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A Survey on Multimodal Data-Driven Smart Healthcare Systems: Approaches and Applications

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ABSTRACT Multimodal data-driven approach has emerged as an important driving force for smart healthcare systems with applications ranging from disease analysis to triage, diagnosis and treatment. Smart healthcare system necessitates new demands for data management and decision-making, which has inspired the rapid development of medical services using artificial intelligence and new transformations in the healthcare industry. In this paper, we provide a comprehensive survey of existing techniques which include not only state-of-the-art methods but also the most recent trends in the field. In particular, this review focuses on the types of decision-making processes used in smart healthcare systems. Firstly, approaches that utilize multimodal association mining with fine-grained data semantics in smart healthcare systems are introduced. We review the smart healthcare-oriented semantic perception, semantic alignment, entity association mining, and discuss the pros and cons of these approaches. Secondly, we discuss approaches for multimodal data fusion and cross-border association that have been employed in developing smart healthcare systems. Finally, we focus specifically on the use of the panoramic decision framework, interactive decision making, and intelligent decision support systems. We introduce how smart healthcare systems can be applied to and benefit a wide variety of fields, including knowledge discovery and privacy protection.

INDEX TERMS Smart healthcare, clinical decision support, data-driven reasoning, multimodal fusion, survey.

I. INTRODUCTION

The aging population has become a global issue which changed the epidemiological spectrum [1].The population of seniors aged over 65 years has exceeded 150 million and the population of patients with various chronic diseases has exceeded 400 million, which has increased the societal need for safe and high-quality medical and healthcare services [2]. A diagnosis and treatment model supported by a single in-hospital data source cannot cope with the challenges associated with the rapidly aging population and the management of widespread chronic diseases [3], [4].

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Traditional computer-aided medical expert systems can assist in decision-making by employing feature-level fusion or rule-based reasoning. The system performance can be significantly affected by decision rules that are usually subjectively determined by experts in the field and cannot be dynamically updated. Therefore, the performance of traditional computer-aided medical expert systems are often unsatisfactory with the loss of key information. Since these methods are not able to gain knowledge and update rules over time, it is easily lead to information loss [5], [6]. Although these systems employ associated-type or adaptive-type intelligent algorithms to alleviate this problem, it is still very challenging to use a set of rules to illustrate the decision mechanism. Especially for multisource, multimodal medical and healthcare data,

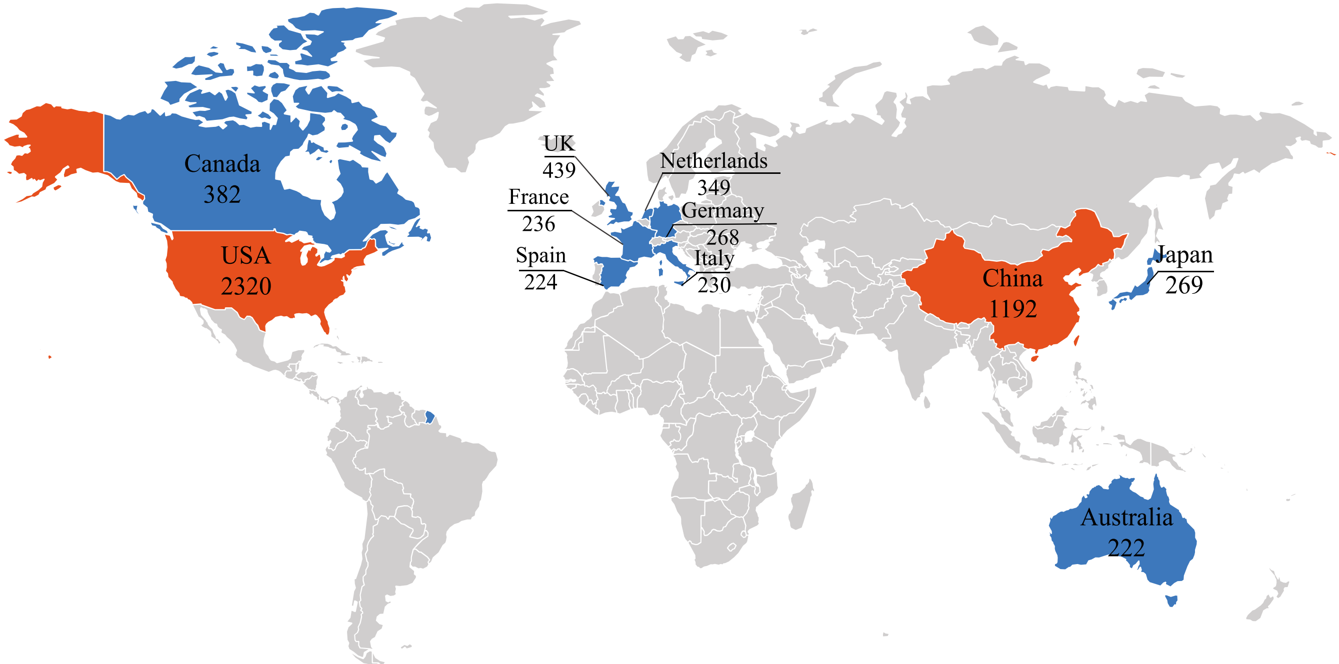

FIGURE 1. Top ten countries publishing papers regarding data-driven smart healthcare systems.

those methods usually ignore the integration, reasoning and interactive decision support.

There are many computer-aided diagnosis and treatment expert systems for multimodal data proposed in academia. They usually employ a multinetwork link or network reconstruction based on a deep neural network with feature coupling, to achieve intelligent auxiliary diagnosis decision-making in complex in-hospital scenes. The authors in [7] proposed a panoramic medical decision-making method which is capable of multimodal cross-border integration has achieved high effectiveness in cross-modal fusion reasoning. Figure 1 shows a global heatmap for research on data-driven smart healthcare system, which mainly concentrated in America and Europe [8].

In December 2016, the Journal of the American Medical Association (JAMA), a flagship medical journal, published an paper on an artificial intelligence model developed by a Google team to screen for diabetic retinopathy based on multimodal information such as Picture Archiving and Communication System (PACS) image information and medical reports [9]. In June 2018, Zolbanin and Delen proposed a medical record-based readmission risk analysis model which comprehensively considers different electronic medical record data including history of heart failure, from multiple time periods. This model has significantly improved the performance of readmission analysis [10]. In January 2017 and February 2018, *Nature* and *Cell* journals introduced intelligent auxiliary diagnosis methods for skin diseases, blinding retinal diseases, and child pneumonia developed by Stanford University and Guangzhou Medical University [11], [12]. Unlike traditional rule-based expert systems, multimodal smart healthcare systems implement new methodologies for information perception, integration, reasoning, and decision making through data-driven approaches. However, they are still facing many challenges. According to [13], the capability of healthcare big data is defined as the ability to collect, store, process and analyze a significant amount of health data in various forms, and generate meaningful information for users that allow them to facilitate clinical diagnosis and treatment to discover business values and insights in a timely fashion. In particular, to deal with healthcare big data, issues like the characteristics of granularity scaling, cross-border association, and global perspective need to be solved.

In general, multimodal data-driven smart healthcare decision-making research can be classified into three categories. The first category includes studies that provide accurate diagnostic guides or diagnosis and treatment services to target patients. These approaches can effectively integrate multisource out-of-hospital data (such as data from the government, community, and the Internet) with in-hospital data to break the hospital data barriers [10], [14]. The second category includes studies that implement joint decision-making by integrating data within and outside a department and data from other medical institutions within a medical association to enhance the decision-making for diagnosis and treatment. The third category includes studies that investigate panoramic cross-border data fusion mechanisms based on semantic associations and support effective intelligent decision-making through reliability estimation and dynamic adaptive adjustment of data sources [15], [16]. These approaches are proposed to mainly deal with the inconsistency among demands or situations requiring smart

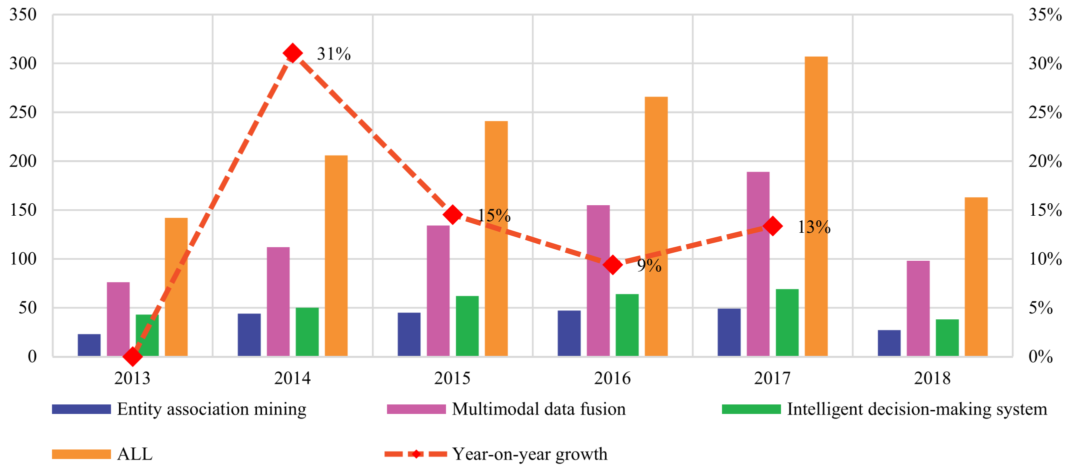

FIGURE 2. The number of papers published in the Web of Science on entity association mining, multimodal data fusion and intelligent decision-making systems from January 2013 to September 2018.

healthcare services as there are differences in medical and healthcare service contents, preferences, and resources in real-world practice. The amount of research works related to multimodal data-driven smart healthcare systems has shown an increasing trend in recent years. Multimodal data-driven smart healthcare decision-making research first began to appear at workshops and conferences, followed by publications in journals. We list the number of papers in the Web of Science from January 2013 to September 2018 according to these three categories, and we can see that the number of papers has grown rapidly in recent years as illustrated in Figure 2.

Open, dynamic and scalable smart decision-making methods are indispensable in smart healthcare applications. The data mining performance, data fusion efficiency and ease of interactive decision-making are directly affecting the effectiveness of smart healthcare applications in specific situations such as consultation triage, diagnosis, and treatment. In this paper, we provide a comprehensive survey of existing techniques, including state-of-the-art techniques and the latest trends in the field. The remainder of the paper is organized as follows. Section 2 reviews the first category of approaches on smart healthcare-oriented semantic perception, semantic alignment, and entity association mining, as well as the pros and cons of these approaches. Section 3 reviews the second category of approaches on multimodal data fusion and cross-border association for developing smart healthcare systems. Section 4 reviews the third category of approaches for panoramic decision framework and intelligent decision support in smart healthcare systems. Finally, Section 5 concludes our work and discusses some further research directions.

II. MULTIMODAL SEMANTIC PERCEPTION AND ENTITY ASSOCIATION MINING

With the general trends of informationization, intelligentization, and mobilization in medicine and healthcare, the amount of multimodal medical and healthcare data generated by hospitals, health screening institutions, health management departments, and Internet platforms is rapidly growing. These data mainly include high-precision multimodal medical data, personalized real-time health precision data, and large sample diversified social network data. Making full use of these cross-border associations of multimodal medical data can help in the development of more efficient and accurate medical services. There are major differences among different sources of medical data due to the diverse generation and collection methods. For example, text-based data generated by the Internet outside hospitals are highly abstract and discrete, and PACS image data within hospitals have natural random continuity. How to realize semantic perception and correlation mining of multimodal data is the key for supporting knowledge fusion and panoramic decision-making.

