems*, 31(2):108–112, 2016.

[29] Héctor Sánchez San Blas, André Sales Mendes, Francisco García Encinas, Luís Augusto Silva, and Gabriel Villarubia González. A multi-agent system for data fusion techniques applied to the internet of things enabling physical rehabilitation monitoring. *Applied Sciences*, 11(1):331, 2021.

[30] Giang Nguyen, Stefan Dlugolinsky, Martin Bobák, Viet Tran, Álvaro López García, Ignacio Heredia, Peter Malík, and Ladislav Hluchỳ. Machine learning and deep learning frameworks and libraries for large-scale data mining: a survey. *Artificial Intelligence Review*, 52(1):77–124, 2019.

[31] Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. Tensorflow: A system for large-scale machine learning. In *12th {USENIX} symposium on operating systems design and implementation ({OSDI} 16)*, pages 265–283, 2016.

[32] Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. Caffe: Convolutional architecture for fast feature embedding. In *Proceedings of the 22nd ACM international conference on Multimedia*, pages 675–678, 2014.

[33] Qingshan Liu, Renlong Hang, Huihui Song, Fuping Zhu, Javier Plaza, and Antonio Plaza. Adaptive deep pyramid matching for remote sensing scene classification. *arXiv preprint arXiv:1611.03589*, 2016.

[34] Marcia R Friesen, Carole Hamel, and Robert D McLeod. A mhealth application for chronic wound care: findings of a user trial. *International journal of environmental research and public health*, 10(11):6199–6214, 2013.

[35] Connie Harris, Barbara Bates-Jensen, Nancy Parslow, Rose Raizman, Mina Singh, and Robert Ketchen. Bates-jensen wound assessment tool: pictorial guide validation project. *Journal of Wound Ostomy & Continence Nursing*, 37(3): 253–259, 2010.

[36] Selvine G Mathiasa and Daniel Grossmanna. Use cases of data reduction to time series data in sensor monitoring. *Journal of Ubiquitous Systems & Pervasive Networks*, 3(1): 00–00, 2011.

[37] N Kashmar, M Adda, and H Ibrahim. Access control metamodels: Review, critical analysis, and research issues. *J. Ubiquitous Syst. Pervasive Netw*, 3, 2021.

[38] Joseph Sclafani, Timothy F Tirrell, and Orrin I Franko. Mobile tablet use among academic physicians and trainees. *Journal of medical systems*, 37(1):1–6, 2013.

[39] Sam Adams, Itmar Arel, Joscha Bach, Robert Coop, Rod Furlan, Ben Goertzel, J Storrs Hall, Alexei Samsonovich, Matthias Scheutz, Matthew Schlesinger, et al. Mapping the landscape of human-level artificial general intelligence. *AI magazine*, 33(1):25–42, 2012.

[40] Min Chen, Jun Yang, Yixue Hao, Shiwen Mao, and Kai Hwang. A 5g cognitive system for healthcare. *Big Data and Cognitive Computing*, 1(1):2, 2017.

[41] Juan P Jiménez, Luis Martin, Iván Axel Dounce, Cynthia Ávila-Contreras, and Félix Ramos. Methodological aspects for cognitive architectures construction: a study and proposal. *Artificial Intelligence Review*, 54(3):2133–2192, 2021.

[42] Iuliia Kotseruba and John K Tsotsos. 40 years of cognitive architectures: core cognitive abilities and practical applications. *Artificial Intelligence Review*, 53(1):17–94, 2020.

[43] Min Chen, Jun Yang, Xuan Zhu, Xiaofei Wang, Mengchen Liu, and Jeungeun Song. Smart home 2.0: Innovative smart home system powered by botanical iot and emotion detection. *Mobile Networks and Applications*, 22(6): 1159–1169, 2017.