Applications Of Natural Language Processing In Healthcare Systems

Moustafa Abdelwahap, and Menatalla Elfarash
Biomedical Engineering program, Faculty of Engineering, Mansoura University, Egypt, mostafamedhat@std.mans.edu.eg, mennaelfarash18@std.mans.edu.eg

Supervisor: Dr. Ahmed Eltanboly
Mansoura University, Egypt, Eng_ahmed_hazem@mans.edu.eg

Abstract– The most sensitive sector in our life is health. The purpose of this research is to explore how Natural Language Processing (NLP) has a vital role in our Healthcare system in diagnosing diseases and facilitating routines as well as discussing the architecture of each application. NLP, which deals with text and speech has a lot of models like sentiment analysis, speech recognition, language modeling, etc. We have looked into the healthcare industry to discover the different products that have NLP - based models. A Medical Chatbot is used to diagnose patients in their early stages of the disease. Speech recognition is used to detect a doctor's voice and turns it into a digitized medical prescription. Other examples are being explained in this research besides discussing how the product is being implemented and then deployed. The goal of this research is to explain that Artificial Intelligence is helping us in our most need, which is health.

Keywords--Natural Language Processing, Healthcare Systems, Electronic Health Records (EHRs), Medical Chatbot, AI in Healthcare

I. Introduction

A. Overview of Linguistics

It is the scientific study of languages that aims to understand the nature and different functions of any language to understand speech sounds (phonetics) and written text of this language. Phonemes are the distinct sound of any word and it is considered as the intermediary between speech and text.

Computational Linguistics starts a new era of analyzing and modeling the language, but It was still challenging to make a machine understand our natural language because of different reasons like the variety of accents, ambiguous words, unstructured sentences, and others. NLP came to begin a new chapter of doing useful things using human language [1].

B. Evolution of NLP

NLP started in the 1950s as a subfield of Linguistics and Artificial Intelligence (AI) concerned with the interpretation of human-generated text and speech. It started with a simple application of word-to-word translation and then it has been developed to be able to check grammar [2]. Year after year until we can see it now in many applications like summarization, information retrieval, sentiment analysis, chatbots, predictive analytics, and others. The field is rapidly growing and has a very large community of active researchers who still exploring it [3].

The pipeline of NLP can be described in three stages as shown in Fig. 1.

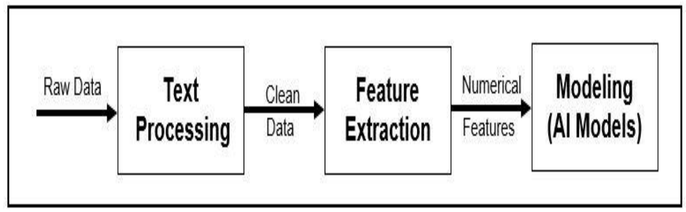

Fig. 1 NLP Pipeline.

C. Clinical Health Data

It is all the information about health status, reports, Prescriptions, and others. It represents all kinds of data about patient health records. The amount of unstructured data among medical organizations is so large that we can't extract useful information or even insights from them until Electronic Health Records (EHRs) were developed to make a big revolution in the healthcare systems and to be the base of Big data in healthcare [4].

Electronic Health Records (EHRs) are powerful tools utilized by healthcare providers to enhance data handling and communication techniques in healthcare settings as well as optimizing the quality of service [5].

II. Applications of NLP in HEALTHCARE Systems

A. Clinical Decision support systems (CDSS)

Clinical Decision support systems have been used for 50 years to aid physicians in making clinical decisions like deciding the best treatment technique, adjusting risk factors, and other important things that we'll present in this review paper [6].

A.1. Treatment Suggestion

Based on patient characteristics, they are matched to a database to generate some recommendations that can be taken into consideration by clinicians when making medical decisions [7]. Also, CDSS can look into the history of the patient, his/her current condition, and the other parameters. Based on a standard guideline, CDSS will describe treatment options for this patient.

A.2. CDSS in precision medicine

There is a strong relationship between CDS and personalized medicine. We are heading to the era of the customization of treatment based on single patient medical status, including genomic variables and others and that is what we call personalized medicine or precision medicine [8]. For example, the framework that was developed for oncology to address the complexity of cancer patient management and integrate the knowledge for providing personalized medicine (PM) [9].