The acquisition of healthcare big data is defined as the collection and retrieval of unlimited raw data, which can be structured, semistructured, or unstructured, from several sources using computational techniques [8]. In general, healthcare big data can be collected from the following four sources: clinical information systems, personal mobile or wearable healthcare devices, Internet Of Things (IoTs) and open medical data [17].

Data collection from information system is analogous to retrieving data from a centralized data warehouse containing all the information about the activities of an organization, such as Electronic Health Records (EHRs), medical imaging data, genetic data and prescription notes. When using personal mobile or wearable healthcare devices such as smartphones, tablets or personal computers, a considerable amount of mobile data can be generated from the healthcare sensors or installed applications. Another data collection method is through open data, containing a large amount of extractable data obtained from web pages, on-line forums, journal articles and so on.

The data collection methods utilizing the emerging Internet of Things (IoT) technologies is thriving, which incorporates various interconnected devices with embedded sensors to provide stream and updated data controlled across the network. IoT-enabled data collection methods have played an important role in the next-generation healthcare industry for quality care.

Personally collected data using IoT technologies potentially captures the personal perspectives on therapies compliance and tolerability, patient's conditions and symptoms, and lifestyles. These new types of data, directly collected by patients in their ecologic environment, can help provide a more realistic view on the target of the clinical investigation that can be synthesized into more accurate medical advices.

A personal health system based on IoT was proposed in [18] to integrate patient-generated and personally collected health data into the clinical research data workflow, using a standards-based architecture that ensures the fulfillment of the major requirements for digital data in clinical studies. Zhang *et al.* [19] proposed an architecture of mobile healthcare networks featuring privacy-preserving data collection and secure transmission. The privacy-preserving data collection was implemented by using cryptography with secret and private keys, while the secure transmission was realized using attribute-based encryption.

A real-time online assessment and mobility monitoring IoT framework based on a smartwatch was presented in [20]. An infrastructure was designed for sensor and user reported data collection, transmission, visualization, and analysis for the framework. A portable ECG monitoring device was proposed by Lee *et al.* [21], which collects ECG signals by connecting the measuring module to a patch with a minimized electrode array using a snap button. A healthcare industrial IoT-enabled monitoring framework was proposed in [22], where ECG and other healthcare data are collected by mobile devices and sensors and securely sent to the cloud for seamless access by healthcare professionals. In our prior work [23], we proposed a smart electronic gastroscope system based on a cloud-edge collaborative framework. In this system, edge computing platforms and cloud platforms work collaboratively to achieve real-time lesion localization and fine-grained disease classification of gastroscopic videos.

Although data fusion inside and outside a hospital or a department can generate smart healthcare innovations, its characteristics such as multimodality, timeliness, and quality consistency, also pose challenges to knowledge discovery and reasoning. To cope with these challenges, scholars have focused on three research topics, viz. multimodal entity semantic perception, multimodal entity semantic alignment, and multimodal entity association mining, and some representative works are shown in Table 1.

A. MULTIMODAL ENTITY SEMANTIC PERCEPTION

To integrate medical images and textual information to narrow the semantic gap among massive medical data, an extended probabilistic latent semantic analysis model was proposed and a new multimodal medical image retrieval method was implemented [24]. Hui and Meng [26] employed a multimodal and lexical terminology to form a query-term matrix that was factorized by singular value decomposition to conduct latent semantic analysis of the speech and gesture information entered by users. In addition to the methods based on probability models, machine learning methods have been used in clinical practice. Pereira *et al.* [25] employed a deep cascaded neural network to conduct semantic analysis on magnetic resonance imaging data to achieve automatic segmentation of glioma. Despotovic *et al.* [27] systematically compared the results of seven different machine learning algorithms for speech input semantic analysis and revealed that the Markov logic network and conditional random field test fields were superior to other machine learning methods in speech and semantic analysis. In our prior work [34], we proposed an approach for diabetic complication prediction based on a similarity-enhanced latent Dirichlet allocation (seLDA) model. We estimate the similarity between textual medical records and perform seLDA-based diabetic complication topic mining based on similarity constraints.

In clinical practice, deep semantic association mining which relies on text-based medical record data and medical images is a common type of intelligent decision-making problem.An effective method at this stage is build a semantic perception and association mining framework that constructs a clinical semantic text data dictionary of medical entities extracted from text-based data (such as electronic medical records and clinical diagnosis and treatment data) using statistical analysis and a hidden Markov model based on medical dictionaries such as the ICD10 [35]. After preprocessing with a classifier, the medical imaging data from an image dictionary via fine-grained semantic segmentation. A multisource heterogeneous fusion feature-based entity association mining model is constructed by introducing interpretable deep learning.

B. MULTIMODAL ENTITY SEMANTIC ALIGNMENT

A medical knowledge base is an important resource for Natural Language Processing (NLP) tasks such as processing electronic health records and hospital records. However, the coverage of a single medical knowledge base is limited and the heterogeneity of different knowledge bases is high. Researchers have attempted to address the challenge of medical and healthcare semantic alignment by providing an organized solution to acquire knowledge of project management and to use and lay the foundation for collaborative sharing and knowledge acquisition among clinicians [28]. When the system was deployed in a clinical setting, precise information exchange between medical records and the decision support system is crucial. Thus, the authors developed a health Cyber Physical System (CPS) in which distributed storage and parallel computing are achieved by implementing a unified standard data acquisition layer. It was demonstrated that multimodality-based cloud computing can improve the performance of a healthcare system [29]. To further realize

TABLE 1. Representative work about multimodal semantic perception and entity association mining.

Paper	Approach	Problem Addressed	Contribution	Limitation
a) Multimodal entity semantic perception				
Cao et al. [24]	Semantic analysis	Medical image retrieval	A medical imaging indexing and retrieval system	Limited by the image source type, and only tested on a small dataset
Pereira et al. [25]	Neural network	Automatic segmentation of glioma	A CNN-based segmentation method for segmentation of glioma	Performance depends on the number and quality of labeled data.
Hui et al. [26]	Singular value decomposition	Latent semantic analysis	A latent semantic analysis system for multimodal resources	Performance depends on the number and quality of labeled data.
Despotovic et al. [27]	Markov logic network	Speech input semantic analysis	A Markov logic networks-based model for speech semantic analysis	Difficult to handle multiple types of semantics
b) Multimodal entity semantic alignment				
Lasierra et al. [28]	Ontology models	Knowledge acquisition	An ontology-based system for clinical knowledge sharing and acquiring	Some valid information is deleted for simplifying alignment process.
Zhang et al. [29]	Neural network	Medical data exchange	A HCP system for multidimensional medical data	Cannot satisfy dynamic system semantic alignment
Pacaci et al. [30]	Semantic transformation	Secure data exchange	A semantic transformation methodology for secure data exchange	The exchange takes longer time to ensure efficiency.
c) Multimodal entity association mining				
Liu et al. [31]	Unified medical language	Data associations	A method for bridging clinical data with genomic data for colorectal cancer.	It is verified only for a single data source and has not yet supported multi-source data.
Buczak et al. [32]	Association Rule Mining	Prediction of malaria	A malaria prediction model	The prediction model is greatly influenced by the environment.
Kavakiotis et al. [33]	Neural network	Diabetes research	A systematic review of methods in the field of diabetes research	The type of model is limited.

semantic alignment, a modular coordinated transformation method that retrieves data from an electronic health record system was used to achieve feature extraction and semantic alignment of descriptive statistics [30]. Some scholars noted that the sharing of electronic health records systems may cause information overload for healthcare providers. To address such an issue, cross-modality, cross-granularity data integration and semantic alignment were achieved by rule-based three-dimensional measurements [42].

C. MULTIMODAL ENTITY ASSOCIATION MINING

Data mining methods such as clustering and association mining have become important research tools for various types of institutions such as information and medical institutions [43], [44]. The essence is to discover unknown patterns and trends in multimodal data [45]. Figure 3 shows the main methods in multimodal entity association mining which typically use two different models to obtain the result. The association mining method was applied in associating clinical aspects of colorectal cancer with genomic data, and significant improvement has been achieved [31]. Additionally, fuzzy association rules have been applied to construct a prediction model for the prediction and classification of malaria. Machine learning has also been successfully applied in the clinic. Kavakiotis *et al.* [33] applied machine learning and data mining methods to extract data and discover useful information for people with diabetes. Lin *et al.* employed a pattern clustering algorithm to design a text-based exploratory pattern analyzer which combines semantically independent NLP, regular expression induction, and statistical association testing. The analyzer can identify the conservative text mode associated with outcome variables with clinical significance which promotes the medical application of textual information [46]. Some scholars have attempted to apply entity recognition and semantic distribution methods to association rule mining in risk factor analyses of diseases, such as prostate cancer and breast cancer [47].

To improve the effectiveness of smart healthcare systems in data fusion and intelligent decision-making, studies that address the following two aspects are needed. First, regarding the semantic perception of multisource medical data, a cross-time-space, cross-modality and cross-granularity semantic perception mechanism and a coupled model and framework of multimodal associated data streams needs to be established to investigate the description and feature extraction methods for associated data streams and to construct a mapping framework and semantic perception model for multisource heterogeneous medical data. Second, regarding multimodal

