Natural Language Processing for Smart Healthcare

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Abstract—Smart healthcare has achieved significant progress in recent years. Emerging artificial intelligence (AI) technologies enable various smart applications across various healthcare scenarios. As an essential technology powered by AI, natural language processing (NLP) plays a key role in smart healthcare due to its capability of analysing and understanding human language. In this work, we review existing studies that concern NLP for smart healthcare from the perspectives of technique and application. We first elaborate on different NLP approaches and the NLP pipeline for smart healthcare from the technical point of view. Then, in the context of smart healthcare applications employing NLP techniques, we introduce representative smart healthcare scenarios, including clinical practice, hospital management, personal care, public health, and drug development. We further discuss two specific medical issues, i.e., the coronavirus disease 2019 (COVID-19) pandemic and mental health, in which NLP-driven smart healthcare plays an important role. Finally, we discuss the limitations of current works and identify the directions for future works.

Index Terms—Natural language processing, smart healthcare, artificial intelligence, NLP techniques, healthcare applications.

I. INTRODUCTION

Smart healthcare is a healthcare system that exploits emerging technologies, such as artificial intelligence (AI), blockchain, Big Data, cloud/edge computing, and the Internet of Things (IOT), for realizing various intelligent systems to connect healthcare participants and promote the quality of healthcare [1]. Major participants in smart healthcare can be classified into three categories, i.e., the public, healthcare service providers, and third-party healthcare participants. Related to the participants, representative smart healthcare scenarios include smart homes, smart hospitals, intelligent research and development for life science, health management, public health, rehabilitation therapy, and etc. Fig. 1 shows the major participants, emerging technologies, and representative scenarios of smart healthcare.

Natural language processing (NLP) is a subfield of computer science and artificial intelligence that is concerned with the automatic analysis, representation and understanding of human language [2]. NLP has become a hot research area and has attracted widespread attention from many research communities in the past several years. As human language is a general form of data entry for intelligent systems, NLP enables machines to understand human language and interact with humans, making it essential to smart healthcare.

The main manifestations of natural language are text and speech, where text encompasses text records, articles, book chapters, dictionaries, and so forth, while speech occurs in human-human and human-machine dialogues. NLP has been developed for several decades following the early origin of artificial intelligence in the 1950s. Approaches to conduct NLP are generally divided into three categories: rule-based approaches, statistical approaches, and deep learning-based approaches. From the 1950s to 1980s, NLP research mainly focused on rule-based approaches, which required expertise in both computer science and linguistics to design rules that fit human language. However, even well-designed rules are quite limited for covering human language due to its flexibility and complex patterns. Since the 1980s, statistical NLP systems have been designed by extracting features from corpora using statistical and machine learning algorithms and have gradually replaced rule-based NLP systems due to their superiority in performance and robustness. With the early application of the neural probabilistic language model [3] and the rapid development of deep learning since 2013, neural NLP, by using neural networks and large corpora for automated feature learning, has dominated current research and achieved SOTA performance of many NLP tasks.

In smart healthcare, NLP is applied to process text data and is associated with human-machine/human-human communication. The text data can be classified into 2 categories: clinical
Fig. 1. Smart healthcare. (a) Major participants in smart healthcare include the public, healthcare service providers, and third-party healthcare participants. (b) Example emerging technologies enable smart healthcare applications include artificial intelligence, blockchain, cloud computing, the Internet of Things, and etc. (c) Representative smart healthcare scenarios include intelligent research and development for life science, public health promotion, smart hospitals, health monitoring, and etc.

text and other text data. Clinical text comes from all clinical scenarios and mainly comprises of unstructured text records from electronic health record (EHR) systems, including medical notes, diagnostic reports, electronic prescriptions, and etc. Other text data include all text that appears within other healthcare scenarios, e.g., surveys in population screening and articles for evidence-based reference. Communication is common in all smart healthcare scenarios, such as patient-provider communication in clinical inquiry and human-robot interaction in rehabilitation therapy, accompanied by applications such as machine translations and user interfaces for rehabilitation robots.

As well recognized, research on and applications of NLP for smart healthcare have received intensive attention in recent years. However, no study has offered a well-organized summary of existing works from technical perspective, in this section, we first introduce the three kinds of NLP approaches and their representative algorithms, and then introduce the NLP pipeline for smart healthcare to show how NLP techniques are used in real smart healthcare applications.

A. Comparisons of Different NLP Approaches

The mainstream NLP approaches can be classified into three categories, i.e., rule-based NLP, statistical NLP and neural NLP, which have different characteristics. Below, we discuss the advantage and disadvantages of the three categories and introduce the representative algorithms of them.