A.3. Clinical Entity

NLP can represent and classify clinical terms inside EHRs into ICD-10 standard which stands for the 10th revision of International Statistical Classification of Diseases and Related Health Problems for reporting diseases and health conditions which represent a medical classification list that was created by the World Health Organization (WHO). After representing the data in the ICD-10 standard, we can adjust a risk factor for each patient based on the Hierarchical Condition Category (HCC) where each HCC is mapped to an ICD-10 code as shown in Fig. 2. That can help physicians in Clinical Decision support as it represents an alert for early detection of various diseases [10].

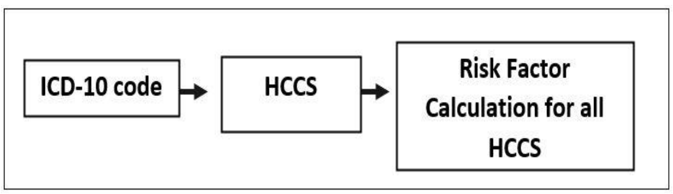

Fig. 2 Adjusting Risk Factors.

A.4. Document summarization

NLP can also be used to summarize the EHR of a specific patient because, in emergency situations, doctors have to familiarize themselves with basic data about the patient as fast as possible to be able to make decisions regarding the patient [11]. NLP can extract the facts, Medical Knowledge, and the latest clinical updates needed to enrich Clinical Decision support systems.

Another NLP approach was created to identify the postoperative surgical complications from an EHR that contains clinical notes, clinical reports, and discharge summaries from other medical centers [12].

A.5. Image Captioning

Each day, Physicians need to examine a lot of medical images and write reports. Using both Computer Vision and NLP, we can make a medical image captioning to generate textual descriptions of any medical images like chest X-Ray images which will help in accelerating the process plus saving time and effort [13].

All of those applications help physicians in Clinical Decision support which means better healthcare, low cost, time-saving.

B. Speech Recognition

Speech recognition or voice recognition is the technology of converting voice into text and also the ability to recognize voice commands.

B.1. Speech-to-Text transcription for EHRs

The electronic health record (EHR) acts as a warehouse of all patient health information. Using high-quality EHR in healthcare is important to minimize medical errors.

EHR provides a different method to the use of keyboards and templates to create progress notes based on a physician's voice for physicians who prefer voice to text. The system [14] was used to support a randomized clinical trial testing to see whether the use of voice to create notes improves the timeliness of note availability, note quality, and physician satisfaction with the note creation process or not.

B.2. Speech-to-Text transcription for Electronic prescribing

The digitization of medical prescriptions provides high accuracy and reliability. In India, they were able to develop a smartphone-based electronic prescribing system [15] using NLP to reduce the cost where it takes the doctor's voice and transcribes it into text, and then we can print an E-prescribing or even take it as a pdf file in our digital devices.

B.3. Computational Phenotyping from speech patterns

Genotyping is the process of analyzing or predicting some characteristics of an organism. A set of parameters, derived from neural and behavioral data, called computational phenotype, is responsible for characterizing an individual's cognitive mechanism. NLP-based computing phenotyping has numerous applications including diagnostic categorization, novel phenotype discovery, and clinical trial screening [16].

Focusing on Computational Phenotyping from speech patterns, speech is a highly sensitive output system; physiological, pathological, and biochemical changes easily affect our speech generation. As a consequence, we can benefit from using speech as a biomarker for emotional, pathological, and mental health conditions.

Bipolar disorder, a type of mood disorder, alone accounts for at least 1% of years lived with disability globally. It can be harder to diagnose, and even when an accurate diagnosis is made, it is often delayed. Here, speech recognition is applied to understand mood and cognition in people with bipolar disorder [17].

Automatic speech recognition (ASR) technologies now incorporate NLP. ASR captures real conversations between people and uses NLP to process them. Remarkable approaches for using this technique are detecting neurocognitive disorders like Alzheimer's disease (AD) and Schizophrenia.

People living with dementia suffer from symptoms at the word level, such as having smaller vocabularies and Part of Speech (POS) misuse; sentence-level symptoms include incomplete sentences. To help in AD diagnosis, the system [18] will typically work on audio recordings and all processing steps will be done automatically, including the acoustic feature extraction and the speech-to-text transcription by an Automatic Speech Recognition (ASR) system.