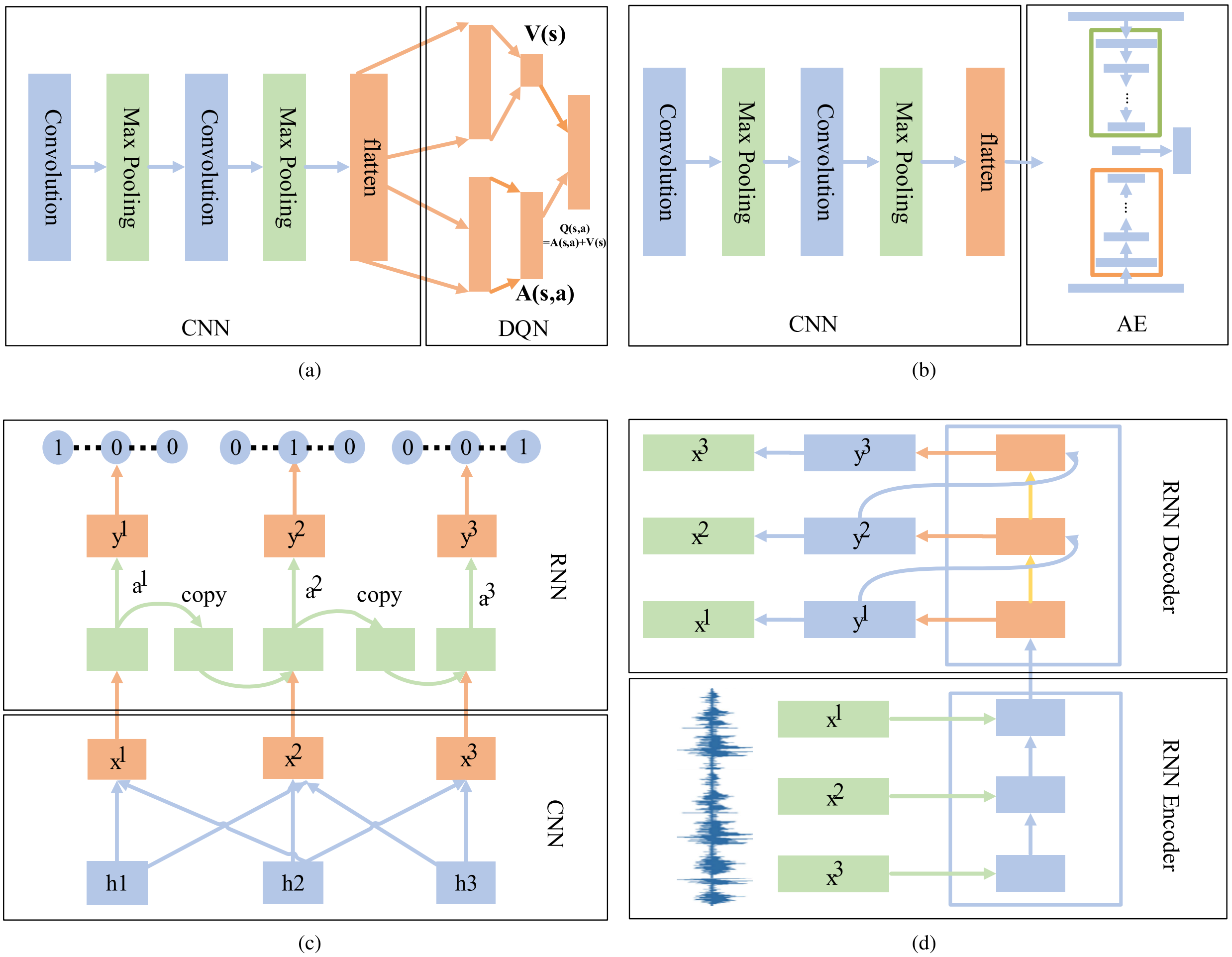

FIGURE 3. Multimodal entity association mining methods can generally be divided into four categories: (a) combined CNN and DQN [36]; (b) CNN and SAE [37], [38]; (c) CNN and RNN [39], [40]; (d) RNN and SAE [41].

medical data association mining, an entity association mining method with integrated semantic features for the medical and healthcare fields needs to be developed to establish a smart healthcare decision-making-oriented multisource multimodal data coupling framework and to construct multimodal data entity alignment and mining models and intelligent algorithms.

III. MULTIMODAL DATA FUSION AND CROSS-BORDER KNOWLEDGE FUSION

Research on management and decision-making in the context of smart healthcare will strengthen the coordinated implementation of national health management systems by various social institutions, such as those focused on public health, medical services, health management, and medical insurance. These studies will also promote intelligent decision-making support throughout the whole healthcare process, including consultation, triage, diagnosis, and treatment for different target groups. Clinical applications include care for patients with chronic diseases, maternal and childcare, and mental healthcare using knowledge retrieval, fusion, storage and panoramic analysis and processing of multimodal data.

Multisource, multimodal medical data belong to a type of massive, rapidly-growing, and diverse information asset. Medical data can be used for decision-making, insight, and process optimization in the context of smart healthcare. Ensuring the reliability of medical data is a precondition for multimodal data-driven smart healthcare decision-making. Data reliability is defined in [57] as the production of the same analytical results on repetitive processes of data collection, processing, storing and display of information. As a measure of stability, data reliability is assessed based on comparison of indicators such as rates and prevalence, and it requires consistent denominator data.

Data reliability is crucial to the credibility of healthcare decision support systems. However, at an operational level, due to the limitation of human resource, medical facilities, and more importantly, proper data collection and preprocessing methodology, it is exceptionally difficult to maintain reliability. Therefore, ensuring or improving data reliability remains an often-cited challenge to the implementation and use of big data methods in health.

Depending on the origin and modal of the data, the sources of healthcare big data can be classified into the following

TABLE 2. Overview of papers on multimodal data fusion and cross-border knowledge fusion.

Paper	Approach	Problem Addressed	Contribution	Limitation
a) Reliability prediction of medical data				
Cortes et al. [48]	Bayesian analysis	Genetic association of medical data	A framework for analyzing correlation between clinical diagnostic reports and genetic variations.	Depends on specific artificial prior knowledge.
Peng et al. [49]	Bayesian analysis	System reliability assessment	A system reliability assessment method for multimodal data.	Unable to handle multilevel heterogeneous data sets.
Shi et al. [50].	Multifactorial risk models	Relevance of genetic testing for the assessment of disease risks	A multifactorial risk models based on information from genetic testing and environmental risk factors.	Limited by data quality, the actual cost is too high.
b) Multisource medical data fusion				
Zheng et al. [51]	Neural network	Topic Modeling of Multimodal Data	A DocNADE based topic model for entity semantic alignment	Performance is limited by the quality of labeled data.
Bhatnagar et al. [52]	Non-subsampled contourlet transform	Medical image fusion	A new contrast based multimodal medical image fusion framework	Tested on single disease data, and the validity has not been evaluated.
Liu et al. [53]	Neural network	Multiclass diagnosis of Alzheimer's disease (AD)	A novel diagnostic framework with deep learning diagnosis the AD	The method relies on a large amount of training data.
c) Medical data-driven knowledge reasoning				
Suchanek et al. [54]	Probabilistic model	Alignments at the schema level.	A probability-based knowledge fusion framework	Methods rely on a large number of prior knowledges.
Dong et al. [55]	Probability risk assessment and neural network	Extracting facts from an entire network	A web-scale approach to probabilistic knowledge fusion	This method only analyzes static data.
Huang et al. [56]	Neural network	Drug–drug interaction extraction	A novel two-stage method based on support vector machine and long short-term memory networks	The method relies on a large number of labeled data..

four categories: (1) in-hospital medical data that are collected using various hospital information systems, (2) out-of-hospital medical data that are acquired and maintained by government, community and a variety of non-hospital healthcare facilities, (3) personal healthcare data that are gathered by wearable devices, body sensor networks, IoT systems and ambient-assisted living systems comprising Internet of Health Things (IoHT), and (4) open healthcare data that can be extracted from, for instance, web sites, on-line forums, and journal articles. [58].

Multimodal data fusion for medical data analysis can improve the accuracy and comprehensiveness of the clinical decision support system. Knowledge can be structured through data crossover fusion using a knowledge graph which is also a vital tool for knowledge reasoning. To satisfy the decision-making needs of multisource, multimodal data intermediation, numerous fruitful investigations on multimode data fusion and cross-border knowledge integration with respect to reliability forecasting, multisource intermediation and knowledge reasoning have been conducted. An overview of representative works is summarized in Table 2.

Deep learning and knowledge graph-based multimodal cross-border medical data fusion has attracted substantial attention from investigators. However, the application of multimodal fusion technology in the field of intelligent auxiliary diagnosis has not addressed the correlation among multimodal data when the decision targets are consistent and has rarely addressed the reliability estimation and dynamic adaptive adjustment method for medical and healthcare big data. Moreover, various aspects, such as the removal and screening of redundant features, have been disregarded. Regarding knowledge graph-based entity mapping, entity similarity estimation, knowledge-based fusion and knowledge storage, their applications in the medical and healthcare field have not led to the formation of a complete system.

To develop a data fusion and knowledge fusion method and a smart healthcare application system, the following tasks should be performed: (1) with respect to reliability, comprehensively consider the characteristics of dominant and recessive relationships among multimodal data in the smart healthcare context to investigate the reliability prediction and credibility evaluation methods for multisource heterogeneous medical and healthcare data sources; (2) with respect to multimodal data fusion, establish a semantic association-oriented multimodal data cross-border polymerization, fusion and evolution mechanism in the smart healthcare context to investigate multimodal deep learning algorithms for integral dynamic sequence and deep convolution characteristics;

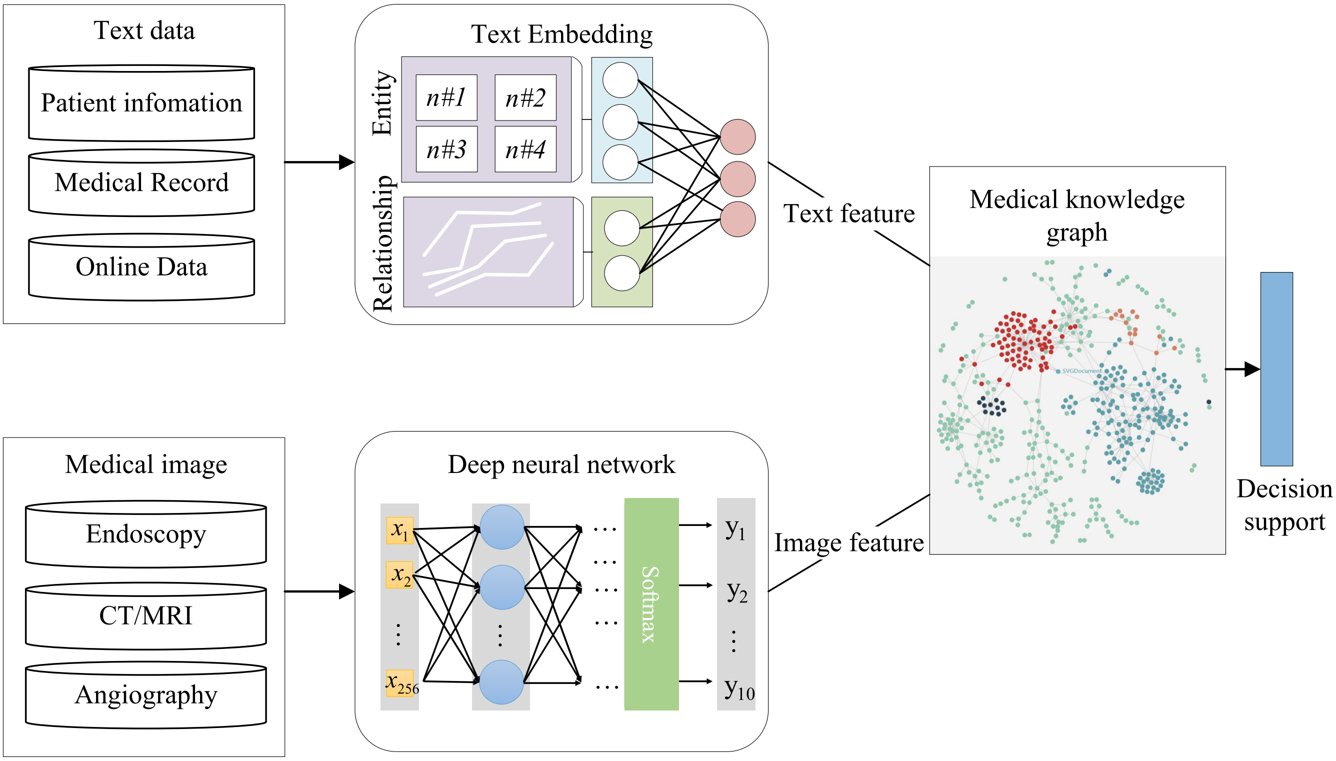

FIGURE 4. Data fusion and knowledge fusion research framework for multimodal medical and healthcare big data.

and (3) with respect to the cross-border fusion method, establish an integrated learning framework-based medical and healthcare entity similarity estimation model, design entity mapping and knowledge classification algorithms for medical and healthcare big data, and investigate a knowledge graph-based semantic layer fusion and storage method for medical and healthcare big data.