Rule-based NLP approaches, e.g., pattern matching [4] and parsing [5], could be quite accurate in specific cases if dedicated studies by experts are conducted. In addition, rule-based NLP approaches are easy to interpret and understand. However, rules are normally too limited to cover all cases considering the flexibility and complex patterns of human language. In addition, rule-based NLP requires expertise in both computer science and linguistics to design appropriate rules to fit human language, hindering it from large-scale applications. Currently, rule-based approaches have been widely considered obsolete by academia [6], and are occasionally used for better preprocessing nowadays [7].

In general, statistical NLP is superior to rule-based NLP in performance and robustness. However, it also requires domain expertise to create handcrafted features, and is therefore conducted for decades and have attracted increased attention in recent years with the advancement of artificial intelligence and general NLP. To connect existing works from technical perspective, in this section, we first introduce the three kinds of NLP approaches and their representative algorithms, and then introduce the NLP pipeline for smart healthcare to show how NLP techniques are used in real smart healthcare applications.
limited to taking full advantage of available data and providing enough accuracy in complex applications. Although statistical NLP requires intensive feature engineering, it is this direct feature design that makes it transparent and interpretable as rule-based NLP. In addition, statistical NLP does not rely on large-scale datasets or large amounts of computational power, and thus is much more efficient than neural NLP. Furthermore, representative statistical NLP models, such as bag-of-words [8], TF-IDF [9], [10], and n-gram [11], [12], [13], have different characteristics. Bag-of-words is easy to implement, but it only considers the frequencies of words in a sentence, which neglects the importance and sequential order of these words. Through the inverse document frequency, TF-IDF improves the measurement of a word’s importance, but still does not take sequential order information into consideration. N-gram considers \( n - 1 \) words before a word, which makes it more accurate than bag-of-words but with higher computational complexity (increases exponentially with \( n \)). It is worth mentioning that despite the dominance of deep learning in recent years, statistical NLP is still active in many healthcare studies and applications.

Recent years have witnessed the success of neural NLP, who has shown better performance than both rule-based NLP and statistical NLP in applications with abundant available data. However, neural NLP is often blamed for low interpretability and dependence on expensive computing platforms. It is also worth noting that, compared with rule-based NLP and statistical NLP, neural NLP usually fails to achieve satisfactory performance if limited data is available. Among neural NLP models, recurrent neural network (RNN)-based models, especially long short-term memory (LSTM) [14], [15], [16]-based models and gated recurrent unit (GRU)-based models [15], [17], are more natural for processing sequential data such as text and speech. They have the ability to remember historical information of the inputs, but suffer from gradient vanishing/explosion, training issues and short-term memories. Convolutional neural networks (CNN)-based models [18], [19], combining with word embeddings, also show good performance in some tasks due to their ability in learning local features and high computational efficiency which enables deep network architectures. Recently, graph neural network (GNN)-based models have been applied to NLP-driven smart healthcare by incorporating knowledge from graph-structured ontology/entities [20], [21], [22]. When graphs are large in scale or complex, GNN-based models are difficult and costly to implement and train. Generally speaking, RNNs, CNNs, and GNNs are all limited in tackling long-term dependencies in sequences. Through the self-attention mechanism, Transformer-based models [23], [24] are very efficient in processing long sequences and support parallel training, but are lack of ability in learning local features and position information. We have witnessed many combinations of the aforementioned models for better feature extraction performance, including CNN-LSTM networks [25], RNN-Attention networks [26], [27], memory networks (MM) [28], [29], graph convolutional networks (GCN) [30], CNN-LSTM-Attention networks [31], [32], graph convolutional attention networks (GCAN) [33], [34], etc. In addition, to further leverage large unlabelled corpora, pretraining, a very effective method, has been widely exploited to obtain non-contextual or contextual embeddings [35]. Word2vec [36], [37], [38], [39], and GloVe (Global Vectors) [36], [40], as representative algorithms of non-contextual embeddings, provide distributed dense vectors as word embeddings, and outperform statistical algorithms such as bag-of-words and n-gram. The non-contextual embedding for a word is static and does not dynamically change as its context changes [35]. Based on the Transformer architecture, contextual embeddings, e.g., ELMo (Embeddings from Language Models) [41], BERT (Bidirectional Encoder Representations from Transformers) [42], [43], [44], [45], and GPT (Generative Pre-Training) [46], are developed to embed dynamic contextual information into word embeddings, achieving outstanding performance than other word embedding algorithms. It should be noted that these models are typically huge and expensive to pre-train, which somehow constraints their broad application in healthcare.

The comparisons of different NLP approaches and representative algorithms are shown in Table I.