C. Medical Robots

Robots have invaded the medical sector, They are being used in the rehabilitation of patients like exoskeletons and surgical procedures like Robotic Endoscopy. Since NLP represents the understanding of the text and speech, it can act as a sensor for Human-robot interaction.

Valencia-Garcia et al [19] presented a system to detect and understand a surgeon's natural language, then translate it into robotic-executive commands using speech recognition techniques and intent extraction. Also, they were able to design a framework for simulating robot-assisted surgical operations using NLP.

Another example is the AESOP 3000 [20] surgical robot, a computer-assisted surgery that is voice-controlled. This robot is mainly used in laparoscopic sensitive surgeries like heart surgery.

Robotic surgery is highly useful because it reduces the number of physicians per surgery "solo-surgery" and therefore they reduce the cost and time.

Now, the question is how to implement such projects using NLP! Using Dialogue systems, we are able to make an interactive conversation between humans and robots as shown in Fig. 3.

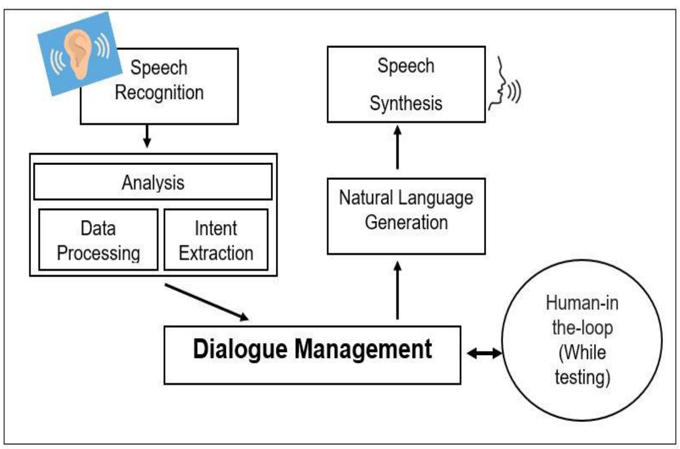

Fig. 3 Architecture Of Spoken Dialogue Systems.

Dialogue management techniques are many [21]. The most common and simple techniques that are used in the industry are state-based techniques. They represent the possible dialogues based on different states. In each state, the user is required to give specific information to the system. Based on the information, the system will generate different responses to the user depending on the current situation.

State-based techniques are very efficient, but only in simple tasks. In complex tasks, it is better to use frame-based techniques where they use frames instead of series.

D. Medical Chatbots

Statistics [22] show that in the situations of simple, small-scale diseases, 80% can be cured by effortless home remedies. There are a lot of chatbots that provide services for the healthcare domain. Current researches are being carried out to enable chatbots to communicate in a way similar to the communication carried out between two humans using natural language so the user can feel that he is communicating with a human, not a machine. This makes the chatbot a virtual trusted friend of the user.

D.1. Chatbots for Mental Health

Many studies [23] have been conducted using chatbots for mental health. It has been estimated that mental disorders may affect 29% of people in their lifetime. According to the World Health Organization, 29% of the 15,000 mobile health apps focused on mental health. One of the main technological solutions to the lack of mental health workforce are chatbots, also known as conversational agents, conversational bots, and chatterbots.

For example, the chatbot "Wysa" uses several evidence-based therapies (e.g. Cognitive behavioral therapy, Behavioural reinforcement, and Mindfulness) to target symptoms of depression for users. LISSA is another chatbot that provides training for people with autism in order to develop their social skills [24].

D.2. Chatbots For Self-Diagnostic Based On Symptoms

To control the spreading of coronavirus, the World Health Organization advised some preventive measures like washing the hands frequently with soap and water or with sanitizers, maintaining social distancing, and practicing respiratory hygiene. Many countries preferred Mobile Technology in giving proper surveillance. In today's healthcare environment using Mobile Technology and mobile devices have proven to be effective.

In South Africa, HealthAlert is implemented to give the right information to the citizens through smartphones. Health Alert is a WhatsApp-based helpline to support users on health queries or concerns and helps them to direct the accurate information sources when they require related to the spread of Coronavirus. This tool helps users self-assess their COVID-19 risk category based on their symptoms and their exposure history [25].