Multisource, multimodal data fusion and knowledge integration for assisting clinical decision-making are prerequisites for panoramic intelligent decision-making. As the available data become more complex and diverse, the decision-making process also needs to consider multiple factors and it is also a question in the current intelligent healthcare system that urgently requires further study [66]. Figure 4 presents a typical framework that integrates data fusion and knowledge integration. The framework performs a word vector feature extraction for multisource text data using a generative Restricted Boltzmann Machine (RBM) to embedding the text feature. Meanwhile, a multimodal discriminant model is constructed in combination with a multicolumn convolutional neural network that registers coded deep convolution features. Afterwards, the framework performs modeling on the mapping between inputs and outputs, and adjusts the parameters using the minimum regularization method to construct a panoramic analysis and processing mechanism for multimodal data. Thus, the fusion of multisource data is realized based on the interconnection.

A. RELIABILITY PREDICTION OF MEDICAL DATA

Reliability assessments of big data in the medical and healthcare fields have practical significance for meeting the need for precise medical treatment and the ability to identify the risk involved in decision-making in advance. The reliability of a smart healthcare decision support system is strongly related to data reliability [67].

Due to the enormous diversity of sources, corresponding approaches are required to improve the data reliability when processing healthcare big data acquired from different sources. For in-hospital medical data, due to historical reason, large amount of medical data is manually fed electronic health records, which are inevitably prone to errors and bias. For instance, a missing in an Electronic Health Record (EHR) does not necessarily indicate the absence of the event. Moreover, systematic bias cannot be simply removed by using regularized systems.

In fact, medical data normally include noisy information and missing data. Therefore, data preparation, typically consisting of data cleaning and data filtering, is pivotal for enhancing reliability of data mining techniques [8], [68], [69]. Data filtering is often realized by removing data entries that are valueless or erroneous for healthcare monitoring based on a priori or a defined criterion. Data cleaning is comprised of procedures such as normalization, noise reduction, and missing data management. Noise treatment is essential during data cleaning since many types of medical big data contain large amount of noise. For instance, data sparsity in electronic medical records finds its origin in irregular collection of parameters over time. Also, many processing techniques have been applied in order to reduce noise in the area of biomedical image processing. Data preparation is more challenging when dealing with out-of-hospital healthcare big data due to its huge volume and informal content.

However, for medical artificial intelligence-assisted decision-making systems, due to the limited amount of reliability data, it is difficult to evaluate whether the results are corresponding to actual levels. [70]. A Bayesian analysis framework was used to analyze the differences between the clinical data and disease perception so as to find associations between Human Leukocyte Antigen (HLA) and immune-mediated diseases [48]. Peng *et al.* [49] applied a Bayesian method for system reliability assessment and multilevel heterogeneous dataset prediction, which offered a natural way to incorporate into system operation and management decision-making procedures. Meeker and Hong [71] reviewed some applications using field reliability data and explored the opportunities to employ more robust statistical methods provided by modern reliability data research to run and predict field system performance. They also provided some application examples of these new technologies. A combination of data mining methods with tools of reliability analysis is proposed to investigate importance of individual database attributes [72]. Methods for inferring the distribution of effect magnitude, cost-effectiveness, and the benefit of alternative scheme-based methods have also been proposed in medical data reliability prediction, such methods provide a new way for data reliability verification and have achieved satisfactory outcomes in practical applications [50], [73].

For enhancing the reliability of personal healthcare data that are collected using wearable devices, body sensor networks, IoT or IoHT, more focus is required on aspects such as stability and accuracy of the sensing hardware, the communication and monitoring protocol and infrastructure, fault-tolerant algorithm, and validation model [58], [74]. For personally-generated healthcare data, the personal medical devices that cannot be correctly synchronized or maintained, the low patient's medical literacy, and the lack of clinical supervision may lead to serious degradation on accuracy and reliability [18].

A rule based lifelogging physical activity validation model, LPAV-IoT, was proposed for effectively eliminating irregular uncertainties and estimating physical activity data reliability in IoT enabled personalized healthcare systems [74]. Zdravevski *et al.* [75] proposed a generic feature engineering approach for selecting robust features from a variety of sensors, which can be used for delivering reliable classification models while reducing the cost of ambient assisted living systems. A novel trust-based decision making protocol was proposed in [76] that considers risk classification, reliability trust, and loss of health probability as three design dimensions for decision making, resulting in a protocol suitable for decision making in health IoT systems. A reliable oneM2M-based IoT system for Personal Healthcare Devices (PHDs) was proposed, as well as a fault-tolerant algorithm for a reliable IoT system [77]. In [78], an innovative end-to-end approach was proposed for gathering, anonymizing, and cleaning medical data, making it interoperable, and finally storing it through 5G network technologies, with the target for delivering results of high-reliability and efficiency. In our prior work [79], we designed a storage scheme to manage personal medical data based on blockchain and cloud storage. Furthermore, a service framework for sharing medical records was proposed.

B. MULTISOURCE MEDICAL DATA FUSION

Artificial intelligence (AI) is widely used to encompass a spectrum of learning, including but not limited to Machine Learning (ML), representation learning, deep learning, and natural language processing [80], [81]. AI technologies can facilitate a wide array of medical activities, such as aiding in diagnosis generation and therapy selection, making risk predictions and stratifying disease, reducing medical errors, and improving productivity. Regardless of the specific techniques, the general aim of these technologies in medicine is to use computer algorithms to mine valuable information from data and improve clinical decision-making.

Data classification is one of the most popular tools in data mining for understanding relationship among various conditions and features of different objects. Typical classification techniques include K-Nearest Neighbor (KNN), Naive Bayes (NB), Decision Tree (DT), Support Vector Machine (SVM), Neural Network (NN), and Ensemble (EM). Classification methods are capable of identifying a new instance belonging to which particular part of categories (sub-populations), based on a training set of data containing instances whose category membership is known in advance [82].

More recently, Deep Learning (DL) techniques are emerging, which evolves from traditional neural networks in the branch of machine learning techniques. DL techniques are based on the concept of neuron processors and the essential architecture of multiple processing layers for transferring non-linear relationships through responses of each layer. DL techniques excel in majority of areas, such as speech and image recognition, natural language processing, biomedical research with strengths in high-level abstractions of features for a large amount of raw data, distributed and parallel computing, sophisticated learning mechanism without excessive manual interventions [82].

From technical point of view, ML is the core technique of data mining. Due to the close relationship between traditional ML and DL, it is natural to make the comparison of ML and DL from multiple aspects. First, ML differs from DL in the scale of data volume. Compared with traditional ML, DL requires a larger volume of data to extract sufficient knowledge and obtain better insights perfectly. Another difference between those two learning strategies is the requirement for computing resources. ML requires comparatively low hardware configuration on target platforms, while DL heavily

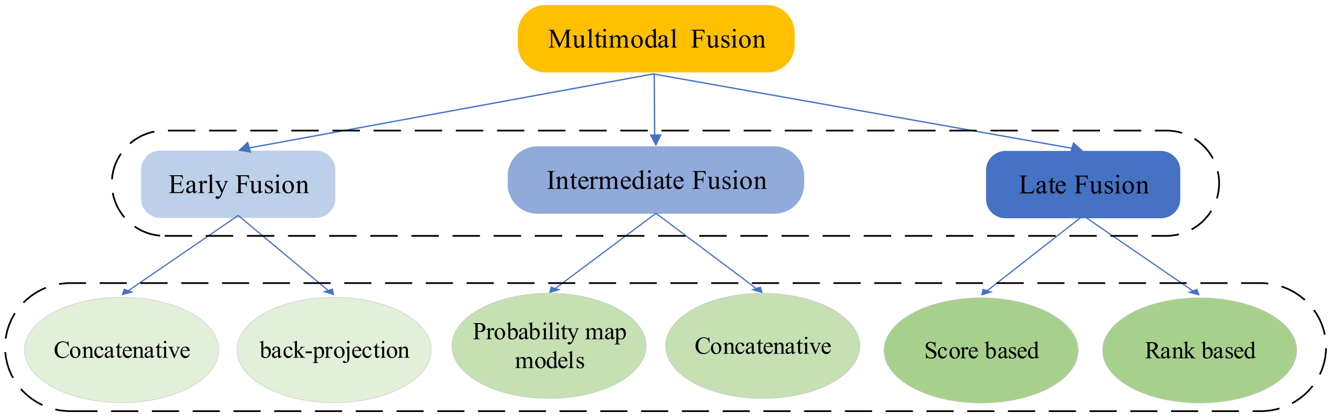

FIGURE 5. Multisource medical data fusion can generally be divided into three categories: early fusion, medium-term fusion and late fusion. Early fusion methods are mainly divided into concatenation [59], [60] and back-projection [61]. The methods of intermediate fusion include probability map models [62] and concatenation [63]. The methods of late fusion focus on score based [64] and rank based [65] models.

relies on high performance computing devices, especially GPUs, for accelerating DL algorithms. Comparatively, more high-level features are extracted from bottom up representation of original data using DL. DL automatically extracts the features for classification tasks, serving as an adaptive feature extractor for ubiquitous problem solving, which is a significant improvement over traditional ML.

However, DL is generally inferior to ML in terms of interpretability. Models generated by ML algorithms, such as decision tree, rule based reasoning and logistic regression, are of many types but they are relatively simple and interpretable. For DL, only several commonly used algorithms and network architectures exist, but most of them are too complicated to get a comprehensive understanding [80], [82].

Medical and healthcare big data present a multimodal form, and there are various types of unstructured data that manifest the characteristics of complexity, functional diversity, varying forms and redundant information [83]. Traditional machine learning methods cannot directly utilize these multimodal unstructured data. Therefore, some researchers have attempted to implement multimodal data fusion using deep learning techniques [84], [85]. The main research procedure, which contains early fusion, medium-term fusion and late fusion, is shown in Figure 5. Zheng *et al.* [51] proposed the DocDDE-based supervision extension mechanism SupDocNADE to enhance the discriminability of hidden theme features and discussed how to apply this mechanism to achieve a united presentation of image visual words, interpretation words, and tag-like information while providing an effective deep model training method. To obtain better results in practical applications, most researchers have adopted a framework-based approach. Bhatnagar *et al.* [52] proposed a novel spatially registered multimodal medical image fusion framework that employs a non-undersampled contourlet transformation to decompose source medical images into low-frequency bands and high-frequency bands in the non-subsampled contourlet transformation domain. To diagnose Alzheimer's disease, Liu *et al.* [53] designed a new diagnostic framework with deep learning architecture that adopts a zero-masking strategy to implement data fusion to enable the extraction of supplemental information from data acquired by various modalities. During the identification process of surgical, diagnostic, and treatment procedures based on multimodal data such as images, texts, and videos, this framework can effectively reduce manual intervention in the supervision of task implementation. Some researchers have proposed a wearable device-based parallel fusion framework with supervision depth which improved the processing capability for multimodal data [86]. The data processing method based on multimodal fusion has high flexibility. This kind of method can take advantage of the performance of traditional data processing methods, respond to dynamic data and reduce the load of data calculation by combining different fusion methods. However, it requires significant efforts to find the right way to fuse data.