### B. NLP Pipeline for Smart Healthcare

As shown in Fig. 2, there are three parts in an NLP pipeline for smart healthcare, i.e., preprocessing, feature extraction, and modelling. An NLP pipeline takes text or speech as illustrated before as the input. After that, preprocessing is conducted considering various inputs and their qualities to facilitate feature extraction and modelling. As the most important step, feature extraction is essential to NLP, which undoubtedly explains the attention it has received from researchers. Finally, models for specific NLP tasks are built with the extracted features to yield the outputs accordingly.

1) **Preprocessing:** Preprocessing, including the procedures of tokenization, stemming, lemmatization, stopword removal, and etc., makes natural language normalized, machine-readable, and easy for post-processing. Text preprocessing mostly paves the way for feature extraction and modelling, since many NLP tasks require normalized text input to guarantee accuracy and efficiency due to significant challenges coming from the flexibility of natural languages and the wide variety of morphological variants of medical terms in medical text [47], [48], [49]. However, with the development of neural NLP, some text preprocessing procedures have become unnecessary and may even cause problems. For example, removing stopwords may lead to the loss of informative context information when using the BERT pre-trained model [50]. As the preprocessing of speech, such as denoising, is typically regarded as a problem in signal processing, we do not discuss it in detail here.

2) **Feature Extraction:** Apart from the increase in accessible digital data and the advances in computing platforms such as graphics processing units, the development of NLP is largely attributed to the improvement in feature design or feature extraction methods. Both rule-based approaches and statistical approaches require expertise for rule design [4], [5] or feature engineering [8], [9], [10], [11], [12], [13]. For neural NLP, automated feature extraction via varieties of neural networks [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26],
[27], [28], [29], [30], [31], [32], [33], [34] have greatly improved the efficiency of data utilization and feature extraction. Automated feature engineering can be conducted directly according to the downstream tasks using supervised learning, unsupervised learning or reinforcement learning. In addition, pretraining is also widely used in NLP to automatically extract features from large unlabelled corpora via self-supervised learning in a generative, contrastive or generative-contrastive manner [51] before the downstream tasks begin. The extracted features, known as contextual or non-contextual embeddings, may encompass features such as lexical meanings, syntactic features, semantic features, and even pragmatics, which contribute to downstream tasks [35].

3) Modelling: For various smart healthcare applications, different models should be built to accomplish various NLP tasks, such as text classification, information extraction, and...
natural language understanding. The extracted feature can be directly processed by classifiers and regressors to yield outputs for simple tasks, e.g., medical text classification [18], [52], while further steps are required to complete complex tasks. In the following subsections, we first introduce several text input-based NLP tasks according to their complexity. At the end of this section, we will introduce two speech-specific tasks, i.e., speech recognition and speech synthesis.

a) Information extraction: Information extraction (IE), a.k.a. text mining, enables harvesting information from text inputs, and plays an important role in text analysis. Works related to information extraction in smart healthcare focus on the extraction of diseases, drugs, events (mainly including temporal expressions, spatial expressions and participant information) through name entity recognition [53], [54], relation extraction [54], [55], [56], and event extraction [57] from medical text, including unstructured text in EHRs, articles, etc.

b) Machine translation: Machine translation (MT) aims to automatically translate text from one language to another [58]. Currently, healthcare resources in various languages are becoming easily accessible as technologies evolve, and they are all of great value in modern medical practice. Machine translation therefore has drawn growing attention for building better (multilingual) translation systems and further leveraging multilingual healthcare resources for other applications, either to provide more accurate translations [59], [60] or to require less time [60] than human translations.

c) Text generation: Text generation (TG) automatically generates text with given inputs while pursuing the goal of appearing indistinguishable from human-written text. Specifically, there are 3 kinds of inputs and corresponding subtasks in smart healthcare: text inputs (e.g., routine reports) associated with text summarization [61], [62], [63], question generation [64], [65], [66], dialogue generation [67], [68], [69], and etc.; data inputs (e.g., neonatal intensive care data) connected with data-to-text [70]; and image inputs (e.g., medical images) related to image captioning [71], [72], visual question answering (VQA) [73], [74], [75], and etc. Note that for data-to-text and image-to-text generation, a combination of NLP with data analysis or computer vision is generally required, respectively.

d) Information retrieval: Information retrieval (IR) obtains materials that meet the query requirements from numerous documents, and is a core of search engines for all applications. To ease the retrieval process [76], [77], improve the relevance and diversity of the retrieval [78], [79], [80] or reduce the query time [81], current works aim to develop fast and efficient information retrieval methods to obtain useful retrieval from a large collection of data sources, ranging from internal health information system (HIS) systems and other digital documents to online resources.