C. MEDICAL DATA-DRIVEN KNOWLEDGE REASONING

Research on knowledge-based fusion began with "ontology matching", in which the semantic similarity of ontology categories is matched in the initial stage [87]. Suchanek *et al.* [54] proposed the probability-based knowledge fusion framework for probabilistic alignment of relations, instances, and schema (PARIS). This framework employs two knowledge bases as input to achieve efficient and simultaneous alignment of cross-ontology categories, instances, attributes and relationships. Dong *et al.* [55] proposed to extract facts from the entire network in the form of disambiguated triples and employed Probability Risk Assessment (PRA) and a neural network model to establish a knowledge fusion method that integrates prior knowledge acquired from Freebase graphs. This method can enable the probabilistic knowledge base to automatically construct a network and significantly improve the computational efficiency. When constructing a knowledge base, differences in the needs and design concepts may

TABLE 3. Overview of papers on panoramic interactive decision-making and intelligent decision-making system.

Paper	Approach	Problem Addressed	Contribution	Limitation
a) Medical decision-making process and evolution mechanism				
Tekin et al. [91]	Context-adaptive algorithm	Discover the expert	An expert selection system depending on the context of the patient.	It is difficult to address a small number of errors in the context.
Yoon et al. [92]	Discovery engine	Discover the best treatment regimen	A personalized treatment regimen discovery method	Did not consider the effect of time change.
Baumgart et al. [93]	Judgment analysis and a lens model	Quality assessment of healthcare initiatives	A pooled comparative information model for quality assessment	The rules are fixed, and it is difficult to match actual changes.
Rahimi et al. [94]	Analytic hierarchy process	Surgical patients' prioritization	A three-step decisional framework considering risks and uncertainties	The frame steps are fixed, and the application is limited.
b) Multisource medical data fusion				
Paul et al. [95]	Social network analysis (SNA)	Multimodal biometric system	A decision fusion model for multimodal biometric system using SNA	The dynamic impact caused by time variation is not considered.
Song et al. [96]	Discrete-event simulation	Pareto patient flow distribution optimization	A methodology to find the optimal macrolevel patient flow distribution in terms of multi-dimension inputs and outputs	This method does not take account of dynamic factors.
Jindal et al. [97]	Fuzzy rule	Remote healthcare applications	A fuzzy rule-based classifier to provide Healthcare-as-a-Service	Require a large amoubt of privacy data, and difficult to ensure security.
Habib et al. [98]	Wireless body sensor networks	Emergency prediction based on physiological data	A biosensor data management framework	The impact of sensor fluctuations has not yet been considered.
Ximeng et al. [99]	Naive Bayesian classification	Privacy in clinical decision making	A Patient-Centric Clinical Decision Support System	Performance is limited by artificial prior knowledge.
Piri et al. [100]	Logistic regression and neural network	Clinical decision support system for diabetic retinopathy	A clinical decision support system for predicting diabetic retinopathy	The data type is not enough to explain the universality of the method.

increase the complexity and heterogeneity of the data in the knowledge base [56]. Existing medical knowledge bases are constructed by focusing on a single department or a single type of disease. Therefore, investigating a fusion strategy for different medical knowledge bases is necessary to drive the evolution of the existing knowledge graphs using knowledge that has not been uncovered [88]–[90]. Currently, human intervention is required for medical and healthcare knowledge graph fusion. Therefore, further studies on intelligent and efficient knowledge fusion algorithms are needed.

IV. PANORAMIC INTERACTIVE DECISION-MAKING AND INTELLIGENT DECISION-MAKING SYSTEM

In practical smart healthcare applications, reliance on existing departmental, regional, and industrial information systems is often necessary to integrate the massive amount of fragmented medical and healthcare data inside and outside the hospital. It is crucial to implement differentiated and complex decision-making tasks for specific patient groups via diversified combination methods such as resource integration, model fusion, and unified modeling. In recent years, with the rapid development of information technology such as cloud computing and artificial intelligence, numerous novel decision-making methods have been developed that consider timeliness, interactivity and adaptive evolution. Thus, intelligent decision-making systems have been extensively explored. To cope with the challenges of increasingly complex and varied panoramic interactive decision-making scenarios, intelligent decision-making systems have been extensively investigated from expert experience systems to multimodal data-driven smart healthcare systems. We summarized the related papers in Table 3.

A. MEDICAL DECISION-MAKING PROCESS AND EVOLUTION MECHANISM

Medical decision-making involves making clinical decisions that focus on diagnosis and treatment and refers to a doctor's preferred behavior when considering a patient's conditions in daily medical practice, which is a process to maximize the avoidance of clinical mistakes. Modern computing platforms provide support for big data processing [108]. The big data-driven paradigm has prompted a large shift in traditional clinical auxiliary decision-making methods. Most medical decision-making methods are based on a patient's health status, age, gender, previous medication dose, and other relevant information [91]. The discovery engine (DE) was developed to study patient characteristics-based design of auxiliary diagnosis and treatment schemes [92]. Zeigler [109] explored the use of Modeling and Simulation (M&S) technology to improve the service efficiency of medical infrastructure and constructed a logical system architecture for medical decision support systems that improves medical efficiency and risk management. Researchers later discovered that Doctors can measure and even enhance the quality of medical decisions by making comparisons with other medical institutions or specific patient groups via pooling multisource and multimodal patient information [93]. In addition, the evolution of actual medical decision-making can be significantly improved by a three-step integrated decision-making framework-based comprehensive modeling to improve coordination and decision support [94].

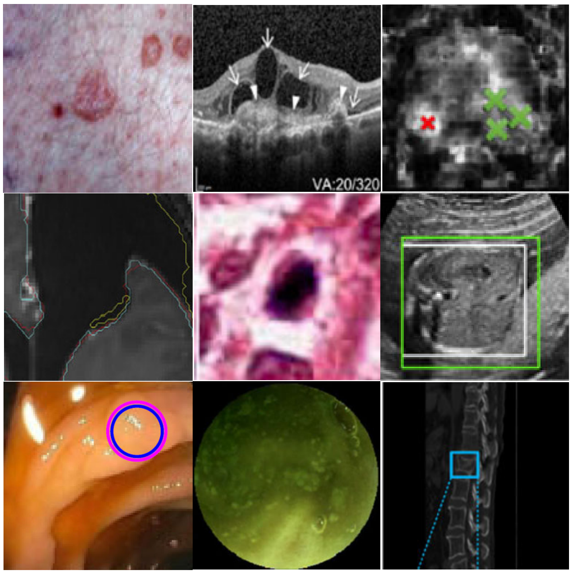

FIGURE 6. Collage of some medical imaging applications in which deep learning has achieved state-of-the-art results. From top-left to bottom-right: skin cancer classification [11], macular degeneration and diabetic retinopathy classification [12], prostate cancer detection [101], MRI brain feature extraction [102], mitosis detection in breast cancer [103], indentification of fetal standard scan planes [104], polyp detection [105], evaluating capsule endoscopy videos [106], and thoracolumbar fractures detection [107].

B. INTELLIGENT CLINICAL DECISION SUPPORT SYSTEM

In the big data-driven clinical decision-making process, solutions to the problems of the knowledge reasoning mechanism, the classification of multimodal data in big data fusion, and the development of a parallel reasoning method for multi-expert shared block data, have become a research priority in the field of data-driven medical and healthcare decision support. In particular, the methods represented by deep learning have achieved remarkable clinical results [110], [111]. Some key contributions are highlighted in Figure 6. Paul *et al.* [95] proposed the use of Social Network Analysis (SNA) to perform fusion in multimodal biometric systems and solve the intelligent identification problem in situations with sparse high-quality data. By combining discrete event simulation, multi-objective optimization, and budget allocation simulation, Song *et al.* [96] developed a method for predicting the patient flow distribution that is applicable to multilevel healthcare systems. Based on big data in a cloud environment, Jindal *et al.* [97] proposed a classifier for the formation and retrieval of initial clusters and the processing of fuzzy rules that are intended for effective decision-making in healthcare programs. Habib *et al.* [98] investigated the biosensor data management framework and focused on resolving data integrity issues in multimodal medical data integration. Liu *et al.* [99] proposed a new clinical decision support system centered on protecting the privacy of patients to help clinicians diagnose disease risks without hindering patient privacy. Piri *et al.* [100] incorporated a fundamental change in the traditional decision-making method and proposed a clinical decision support system for predicting diabetic retinopathy, by which a variety of retinopathy-related diseases were predicted via combination modeling and the poor compliance issue of retinopathy screening was solved. Regarding to the environmental dynamics of a panoramic intelligent decision system and the continuous interaction of a computing system, related studies on mobile computing and clinical data generation rules have also been conducted [112], [113].

V. CHALLENGES AND OPEN ISSUES

A. OVERVIEW

From the 114 papers reviewed in this survey, it is evident that significant progress has been made in multimodal semantic perception, multimodal entity semantic alignment, and heterogeneous association mining in the context of smart healthcare. However, for semantic label analysis of medical images, existing studies on semantic perception have primarily employed deep neural networks but overlooked the significant role of latent semantics in texts such as electronic medical records for clinical decision support. Therefore, it lacks multi-granularity semantic annotations on medical images, and fails to establish the semantic alignment between medical image- and text-oriented multimodal entities.

B. CHALLENGES IN INTERACTIVE AND INTELLIGENT HEALTHCARE DECISION-MAKING

Existing studies on the medical decision-making process and mechanism have primarily focused on specific scenarios or specific patient groups and have not systematically summarized or investigated panoramic interactive medical decision-making processes. The medical and healthcare big data-based intelligent decision-making method is in the preliminary stage, and knowledge reasoning and intelligent decision-making methods that integrate multisource and multimodal data, such as electronic medical records, medical images, community health archives, and third-party evaluation, need further study. These challenges hinder the ability of existing systems to interconnect and communicate with each other and render information flow aggregation and system interoperability unattainable, which hinders the cross-border integration and efficient decision-making of medical and healthcare resources.

Medical and healthcare big data-driven panoramic interactive decision-making in the smart healthcare context should focus on the following issues: (1) Intelligent decision-making tasks in the consultation, triage, diagnosis, and treatment of specific patient populations; their dynamic evolution mechanisms; and panoramic smart decision-making methods that couple out-of-hospital services with in-hospital diagnosis and treatment should be combined to develop a smart healthcare decision-making process model and a panoramic imaging method that consider time-sensitive, interactive and adaptive evolution characteristics. Multimodal combination modeling-based smart healthcare knowledge reasoning and dynamic decision-making methods should also be investigated. (2) A cloud-side collaborative smart healthcare service architecture based on an intelligent engine and resource reflection interoperability interface could be used to develop basic acceleration engines, such as the cross-border entity association and knowledge fusion that satisfy the medical requirements of automated mass customization. Dedicated decision engines for consultation, triage, and auxiliary diagnosis and data-driven type intelligent decision support systems in smart healthcare situations can be used to obtain a medical and healthcare big data-driven intelligent decision-making system.

The implementation of panoramic interactive and intelligent healthcare decision-making needs the support of multiple information systems, such as hospital business system, regional health information platform, internet medical platform, etc. During the decision-making process, the data systems of medical institutions, health authorities and government systems also need to be capable of interoperation. By utilizing the architecture resource reflection method and mechanism of the client-driven software system, a panoramic interactive decision support system for intelligent medical applications can be designed based on the existing medical business system. To be specific, a panoramic interactive and intelligent decision-making system should contain multiple basic acceleration engines. For example, a association mining engine and multi-mode fusion engine can meet the large-scale needs of automation. And the decision support engine based on knowledge map or neural network can support the process of medical treatment, diagnosis and treatment. This design provides users with panoramic intelligent clinical decision support through hospital clinical data repository, operational data repository and cloud hospital.

C. CHALLENGES IN HEALTHCARE BIG DATA UTILIZATION

In order to fully exploit the value of healthcare big data characterized by large amount of volume with abundant diversity, including structured, semistructured and unstructured medical data, plenty of hurdles and barriers need to be overcome to improving the quality of clinical services, the accuracy and effect of medical diagnosis and treatment, the optimization of medical circuit. The aspects of challenges pertinent to healthcare big data utilization are discussed as follows.

The reliability of healthcare big data has to be guaranteed as it plays a decisive role in data collection phase for the overall success of applying data mining technologies. During data acquisition, reliable data sources with few errors and less noise need to be chosen to deliver consistent and complete medical datasets. For personal healthcare devices using IoT technologies, the accuracy and stability of sensors are critical for the quality of data, so are the devices used for data collection and communication [114]. Especially, the data transmission and aggregation are becoming more and more challenging for the reliability of personal healthcare big data.

The consistency and precision must be retained during decision making when processing dissimilar data in multiple modals. A majority of existing data processing tools have performance issues for multimodal healthcare big data with computational uncertainties, unconsistencies and complexities. In addition, real-time medical decision making, categorized into hard, firm and soft real-time [114], is becoming more and more demanding in modern clinical practice as well as personal healthcare scenarios. The real-time capability relies on the rapid processing of huge volume of multimodal healthcare big data. Hence, higher scalability must be provided by big data processing technologies [68]. Furthermore, due to the growing size of healthcare data set, more challenges are imposed on the data storage mediums. Larger size of storage space and faster input/output speed are required for ensuring data availability and accessibility.

VI. CONCLUSION

A multimodal data-driven smart healthcare system is capable of achieving a shift in the decision-making model from in-hospital care business-oriented linear management to data-centered panoramic whole-process medical decision-making services via the interoperability or seamless series-parallel integration of cross-sectoral, cross-regional data resources and the acquisition and modeling of in-hospital multimodal diagnosis and treatment data and out-of-hospital data of a patient's symptoms, experience, social relations, and environment. Since the beginning of this century, a plethora of fruitful investigations of cross-border association mining, multimodal fusion, and panoramic intelligent decision-making have been conducted in the context of smart healthcare. In particular, numerous methods and application systems with clinical significance to the semantic association, knowledge fusion, panoramic decision-making, and intelligent decision support system of multimodal medical data have been developed.

With the extensive penetration of next-generation information technologies, the multimodal data-driven smart healthcare system is becoming an important technical carrier and driving force for the entire process of healthcare, including consultation, triage, diagnosis and treatment. The study of cross-border data fusion-based panoramic management decision-making should have a positive impact on the existing fragmented service delivery system of healthcare and senior care. Knowledge graph-, neural network-, and multimodal deep learning-based intelligent decision-making engines, such as semantic perception and knowledge reasoning, represent an important research direction in the fields of information, management, and medicine. The clinical performance of smart healthcare systems must be continually improved by further developing these theoretical algorithms and methods. More importantly, security and privacy protection issues must be emphasized in data utilization.

REFERENCES

[1] E. Barbi, F. Lagona, M. Marsili, J. W. Vaupel, and K. W. Wachter, "The plateau of human mortality: Demography of longevity pioneers," *Science*, vol. 360, no. 6396, pp. 1459–1461, Jun. 2018.
[2] E. Crist, C. Mora, and R. Engelman, "The interaction of human population, food production, and biodiversity protection," *Science*, vol. 356, no. 6335, pp. 260–264, Apr. 2017.
[3] P. Gerland, A. E. Raftery, H. Ševcíková, N. Li, D. Gu, T. Spoorenberg, L. Alkema, B. K. Fosdick, J. Chunn, N. Lalic, and G. Bay, "World population stabilization unlikely this century," *Science*, vol. 346, no. 6206, pp. 234–237, Oct. 2014.
[4] S. Walczak and V. Velanovich, "Improving prognosis and reducing decision regret for pancreatic cancer treatment using artificial neural networks," *Decis. Support Syst.*, vol. 106, pp. 110–118, Feb. 2018.
[5] A. Dag, A. Oztekin, A. Yucel, S. Bulur, and F. M. Megahed, "Predicting heart transplantation outcomes through data analytics," *Decis. Support Syst.*, vol. 94, pp. 42–52, Feb. 2017.
[6] A. J. Aljaaf, C. Mallucci, D. Al-Jumeily, A. Hussain, M. Alloghani, and J. Mustafina, "A study of data classification and selection techniques to diagnose headache patients," in *Applications of Big Data Analytics: Trends, Issues, and Challenges*, M. M. Alani, H. Tawfik, M. Saeed, and O. Anya, Eds. Cham, Switzerland: Springer, 2018, pp. 121–134.
[7] H. Wimmer, V. Yoon, and V. Sugumaran, "A multi-agent system to support evidence based medicine and clinical decision making via data sharing and data privacy," *Decis. Support Syst.*, vol. 88, pp. 51–66, Aug. 2016.
[8] S. Bahri, N. Zoghlami, M. Abed, and J. M. R. Tavares, "Big data for healthcare: A survey," *IEEE Access*, vol. 7, pp. 7397–7408, 2018.
[9] V. Gulshan, L. Peng, M. Coram, M. C. Stumpe, D. Wu, A. Narayanaswamy, S. Venugopalan, K. Widner, J. Cuadros, and R. Kim, "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *J. Amer. Med. Assoc.*, vol. 316, no. 22, pp. 2402–2410, Dec. 2016.
[10] H. M. Zolbanin and D. Delen, "Processing electronic medical records to improve predictive analytics outcomes for hospital readmissions," *Decis. Support Syst.*, vol. 112, pp. 98–110, Aug. 2018.
[11] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, Jan. 2017.
[12] D. S. Kermany *et al.*, "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122–1124, Feb. 2018.
[13] Y. Wang, L. Kung, and T. A. Byrd, "Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations," *Technol. Forecasting Social Change*, vol. 126, pp. 3–13, Jan. 2018.
[14] Y. Li, A. Vo, M. Randhawa, and G. Fick, "Designing utilization-based spatial healthcare accessibility decision support systems: A case of a regional health plan," *Decis. Support Syst.*, vol. 99, pp. 51–63, Jul. 2017.
[15] L. Chen, X. Li, Y. Yang, H. Kurniawati, Q. Z. Sheng, H.-Y. Hu, and N. Huang, "Personal health indexing based on medical examinations: A data mining approach," *Decis. Support Syst.*, vol. 81, pp. 54–65, Jan. 2016.
[16] H. J. Gómez-Vallejo, B. Uriel-Latorre, M. Sande-Meijide, B. Villamarín-Bello, R. Pavón, F. Fdez-Riverola, and D. Glez-Peña, "A case-based reasoning system for aiding detection and classification of nosocomial infections," *Decis. Support Syst.*, vol. 84, pp. 104–116, Apr. 2016.
[17] G. Manogaran, C. Thota, D. Lopez, V. Vijayakumar, K. M. Abbas, and R. Sundarsekar, "Big data knowledge system in healthcare," in *Internet of Things and Big Data Technologies for Next Generation Healthcare*. Cham, Switzerland: Springer, 2017, pp. 133–157.
[18] P. D'Antrassi, M. Prenassi, L. Rossi, R. Ferrucci, S. Barbieri, A. Priori, and S. Marceglia, "Personally collected health data for precision medicine and longitudinal research," *Frontiers Med.*, vol. 6, p. 125, Jun. 2019.
[19] K. Zhang, K. Yang, X. Liang, Z. Su, X. Shen, and H. H. Luo, "Security and privacy for mobile healthcare networks: From a quality of protection perspective," *IEEE Wireless Commun.*, vol. 22, no. 4, pp. 104–112, Aug. 2015.
[20] M. Kheirkhahan, S. Nair, A. Davoudi, P. Rashidi, Amal A. Wanigatunga, D. B. Corbett, T. Mendoza, T. M. Manini, and S. Ranka, "A smartwatch-based framework for real-time and online assessment and mobility monitoring," *J. Biomed. Inform.*, vol. 89, pp. 29–40, Jan. 2019.
[21] W. Lee, H. Yoon, and K. Park, "Smart ECG monitoring patch with built-in R-peak detection for long-term HRV analysis," *Ann. Biomed. Eng.*, vol. 44, no. 7, pp. 2292–2301, Jul. 2016.
[22] M. S. Hossain and G. Muhammad, "Cloud-assisted industrial Internet of Things (IIoT)—Enabled framework for health monitoring," *Comput. Netw.*, vol. 101, pp. 192–202, Jun. 2016.
[23] S. Ding, L. Li, Z. Li, H. Wang, and Y. Zhang, "Smart electronic gastroscope system using a cloud–edge collaborative framework," *Future Gener. Comput. Syst.*, vol. 100, pp. 395–407, Nov. 2019.
[24] Y. Cao, S. Steffey, J. He, D. Xiao, C. Tao, P. Chen, and H. Müller, "Medical image retrieval: A multimodal approach," *Cancer Inform.*, vol. 13, pp. 125–136, Jul. 2015.
[25] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Trans. Med. Imag.*, vol. 35, no. 5, pp. 1240–1251, May 2016.
[26] P.-Y. Hui and H. Meng, "Latent semantic analysis for multimodal user input with speech and gestures," *IEEE/ACM Trans. Audio, Speech, Language Process.*, vol. 22, no. 2, pp. 417–429, Feb. 2014.
[27] V. Despotovic, O. Walter, and R. Haeb-Umbach, "Machine learning techniques for semantic analysis of dysarthric speech: An experimental study," *Speech Commun.*, vol. 99, pp. 242–251, May 2018.
[28] N. Lasierra, F. Roldán, A. Alesanco, and J. García, "Towards improving usage and management of supplies in healthcare: An ontology-based solution for sharing knowledge," *Expert Syst. Appl.*, vol. 41, no. 14, pp. 6261–6273, Oct. 2014.
[29] Y. Zhang, M. Qiu, C.-W. Tsai, M. M. Hassan, and A. Alamri, "Health-CPS: Healthcare cyber-physical system assisted by cloud and big data," *IEEE Syst. J.*, vol. 11, no. 1, pp. 88–95, Mar. 2017.
[30] A. Pacaci, S. Gonul, A. A. Sinaci, M. Yuksel, and G. B. L. Erturkmen, "A semantic transformation methodology for the secondary use of observational healthcare data in postmarketing safety studies," *Frontiers Pharmacol.*, vol. 9, p. 435, Apr. 2018.
[31] F. Liu, Y. Feng, Z. Li, C. Pan, Y. Su, R. Yang, L. Song, H. Duan, and N. Deng, "Clinic-genomic association mining for colorectal cancer using publicly available datasets," *Biomed. Res. Int.*, vol. 2014, no. 1, Jun. 2014, Art. no. 170289.
[32] A. L. Buczak, B. Baugher, E. Guven, L. C. Ramac-Thomas, Y. Elbert, S. M. Babin, and S. H. Lewis, "Fuzzy association rule mining and classification for the prediction of malaria in South Korea," *BMC Med. Informat. Decis. Making*, vol. 15, no. 1, p. 47, Dec. 2015.
[33] I. Kavakiotis, O. Tsave, and A. Salifoglou, "Machine learning and data mining methods in diabetes research," *Comput. Struct. Biotechnol. J.*, vol. 15, no. 9, pp. 104–116, 2017.
[34] S. Ding, Z. Li, X. Liu, H. Huang, and S. Yang, "Diabetic complication prediction using a similarity-enhanced latent Dirichlet allocation model," *Inf. Sci.*, vol. 499, pp. 12–24, Oct. 2019.
[35] R. Khera, K. B. Dorsey, and H. M. Krumholz, "Transition to the ICD-10 in the United States: An emerging data chasm," *JAMA*, vol. 320, no. 2, pp. 133–134, Jul. 2018.
[36] F. C. Ghesu, B. Georgescu, and T. Mansi, *Medical Image Computing and Computer-Assisted Intervention—MICCAI* (Lecture Notes in Computer Science), vol. 9902, S. Ourselin, L. Joskowicz, M. R. Sabuncu, G. Unal, and W. Wells, Eds. Cham, Switzerland: Springer, 2016.
[37] J. Z. Cheng, D. Ni, Y. H. Chou, J. Qin, C. M. Tiu, Y. C. Chang, C. S. Huang, D. Shen, and C. M. Chen, "Computer-aided diagnosis with deep learning architecture: Applications to breast lesions in US images and pulmonary nodules in CT scans," *Sci. Rep.*, vol. 6, no. 1, Jul. 2016, Art. no. 24454.
[38] H. Chen, Y. Zhang, M. K. Kalra, F. Lin, Y. Chen, P. Liao, J. Zhou, and G. Wang, "Low-dose CT with a residual encoder-decoder convolutional neural network," *IEEE Trans. Med. Imag.*, vol. 36, no. 12, pp. 2524–2535, Dec. 2017.