e) Question answering and dialogue systems: Question answering (QA) involves automatically providing answers to questions raised by humans in a natural language. Question answering requires the machine to understand natural language and infer the answers, making it highly dependent on natural language understanding and information retrieval. To date, QA systems for healthcare have developed from information retrieval based QA systems [82], [83], [84], [85] and knowledge-based QA systems [86], [87], [88], [89] to hybrid QA systems [90], [91]. Compared to question answering, dialogue is also presented in an interactive manner between humans and machines. Common dialogue systems in smart healthcare include task-oriented dialogue systems [92], [93], [94], and non-task-oriented (a.k.a. chat-oriented) [95] dialogue systems, which assume different functions in various applications.

f) Knowledge engineering: Knowledge engineering (KE) is a field within artificial intelligence that tries to construct and use knowledge-based systems [96]. It does not refer to a pure NLP technique, but receives much attention in NLP for smart healthcare since medical text is one of the major sources for knowledge engineering. Within knowledge engineering, knowledge acquisition and knowledge representation are coupling with information extraction, aiming at the acquisition and representation of medical knowledge in a certain way, e.g., knowledge graphs [97], [98], [99]. Besides, knowledge engineering also concerns building knowledge-based systems to exploit existing knowledge, such as knowledge-based question answering (KBQA) systems [86], [87], [88], [89], knowledge-based information retrieval systems [100], text generation systems [65], [101], etc.

g) Natural language understanding: Natural language understanding (NLU) focuses on machines’ comprehension of human language in the form of unstructured text or speech. Many of the aforementioned tasks, e.g., question answering, information retrieval, require NLU to fully understand the input queries. The difficulties of natural language understanding include the ambiguity of natural language, the lack of context, and the variability in expression.

Fig. 2. The NLP pipeline for smart healthcare. There are three parts in an NLP pipeline for smart healthcare, i.e., preprocessing, feature extraction, and modelling. NLP takes text or speech as the input, followed by preprocessing to facilitate feature extraction and modelling. Features can be extracted with various methods and models. Models for specific NLP tasks are finally built with the extracted features to yield the outputs.
understanding come from the diversity, ambiguity, and potential
dependence of natural language, making slow progress in natural
language understanding compared with other NLP techniques. After
years of development in both general areas and smart
healthcare, the mainstream route of NLU is still to use various
methods to conduct slot filling and intent detection [102], [103],
[104]. NLU is the core of multiple intelligent agents, assuming a
role in understanding human intentions during human-machine
interactions [102], [105], [106], medical queries [103], [104],
etc.

h) Causal inference: Generally, causal inference is
a discipline concerning the determination of actual effects of
specific things, events or phenomena. Causal inference in NLP
has long received insufficient attention since the goal of clas-
cical NLP applications is simply to make accurate predictions
with all available statistical correlations regardless of the un-
derlying causal relationship [107]. Recently, with growing con-
cerns about uninterpretable black box models, the importance
of causal inference has gradually been recognized by NLP
researchers, especially in the area of healthcare. Specifically,
recent advances of causal inference in NLP for smart healthcare
have been made in uncovering causality from medical text [108],
[109], [110] and realizing reliable NLP-driven applications with
discovered causal effects [108], [109], [110].

i) Speech recognition and speech synthesis:
Speech recognition (SR) aims to convert human speech into
text information. Contrary to speech recognition, speech syn-
thesis, a.k.a. text-to-speech (TTS), is concerned with repre-
senting text information with speech. Basically, SR-oriented
and SS-oriented studies attempt to build automatic computer
systems for interconversion between speech and text in the
area of smart healthcare, making human-machine interaction
as natural and flexible as human-human interaction [111]. For
speech recognition, these efforts encompass the improvement in
acoustic modelling [112], [113], language modelling [114], and
the whole system pipeline [115], [116] to enhance recognition
accuracy. For speech synthesis, recent advancements have been
made in investigating and making synthesized speech natu-
ral [117], [118], intelligible [119], [120], [121], [122], [123]
and expressive [124], [125], [126], which will help stimulate
the enthusiasm of human-machine interaction [127].

III. APPLICATIONS OF NLP FOR SMART HEALTHCARE

NLP has been widely applied in smart healthcare and has
driven dramatic improvements in many applications. As shown
in Fig. 3, a typical NLP-driven application is composed of two
parts: user interface (UI) and backend. The user provides text
or speech input to the backend through the UI, and then, the
backend processes these inputs with the NLP models with or
without the knowledge bases according to the specific task type.

UIs are critical for enhancing the experience of using intelligent
systems and realizing smart healthcare. Such user interfaces can
be implemented by using NLP techniques, especially speech
recognition and natural language understanding.

According to their application scenarios, smart healthcare
applications employing NLP techniques can be classified into
5 major categories, i.e., clinical practice, hospital management,
personal care, public health, and drug development. A summary
of the applications and related NLP techniques is presented in
Table II. Below we introduce the five categories in detail.

A. Clinical Practice

1) Clinical Communication and Data Collection: Clinical
data, including but not limited to demographics, medical history,
comorbidities, medical notes, physical examination notes, elec-
tronic recordings from medical devices, and clinical laboratory
testing data and medical images [128], are the most important
data for diagnosis, treatment and even further retrospection.
Patient-provider communication is an important way to obtain
first-hand clinical data. When necessary, machine translation
may assist doctors in communicating with patients who speak
different languages or have low literacy and limited levels of
health education [129], [130]. Meanwhile, free text notes can
be taken through speech recognition [131], [132], [133], which
will significantly reduce medical staff’s time on labour-intensive
clinical documentation.

2) Clinical Decision Support: Clinical decision support
(CDS) systems can provide physicians with diagnosis and treat-
ment suggestions, which play an increasingly important role in
clinical medicine with the surge of clinical cases and growing
| Category | Sub-Category | Representative Applications | Related Techniques |
|----------|--------------|---------------------------|-------------------|
| **Clinical Practice** | clinical decision support | build QA-based clinical decision support systems [84], [134], [135] | information extraction |
| | | build clinical decision support systems with extracted information: family history information [136], entities and relations [137], treatment and prognosis data [139], clinical data concepts and features [140], causal relations [109], [110] | question answering |
| | | healthcare quality control: assess clinical procedures [141], [142], warning of ADEs [143], disease symptoms [144], [145], and outcome-related causal effects [146] | information extraction, causal inference |
| | | provide supporting evidence for decisions under evidence-based fashion [108], [147]-[150] | information retrieval, causal inference |
| **Hospital Management** | medical resource allocation | patient triage [151], [152] | information extraction |
| | | predict and reduce readmission rate [160]-[162] | information extraction |
| | | free medical staff from routine text writing [70], [163] | information extraction |
| | data management | manage clinical documents [158], [162], [163], [164] | text generation, text summarization, information extraction |
| | service quality control | improve service quality and patient experience [156]-[158] | information retrieval, question answering |
| **Personal Care** | personal health assistants | access online medical information [169] | information retrieval |
| | | enable remote healthcare [170] | speech recognition |
| | assisting the elderly and the disabled | daily assistance [171] | speech recognition, natural language understanding |
| | | social interaction and company [172], [173] | speech recognition, speech synthesis |
| | | assist people with speech impairments [122], [174]-[178], hearing loss [179], dyslexia [180], or neurological disorders [119]-[121] | speech recognition, speech synthesis |
| **Public Health** | health knowledge popularization and medical education | acquisition and representation of medical knowledge [86]-[89], [97]-[100] | knowledge engineering |
| | | ease the access of medical knowledge [1], [79], [81], [130], [182], [184], [185] | question answering, information retrieval, machine translation |
| | | generate medical case-based questions [186] | question generation |
| | | construct simplified summaries [81] | text summarization |
| | population screening | identify target populations [188] | information extraction |
| | | analyse of healthcare questionnaire and surveys [189] | information extraction |
| | drug discovery | map the interactions between diseases, chemical compounds, and biomolecules, predict molecular properties, and design novel molecules [190] | information extraction, information retrieval, knowledge engineering |
| **Drug Development** | preclinical research | drug screening [191]-[193] | information extraction |
| | | predict adverse drug reactions: side effect prediction [194], and toxicity prediction [195], [196] | information extraction |
| | clinical research | clinical trial design [110] | information extraction, causal inference |
| | | patient recruitment [197]-[199] | information extraction |
| | | clinical trial analytics [200] | information extraction |
| | drug review and safety monitoring | adverse drug events discovery and drug safety monitoring [201]-[203] | information extraction |

**B. Hospital Management**

1) **Medical Resource Allocation:** Due to limited medical resources, including hospital spaces, personnel, and materials, efficient resource allocation is critical in hospitals and other medical facilities. By building patient triage systems, medical resources can attend to critical cases with priority and enhance medical resource allocation effectiveness and efficiency [151], [152]. Virtual assistants [153], [154], [155], hospital automation systems [156], [157] and collaborative robots [158], [159] with voice control can further reduce the burden on medical staff, thereby improving hospital management efficiency. There are also some interesting works that have explored the prediction of patient readmission to rearrange medical resources/interventions and reduce the readmission rate [160], [161], [162]. In addition, by leveraging text generation techniques, part of text writing in healthcare, especially routine reports, can be taken over by machines, freeing medical staff from many administrative duties and making them available for direct patient care [70], [163].