[39] Y. Jin, Q. Dou, H. Chen, L. Yu, J. Qin, C.-W. Fu, and P.-A. Heng, "SV-RCNet: Workflow recognition from surgical videos using recurrent convolutional network," *IEEE Trans. Med. Imag.*, vol. 37, no. 5, pp. 1114–1126, May 2018.
[40] H. Al Hajj, M. Lamard, P.-H. Conze, B. Cochener, and G. Quellec, "Monitoring tool usage in surgery videos using boosted convolutional and recurrent neural networks," *Med. Image Anal.*, vol. 47, pp. 203–218, Jul. 2018.
[41] Y. Zhao, Q. Dong, H. Chen, A. Iraji, Y. Li, M. Makkie, Z. Kou, and T. Liu, "Constructing fine-granularity functional brain network atlases via deep convolutional autoencoder," *Med. Image Anal.*, vol. 42, pp. 200–211, Dec. 2017.
[42] G. Duftschmid, C. Rinner, M. Kohler, G. Huebner-Bloder, S. Saboor, and E. Ammenwerth, "The EHR-ARCHE project: Satisfying clinical information needs in a shared electronic health record system based on IHE XDS and archetypes," *Int. J. Med. Informat.*, vol. 82, no. 12, pp. 1195–1207, Dec. 2013.
[43] H. Wang, S. Ding, D. Wu, Y. Zhang, and S. Yang, "Smart connected electronic gastroscope system for gastric cancer screening using multi-column convolutional neural networks," *Int. J. Prod. Res.*, vol. 7543, pp. 1–12, Apr. 2018.
[44] E. E. Papalexakis, C. Faloutsos, and N. D. Sidiropoulos, "Tensors for data mining and data fusion: Models, applications, and scalable algorithms," *ACM Trans. Intell. Syst. Technol.*, vol. 8, no. 2, Jan. 2017, Art. no. 16.
[45] A. J. Aljaaf, D. Al-Jumeily, H. M. Haglan, M. Alloghani, T. Baker, A. J. Hussain, and J. Mustafina, "Early prediction of chronic kidney disease using machine learning supported by predictive analytics," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2018, pp. 1–9.
[46] F. P. Lin, A. Pokorny, C. Teng, and R. J. Epstein, "TEPAPA: A novel in silico feature learning pipeline for mining prognostic and associative factors from text-based electronic medical records," *Sci. Rep.*, vol. 7, no. 1, p. 6918, Jul. 2017.
[47] A. Singhal, M. Simmons, and Z. Lu, "Text mining for precision medicine: Automating disease-mutation relationship extraction from biomedical literature," *J. Amer. Med. Informat. Assoc.*, vol. 23, no. 4, pp. 766–772, Jul. 2016.
[48] A. Cortes, C. A. Dendrou, A. Motyer, L. Jostins, D. Vukcevic, A. Dilthey, P. Donnelly, S. Leslie, L. Fugger, and G. McVean, "Bayesian analysis of genetic association across tree-structured routine healthcare data in the UK Biobank," *Nature Genet.*, vol. 49, no. 9, pp. 1311–1318, Jul. 2017.
[49] W. Peng, H.-Z. Huang, M. Xie, Y. Yang, and Y. Liu, "A Bayesian approach for system reliability analysis with multilevel pass-fail, lifetime and degradation data sets," *IEEE Trans. Rel.*, vol. 62, no. 3, pp. 689–699, Sep. 2013.
[50] N. Chatterjee, J. Shi, and M. García-Closas, "Developing and evaluating polygenic risk prediction models for stratified disease prevention," *Nature Rev. Genet.*, vol. 17, no. 7, pp. 392–406, Jul. 2016.
[51] Y. Zheng, Y.-J. Zhang, and H. Larochelle, "A deep and autoregressive approach for topic modeling of multimodal data," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 38, no. 6, pp. 1056–1069, Jun. 2016.
[52] G. Bhatnagar, Q. M. J. Wu, and Z. Liu, "A new contrast based multimodal medical image fusion framework," *Neurocomputing*, vol. 157, pp. 143–152, Jun. 2015.
[53] S. Liu, S. Liu, W. Cai, H. Che, S. Pujol, R. Kikinis, D. Feng, and M. J. Fulham, "Multimodal neuroimaging feature learning for multiclass diagnosis of alzheimer's disease," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 4, pp. 1132–1140, Apr. 2015.
[54] F. M. Suchanek, S. Abiteboul, and P. Senellart, "PARIS: Probabilistic alignment of relations, instances, and schema," *Proc. VLDB Endowment*, vol. 5, no. 3, pp. 157–168, Nov. 2011.
[55] X. Dong, E. Gabrilovich, G. Heitz, W. Horn, N. Lao, K. Murphy, T. Strohmann, S. Sun, and W. Zhang, "Knowledge vault: A Web-scale approach to probabilistic knowledge fusion," in *Proc. 20th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2014, pp. 601–610.
[56] D. Huang, Z. Jiang, L. Zou, and L. Li, "Drug–drug interaction extraction from biomedical literature using support vector machine and long short term memory networks," *Inf. Sci.*, vols. 415–416, pp. 100–109, Nov. 2017.
[57] R. Bailie, J. Bailie, A. Chakraborty, and K. Swift, "Consistency of denominator data in electronic health records in Australian primary healthcare services: Enhancing data quality," *Austral. J. Primary Health*, vol. 21, no. 4, pp. 450–459, 2015.
[58] J. J. P. C. Rodrigues, D. B. De Rezende Segundo, H. A. Junqueira, M. H. Sabino, R. M. Prince, J. Al-Muhtadi, and V. H. C. De Albuquerque, "Enabling technologies for the Internet of health things," *IEEE Access*, vol. 6, pp. 13129–13141, 2018.
[59] X. Meng, R. Jiang, D. Lin, J. Bustillo, T. Jones, J. Chen, Q. Yu, Y. Du, Y. Zhang, T. Jiang, J. Sui, and V. D. Calhoun, "Predicting individualized clinical measures by a generalized prediction framework and multimodal fusion of MRI data," *NeuroImage*, vol. 145, pp. 218–229, Jan. 2017.
[60] T. Xu, H. Zhang, X. Huang, S. Zhang, and D. Metaxas, "Multimodal deep learning for cervical dysplasia diagnosis," in *Medical Image Computing and Computer-Assisted Intervention—MICCAI* (Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), G. Unal, S. Ourselin, L. Joskowicz, M. Sabuncu, and W. Wells, Eds. Cham, Germany: Springer-Verlag, Jan. 2016, pp. 115–123.
[61] J. C. Caicedo, J. A. Vanegas, F. Páez, and F. A. González, "Histology image search using multimodal fusion," *J. Biomed. Inform.*, vol. 51, pp. 114–128, Oct. 2014.
[62] M. Liang, Z. Li, T. Chen, and J. Zeng, "Integrative data analysis of multi-platform cancer data with a multimodal deep learning approach," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 12, no. 4, pp. 928–937, Jul./Aug. 2015.
[63] J. Shi, X. Zheng, Y. Li, Q. Zhang, and S. Ying, "Multimodal neuroimaging feature learning with multimodal stacked deep polynomial networks for diagnosis of Alzheimer's disease," *IEEE J. Biomed. Health Inform.*, vol. 22, no. 1, pp. 173–183, Jan. 2018.
[64] Y.-T. Peng, C.-Y. Lin, M.-T. Sun, and C. A. Landis, "Multimodality sensor system for long-term sleep quality monitoring," *IEEE Trans. Biomed. Circuits Syst.*, vol. 1, no. 3, pp. 217–227, Sep. 2007.
[65] A. Mourão, F. Martins, and J. Magalhães, "Multimodal medical information retrieval with unsupervised rank fusion," *Comput. Med. Imag. Graph.*, vol. 39, pp. 35–45, Jan. 2015.
[66] M. Alloghani, T. Baker, D. Al-Jumeily, A. Hussain, A. Kaky, and J. Mustafina, "Early detection and prediction of lung cancer using machine learning algorithms applied on a secure healthcare data system architecture," in *Machine Learning for Computer and Cyber Security: Principle, Algorithms, and Practices*. Boca Raton, FL, USA: CRC Press, 2019, pp. 233–257.
[67] M. D. Berrade, P. A. Scarf, C. A. V. Cavalcante, and R. A. Dwight, "Imperfect inspection and replacement of a system with a defective state: A cost and reliability analysis," *Rel. Eng. Syst. Safety*, vol. 120, pp. 80–87, Dec. 2013.
[68] L. Benhlima and L. Benhlima, "Big data management for healthcare systems: Architecture, requirements, and implementation," *Adv. Bioinf.*, vol. 2018, Jun. 2018, Art. no. 4059018.
[69] S. Salas-Vega, A. Haimann, and E. Mossialos, "Big data and health care: Challenges and opportunities for coordinated policy development in the EU," *Health Syst. Reform*, vol. 1, no. 4, pp. 285–300, 2015.
[70] S. Gao and J. Wang, "Performance and reliability analysis of an M/G/1-G retrial queue with orbital search and non-persistent customers," *Eur. J. Oper. Res.*, vol. 236, no. 2, pp. 561–572, Jul. 2014.
[71] W. Q. Meeker and Y. Hong, "Reliability meets big data: Opportunities and challenges," *Qual. Eng.*, vol. 26, no. 1, pp. 102–116, Jan. 2014.
[72] E. Zaitseva, M. Kvassay, V. Levashenko, and J. Kostolny, "Introduction to knowledge discovery in medical databases and use of reliability analysis in data mining," in *Proc. Federated Conf. Comput. Sci. Inf. Syst. (FedCSIS)*, Sep. 2015, pp. 311–320.
[73] A. J. Aljaaf, A. J. Hussain, P. Fergus, A. Przybyla, and G. J. Barton, "Evaluation of machine learning methods to predict knee loading from the movement of body segments," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2016, pp. 5168–5173.
[74] P. Yang, D. Stankevicius, V. Marozas, Z. Deng, E. Liu, A. Lukosevicius, F. Dong, L. Xu, and G. Min, "Lifelogging data validation model for Internet of Things enabled personalized healthcare," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 48, no. 1, pp. 50–64, Jan. 2016.
[75] E. Zdravevski, P. Lameski, V. Trajkovik, A. Kulakov, I. Chorbev, R. Goleva, N. Pombo, and N. Garcia, "Improving activity recognition accuracy in ambient-assisted living systems by automated feature engineering," *IEEE Access*, vol. 5, pp. 5262–5280, 2017.
[76] H. Al-Hamadi and I. R. Chen, "Trust-based decision making for health IoT systems," *IEEE Internet Things J.*, vol. 4, no. 5, pp. 1408–1419, Oct. 2017.