Authorized licensed use limited to the terms of the applicable license agreement with IEEE. Restrictions apply.
2) **Data Management:** To manage large volumes of medical documentation, text classification, information extraction and text summarization can be used to generate category labels, informative keywords and simplified summaries [18], [52], [62], [63], [164] for management, while information retrieval systems, especially those systems based on semantic search [76], [165] and question answering [77], can be used in healthcare information systems to ease the retrieval process.

3) **Service Quality Control:** Sentiment analysis with patient experience feedback will help hospitals improve their service quality and patient experience. Such analysis required substantial personnel resources in the past, while NLP makes this work easier and greatly improves the efficiency of sentiment analysis [166], [167], [168].

**C. Personal Care**

1) **Personal Health Assistants:** Personal health assistants enable people to easily access useful medical information and healthcare services without visiting the healthcare institutions. Personal health assistants may incorporate several subsystems, such as medical information access systems [169] and remote healthcare systems [170], for various purposes.

2) **Assisting Elderly Individuals and Disabled Individuals:** NLP techniques can help elderly individuals and disabled individuals to greatly enhance their quality of life and social integration. Voice-controlled home automation systems and robots may assist the elderly and the disabled in their daily lives [171], while robots (especially androids and other robots that communicate with people) can even encourage and accompany them through social interactions [172], [173]. In addition, NLP techniques are also of great value for providing essential aids to people with various disabilities, e.g., speech impairments [122], [174], [175], [176], [177], [178], hearing loss [179], dyslexia [180], or neurological disorders [119], [120], [121].

**D. Public Health**

1) **Health Knowledge Popularization and Medical Education:** Health knowledge popularization and medical education are essential public health interventions since they can improve people’s health literacy and help them develop healthy living habits. Through knowledge engineering, accurate and complete medical knowledge bases can be established to promote the popularization of medical knowledge among the population [86], [87], [88], [89], [97], [98], [99], [100], [181]. Specifically, people can easily access medical knowledge through question answering systems [182], [183], information retrieval systems [79], [81], and machine translation systems [1], [130], [184], [185], facilitating the popularization and education of medical knowledge. In addition, text generation techniques, such as question generation and text summarization, can also be used in medical education to generate medical case-based questions [186] and construct simplified summaries [61].

2) **Population Screening:** In addition to the health knowledge popularization, population screening, which refers to the process of assessing the prevalence of a disease or condition in a population or subgroup, is also an important intervention for delivering public health. The population screening starts with identifying target populations, followed by the screening test. After that, further actions such as further tests, advice, or treatment can be taken considering the screening results [187]. NLP can play two main roles in population screening. First, NLP helps identify populations with higher health risk factors, which may improve the efficiency of population screening [188]. Second, NLP can also assist in the analysis of healthcare questionnaires and surveys [189], especially for open-ended questions.

**E. Drug Development**

1) **Drug Discovery:** NLP helps construct textual representations of biochemical entities for mapping the interactions between diseases, drugs/chemical compounds, and biomolecules (e.g., genes, proteins); predicting molecular properties; and designing novel molecules. Readers are referred to the comprehensive review by Öztürk et al. [190] for a deeper understanding of NLP methodologies for drug discovery.

2) **Preclinical Research:** NLP techniques, especially information extraction, are also able to identify the relations between chemical structures and biological activity [191] and further help researchers search for potentially effective chemical compounds, i.e., virtual screening [192], [193], in a huge chemical space. In addition, they are also applied in the prediction of adverse drug reactions, including side effect prediction [194], toxicity prediction [195], [196], and etc., in preclinical research.

3) **Clinical Research:** Across the clinical research stage, NLP may enable efficient clinical trial design [110], patient recruitment [197], [198], [199], clinical trial analytics [200], and etc.

4) **Drug Review and Safety Monitoring:** Recently, the FDA and other institutions have reported being interested in using NLP for adverse drug event discovery and drug safety monitoring [201], [202], [203], showing the full range of NLP’s key role in drug development.

**IV. NLP-Driven Smart Healthcare for Specific Medical Issues**

NLP-driven smart healthcare plays an important role in many medical issues. In this section, we discuss how NLP-driven smart healthcare works in medical issues by taking two specific medical issues, i.e., COVID-19 pandemic and mental health, as examples.

**A. COVID-19 Pandemic**

Worldwide outbreak of COVID-19 has triggered an unprecedented global health crisis and has attracted much attention from researchers [204]. No wonder, the COVID-19 pandemic has become one of the most influential medical issues over the past few years. In the COVID-19 pandemic, NLP-driven smart healthcare can be utilized for pandemic prevention, diagnosing, and drug development.

Early forecasts of COVID-19 cases and pandemic knowledge popularization are crucial to the prevention of the COVID-19...
pandemic. In [205], an NLP module is embedded into an improved susceptible–infected model to build the proposed hybrid AI model for COVID-19 prediction, showing that the forecasting accuracy of COVID-19 cases can be improved by incorporating text inputs and with NLP techniques. In [206], the authors conclude that NLP techniques, e.g., NLP-aided information retrieval, literature-based discovery, question answering and etc., can be applied to address the information/knowledge needs of both researchers and the public in the COVID-19 pandemic.

In clinical practice, NLP can be utilized to identify positively diagnosed COVID19 patients from free text narratives [207], assess thoracic CT imaging reports [208], and identify individuals with the greatest risk of severe complications due to COVID-19 [209], and provide COVID-19 testing advice [210]. Such applications would be very useful to accelerate the diagnosis of COVID-19, mitigate its worst effects, and also reduce costs for combating the COVID-19 pandemic.

NLP has also been applied to drug development confronting COVID-19. In [211], the authors developed an NLP method to automatically recognize the associations among potential targeted host organ systems, associated clinical manifestations and pathways, and suggest potential drug candidates. NLP models have also made great impacts in COVID-19 vaccine discovery through protein interaction prediction, molecular reaction modelling [212]. In addition, great opportunities for NLP can also be found in clinical design, regulatory decision-making, and pharmacovigilance [213]. These applications would significantly reduce the time and cost of drug development for COVID-19.

B. Mental Health

The mental health issues have received widespread and continuously increasing attention for many years. Specially, the World Health Organization (WHO) claimed that the pandemic and the resulting lockdowns, economic security, fear and uncertainty would further cause devastating impacts on people’s mental health the world over in the past several years [214]. NLP-driven smart healthcare has great value in predicting/diagnosing and treating mental health conditions.

NLP techniques have been applied to early predict or identify/screen various mental disorders, such as psychiatric illness [215], late-life depression [216], severe mental illness (schizophrenia, schizoaffective disorder and bipolar disorder) [144]. In addition, some works have shown that NLP techniques can predict risk-taking behaviours (e.g., suicide) with good discrimination [217], [218] so that early interventions can be taken to save lives. The data collected for such analysis may include text data such as social media posts, screening surveys, EHRs [219], and also speech data come from narrative interviews [220], etc.

NLP techniques could also (automatically) provide effective psychotherapeutic interventions through web-based psycho-educational interventions, online counseling, etc., to augment therapist-based mental health interventions, showing potential future opportunities for their integration into online mental health tools [221]. For example, the insights of [222] could help improve counselor training and generate real-time counseling quality monitoring and answer suggestion support tools. In addition, several mental health related areas that may benefit from NLP techniques, including characterizing and understanding mental disorders, measuring health outcomes, studying of social and occupational functioning, etc, were shown in [218]. Specifically, [223] showed that the older would respond better to digital assistants employing a socially-oriented interaction style rather than the one with a task-oriented style, which is promising to promote mental health in older adults by providing social interaction and company.

V. LIMITATIONS AND OUTLOOK

Although recent advancements in deep learning and neural NLP have brought extraordinary enhancement to smart healthcare, there are still some limitations that current methods have yet to overcome.

A. Understanding Human Language

Although substantial efforts have been made to enable natural language understanding, the flexibility of human language still makes full understanding difficult, especially when ambiguity in biomedical texts is encountered. Misunderstanding could lead to inaccurate actions taken by robots, useless information returned by engines, and even wrong decisions made by decision support systems, leading to economic loss, time wasting, and even more serious consequences.

B. Interpretability

Although applications that rely on neural NLP to extract features and make decisions show excellent performance in real tasks, they are usually challenged by users due to their weakness in interpretability. Interpretability is essential for smart healthcare applications, especially in clinical scenarios that require quality assurance in cases of low confidence. One of the major interpretability issues is that the learned features are usually not understood by humans. In addition, when tuning pre-trained language models to downstream tasks, no enough intuitions on data for fine-tuning or types of applications can be given to guarantee good performance. Although efforts have been made to achieve interpretable NLP-driven applications, existing theories and methodologies are still not convincing and acceptable for many healthcare researchers and institutions. Before the interpretability issue is fully explored, the role of decision support systems in clinical practice can only be auxiliary from the perspectives of medical ethics and practical application.

C. Implementation

There are still many issues concerning the implementation of NLP-driven applications in smart healthcare. With the development of neural NLP, large deep neural networks (e.g., pre-trained language models) have been quickly migrated to smart healthcare. What followed are the increased requirements in computing power and training cost, and the concerns about the
reliability of neural NLP systems. Patient privacy also prevents these models from achieving more prominent effects in smart healthcare for further practice. The consideration of medical ethics when applying such systems makes practical implementation more difficult.

In addition to tackling the aforementioned limitations, there are some other directions to enhance existing NLP systems for smart healthcare.