[77] M. Woo, J. Lee, and K. Park, "A reliable IoT system for personal healthcare devices," *Future Gener. Comput. Syst.*, vol. 78, pp. 626–640, Jan. 2018.
[78] A. Mavrogiorgou, A. Kiourtis, M. Touloupou, E. Kapassa, D. Kyriazis, and M. Themistocleous, "The road to the future of healthcare: Transmitting interoperable healthcare data through a 5G based communication platform," in *Proc. Eur., Medit., Middle Eastern Conf. Inf. Syst.* Cham, Switzerland: Springer, 2018, pp. 383–401.
[79] Y. Chen, S. Ding, Z. Xu, H. Zheng, and S. Yang, "Blockchain-based medical records secure storage and medical service framework," *J. Med. Syst.*, vol. 43, no. 1, p. 5, Nov. 2019.
[80] K.-H. Yu, A. L. Beam, and I. S. Kohane, "Artificial intelligence in healthcare," *Nature Biomed. Eng.*, vol. 2, no. 10, pp. 719–731, Oct. 2018.
[81] J. He, S. L. Baxter, J. Xu, J. Xu, X. Zhou, and K. Zhang, "The practical implementation of artificial intelligence technologies in medicine," *Nature Med.*, vol. 25, no. 1, pp. 30–36, Jan. 2019.
[82] K. Lan, D.-T. Wang, S. Fong, L.-S. Liu, K. K. L. Wong, and N. Dey, "A survey of data mining and deep learning in bioinformatics," *J. Med. Syst.*, vol. 42, no. 8, p. 139, Aug. 2018.
[83] M. Žitnik and B. Zupan, "Data fusion by matrix factorization," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 1, pp. 41–53, Jan. 2015.
[84] V. Kubelka, M. Reinstein, and T. Svoboda, *Improving Multimodal Data Fusion for Mobile Robots by Trajectory Smoothing*, vol. 84. Amsterdam, The Netherlands: North-Holland, Oct. 2016.
[85] L. Wang, B. Li, and L.-F. Tian, "Multi-modal medical image fusion using the inter-scale and intra-scale dependencies between image shift-invariant shearlet coefficients," *Inf. Fusion*, vol. 19, no. 9, pp. 20–28, 2014.
[86] E. A. Bernal, X. Yang, Q. Li, J. Kumar, S. Madhvanath, P. Ramesh, and R. Bala, "Deep temporal multimodal fusion for medical procedure monitoring using wearable sensors," *IEEE Trans. Multimedia*, vol. 20, no. 1, pp. 107–118, Jan. 2018.
[87] F. Zhang, Y. Song, W. Cai, S. Liu, S. Liu, S. Pujol, R. Kikinis, Y. Xia, M. J. Fulham, D. D. Feng, "Pairwise latent semantic association for similarity computation in medical imaging," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 5, pp. 1058–1069, May 2016.
[88] M. Rotmensch, Y. Halpern, A. Tlimat, S. Horng, and D. Sontag, "Learning a health knowledge graph from electronic medical records," *Sci. Rep.*, vol. 7, no. 1, Jul. 2017, Art. no. 5994.
[89] H. Cai, V. W. Zheng, and K. C.-C. Chang, "A comprehensive survey of graph embedding: Problems, techniques, and applications," *IEEE Trans. Knowl. Data Eng.*, vol. 30, no. 9, pp. 1616–1637, Sep. 2018.
[90] Q. Wang, Z. Mao, and B. Wang, "Knowledge graph embedding: A survey of approaches and applications," *IEEE Trans. Knowl. Data Eng.*, vol. 29, no. 12, pp. 2724–2743, Dec. 2017.
[91] C. Tekin, O. Atan, and M. V. D. Schaar, "Discover the expert: Context-adaptive expert selection for medical diagnosis," *IEEE Trans. Emerg. Topics Comput.*, vol. 3, no. 2, pp. 220–234, Jun. 2015.
[92] J. Yoon, C. Davtyan, and M. van der Schaar, "Discovery and clinical decision support for personalized healthcare," *IEEE J. Biomed. Health Inform.*, vol. 21, no. 4, pp. 1133–1145, Jul. 2017.
[93] L. A. Baumgart, E. J. Bass, J. D. Voss, and J. A. Lyman, "Effect of pooled comparative information on judgments of quality," *IEEE Trans. Human-Mach. Syst.*, vol. 45, no. 6, pp. 773–781, Dec. 2015.
[94] S. A. Rahimi, A. Jamshidi, A. Ruiz, and D. Ait-kadi, "A new dynamic integrated framework for surgical patients' prioritization considering risks and uncertainties," *Decis. Support Syst.*, vol. 88, pp. 112–120, Aug. 2016.
[95] P. P. Paul, M. L. Gavrilova, and R. Alhajj, "Decision fusion for multimodal biometrics using social network analysis," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 44, no. 11, pp. 1522–1533, Nov. 2014.
[96] J. Song, Y. Qiu, and Z. Liu, "Integrating optimal simulation budget allocation and genetic algorithm to find the approximate Pareto patient flow distribution," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 1, pp. 149–159, Jan. 2016.
[97] A. Jindal, A. Dua, N. Kumar, A. K. Das, A. V. Vasilakos, and J. J. P. C. Rodrigues, "Providing healthcare-as-a-service using fuzzy rule based big data analytics in cloud computing," *IEEE J. Biomed. Health Inform.*, vol. 22, no. 5, pp. 1605–1618, Sep. 2018.
[98] C. Habib, A. Makhoul, R. Darazi, and C. Salim, "Self-adaptive data collection and fusion for health monitoring based on body sensor networks," *IEEE Trans. Ind. Informat.*, vol. 12, no. 6, pp. 2342–2352, Dec. 2016.
[99] X. Liu, R. Lu, J. Ma, L. Chen, and B. Qin, "Privacy-preserving patient-centric clinical decision support system on naive Bayesian classification," *IEEE J. Biomed. Health Inform.*, vol. 20, no. 2, pp. 655–668, Mar. 2016.
[100] S. Piri, D. Delen, T. Liu, and H. M. Zolbanin, "A data analytics approach to building a clinical decision support system for diabetic retinopathy: Developing and deploying a model ensemble," *Decis. Support Syst.*, vol. 101, pp. 12–27, Sep. 2017.
[101] Z. Wang, C. Liu, D. Cheng, L. Wang, X. Yang, and K.-T. Cheng, "Automated detection of clinically significant prostate cancer in mp-MRI images based on an end-to-end deep neural network," *IEEE Trans. Med. Imag.*, vol. 37, no. 5, pp. 1127–1139, May 2018.
[102] J. Kleesiek, G. Urban, A. Hubert, D. Schwarz, K. Maier-Hein, M. Bendszus, and A. Biller, "Deep MRI brain extraction: A 3D convolutional neural network for skull stripping," *NeuroImage*, vol. 129, pp. 460–469, Apr. 2016.
[103] D. C. Cireşan, A. Giusti, L. M. Gambardella, and J. Schmidhuber, "Mitosis detection in breast cancer histology images with deep neural networks," in *Proc. 16th Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.*, vol. 8150. 2013, pp. 411–418.
[104] C. F. Baumgartner, K. Kamnitsas, "SonoNet: Real-time detection and localisation of fetal standard scan planes in freehand ultrasound," *IEEE Trans. Med. Imag.*, vol. 36, no. 11, pp. 2204–2215, Nov. 2017.
[105] L. Yu, H. Chen, Q. Dou, J. Qin, and P. A. Heng, "Integrating online and offline three-dimensional deep learning for automated polyp detection in colonoscopy videos," *IEEE J. Biomed. Health Inform.*, vol. 21, no. 1, pp. 65–75, Jan. 2017.
[106] H. Chen, X. Wu, G. Tao, and Q. Peng, "Automatic content understanding with cascaded spatial–temporal deep framework for capsule endoscopy videos," *Neurocomputing*, vol. 229, no. Nov. 2016, pp. 77–87, 2017.
[107] U. Raghavendra, N. S. Bhat, A. Gudigar, and U. R. Acharya, "Automated system for the detection of thoracolumbar fractures using a CNN architecture," *Future Gener. Comput. Syst.*, vol. 85, pp. 184–189, Aug. 2018.
[108] R. Keight, A. J. Aljaaf, D. Al-Jumeily, A. J. Hussain, A. Özge, and C. Mallucci, "An intelligent systems approach to primary headache diagnosis," in *Intelligent Computing Theories and Application*, D.-S. Huang, K.-H. Jo, and J. C. Figueroa-García, Eds. Cham, Switzerland: Springer, 2017, pp. 61–72.
[109] B. P. Zeigler, "Discrete event system specification framework for self-improving healthcare service systems," *IEEE Syst. J.*, vol. 12, no. 1, pp. 196–207, Mar. 2018.
[110] A. S. Al-Kafri, S. Sudirman, A. Hussain, D. Al-Jumeily, F. Natalia, H. Meidia, N. Afriliana, W. Al-Rashdan, M. Bashtawi, and M. Al-Jumaily, "Boundary delineation of MRI images for lumbar spinal stenosis detection through semantic segmentation using deep neural networks," *IEEE Access*, vol. 7, pp. 43487–43501, 2019.
[111] H. Alaskar, A. Hussain, N. Al-Aseem, P. Liatsis, and D. Al-Jumeily, "Application of convolutional neural networks for automated ulcer detection in wireless capsule endoscopy images," *Sensors*, vol. 19, no. 6, p. 1265, Mar. 2019.
[112] A. Banerjee and S. K. S. Gupta, "Analysis of smart mobile applications for healthcare under dynamic context changes," *IEEE Trans. Mobile Comput.*, vol. 14, no. 5, pp. 904–919, May 2015.
[113] P. Karakitsos, D. Koutsouris, P. Bountris, E. Topaka, A. Pouliakis, and M. Haritou, "Development of a clinical decision support system using genetic algorithms and Bayesian classification for improving the personalised management of women attending a colposcopy room," *Healthcare Technol. Lett.*, vol. 3, no. 2, pp. 143–149, Jun. 2016.
[114] M. Mohammadi, A. Al-Fuqaha, S. Sorour, and M. Guizani, "Deep learning for IoT big data and streaming analytics: A survey," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 4, pp. 2923–2960, 4th Quart., 2018.

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