D. Combining Multiple NLP Techniques

One direction to enhance existing NLP systems can be the combination of multiple NLP techniques. For example, text generation can work as a data augmentation method for achieving comparable results in many applications with limited original data, such as training QA systems [65], [85] and other clinically relevant tasks [224], [225]. Through automatic question generation, questionnaires and surveys for population screening can be generated from EHRs, which may outperform handcrafted ones. Machine translation has also proven beneficial for various text-based tasks by increasing the availability of multilingual healthcare information [226], [227], [228], implying the possibility of improving the performance of current CDS systems. In addition, exploration of general knowledge and domain knowledge in the field of NLP for smart healthcare deserves further attention and verification.

E. End-to-End Applications

Current NLP driven applications for smart healthcare usually focus on dealing with tasks step by step and do not fully explore the feature extraction capability of advanced neural NLP for complex smart healthcare tasks. A deeper integration of NLP techniques and healthcare applications in an end-to-end manner can map the inputs and outputs directly, significantly simplify traditional pipelines for complex applications, eliminate the biases of intermediate components, and therefore achieve better performance. Taking population screening as an example, although NLP has been applied to identify populations and analyse screening test results in traditional screening procedures, NLP techniques can be further applied to build end-to-end population screening systems, with which the correlations between populations and optimal actions can be found to improve the screening performance and the quality of healthcare. Another example would be reducing the readmission rate. As mentioned before, some works have revealed that NLP has the ability to predict patient readmission, but further studies on providing appropriate interventions to reduce the readmission rate are not fully conducted. We look forward to studies that integrate the two parts to reveal every possibility for readmission rate reducing.

F. Few-Shot Learning and Incorporating Domain Knowledge

By exploiting the learning capability of neural networks and large available corpora, neural NLP has shown powerful ability in learning language representations. However, for downstream tasks or smart healthcare applications, there is still a long way for NLP to go. Taking clinical decision support as an example, there are a lot of rare diseases with only a small number of observations available for training a clinical decision support system to distinguish rare diseases from common diseases. This is a quite challenging task, especially when there are similar outcomes among some rare diseases and common diseases. In addition, high-quality labelled data are undoubtedly essential to guarantee task accuracy in developing practical applications for smart healthcare. However, quality-controlled annotation not only requires a large amount of cost, but is also challenging due to the bias of experts’ level of expertise. Therefore, even with well-learned pre-trained language models, few-shot learning algorithms and domain knowledge are expected to be applied so that the fine-tuned models would be effective in learning from few rare disease observations or limited high-quality labelled data.

G. Incorporating Multimodal and Longitudinal Data

Finally, we also anticipate future intelligent systems to utilize all available AI techniques, not only NLP, for practical applications with high accuracy and reliability. The past few years have witnessed the dominance of data-driven approaches in many applications across various fields. NLP, computer vision, and other machine learning algorithms can be applied to analyse medical text, medical images, electronic recordings (e.g., heart sound), sensors data, laboratory results, and even genetic information. With multimodal learning, useful information extracted from these modalities can be combined together to perfectly fit the need for a complete and accurate analysis of available healthcare data and patients’ health status. In addition, all of these data and clinical events can be longitudinal, where time series analysis can be applied to extract long-term dependencies and improve health care delivery. By combining these techniques to analyse multimodal and longitudinal data, future intelligent systems would become more powerful and reliable for patients, physicians, and healthcare institutions for applications such as 24/7 health monitoring, chronic-condition management, healthy lifestyle promotion, and precision medicine.

VI. Conclusion

In the context of smart healthcare, NLP takes text or speech as the input in various scenarios involving humans and machines, and realizes the functions of analysing and understanding human language. In this paper, we review existing studies concerning NLP for smart healthcare from the perspectives of technique and application. We elaborate on different NLP approaches and the NLP pipeline for smart healthcare from the technical point of view. Table I provides the comparisons of different NLP approaches and their representative algorithms. Various text-oriented and speech-oriented NLP tasks are elaborated to conclude existing methodologies for tackling such tasks. By introducing smart healthcare applications employing NLP techniques in various smart healthcare scenarios (including clinical practice, hospital management, personal care, public health, and drug development), we show the strength and possibility of NLP for delivering smart healthcare. Table II provides a
detailed list of representative applications in smart healthcare and their related NLP techniques. We further discuss two specific medical issues, i.e., COVID-19 pandemic and mental health, in which NLP-driven smart healthcare plays an important role. After that, we discuss the limitations of current works across understanding human language, interpretability, and implementation of NLP systems for smart healthcare. Finally, we identify several directions for future works, notably combining multiple NLP techniques, developing end-to-end applications, few-shot learning, and incorporating multimodal and longitudinal data.

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