D.3. Chatbots For Emergency And First Aid

Sudden illness and injuries require quick emergency intervention in order to help individuals with no first-aid skills or help to avoid deterioration of the subject's condition and maintaining his/her physical integrity until the aid arrives. A Cloud computing-based chatbot called SPeCECA [26] assists victims or incident witnesses. Therefore, even a person with no first aid skills can help the victim to survive by performing first aid support as suggested by the virtual assistant. This chatbot presents an online human-bot interaction that supports different scenarios for every single emergency case.

The architecture of the system is introduced by its six components: information pre-processing component (IPPC), natural language processing component (NLPC), context component (CC), informative post-processing component (IPoPC), response generator component (RGC), and Alert message constructor component (AMCC).

III. CHALLENGES OF INTEGRATING NLP TOOLS INTO HEALTHCARE SYSTEMS?

To achieve widespread NLP applications in healthcare systems, We are required to adapt existing NLP systems to be able to work in different settings with various situations. The adoption process is very challenging because it depends on the structure, linguistic content, and other characteristics of the existing NLP system that will be heterogeneous with the new system [27].

There are other challenges subjected to NLP itself like the language barrier as we have many languages in the world with unique grammar and vocabulary for each one so we will have to make a lot of effort to process languages other than English. Other challenges can present in extracting meaning from strings of text, multipurpose words, unstructured data, different accents of a single language, and other challenges, but the most difficult challenge related to linguistics is Crash Blossom which refers to the syntactic ambiguity in languages [28].

IV. CONCLUSION

In this paper, we have summarized most of the NLP applications that are currently used in healthcare systems. We categorized them into four categories which are Clinical Decision support systems (CDSS), Speech Recognition, Medical Robots, and last but not least Medical Chatbots. We discussed the Evolution of NLP and how it started as a machine translator and now we use it in our healthcare systems and it is still growing with more and more applications in different sectors in our lives. Hopefully, we will make another paper like this 5 years later to discuss the latest use of NLP in our healthcare systems.

ACKNOWLEDGMENT

We would like to express our gratitude to our supervisor Dr. Ahmed Eltantawy, Vice Manager of the Biomedical Engineering program at Mansoura University, for his always support.

NOMENCLATURE

NLP: Natural Language Processing
EHRs: Electronic Health Records
CDSS: Clinical Decision support systems
PM: Personalized Medicine
ASR: Automatic Speech Recognition
AD: Alzheimer's disease

REFERENCES

[1] T. Briscoe, "Introduction to Linguistics for Natural Language Processing," *October*, pp. 1–37, 2011.

[2] P. M. Nadkarni, L. Ohno-Machado, and W. W. Chapman, "Natural language processing: An introduction," *J. Am. Med. Informatics Assoc.*, vol. 18, no. 5, pp. 544–551, 2011, doi: 10.1136/amiajnl-2011-000464.

[3] B. J. Grosz, "Natural language processing," *Artif. Intell.*, vol. 19, no. 2, pp. 131–136, 1982, doi: 10.1016/0004-3702(82)90032-7.

[4] D. Capurro, M. Yetisgen, E. Eaton, R. Black, and P. Tarczy-Hornoch, "Availability of Structured and Unstructured Clinical Data for Comparative Effectiveness Research and Quality Improvement: A Multi-Site Assessment," *eGEMs (Generating Evid. Methods to Improve. patient outcomes)*, vol. 2, no. 1, p. 11, 2014, doi: 10.13063/2327-9214.1079.

[5] G. Fitzpatrick, "Understanding the Paper Health Record in Practice: Implications for EHRs," *HIC 2000 Proc.*, no. 6, p. 323, 2000, [Online]. Available: http://search.informit.com.au.ezp.lib.unimelb.edu.au/documentSummary%5Cndn=923212919867674%5Cnres=IELHEA.

[6] D. Demner-Fushman, W. W. Chapman, and C. J. McDonald, "What can natural language processing do for clinical decision support?," *J. Biomed. Inform.*, vol. 42, no. 5, pp. 760–772, 2009, doi: 10.1016/j.jbi.2009.08.007.

[7] L. Moja *et al.*, "Effectiveness of a Hospital-Based Computerized Decision Support System on Clinician Recommendations and Patient Outcomes: A Randomized Clinical Trial," *JAMA Netw. Open*, vol. 2, no. 12, pp. 1–16, 2019, doi: 10.1001/jamanetworkopen.2019.17094.

[8] G. J. Downing, S. N. Boyle, K. M. Brinner, and J. A. Osheroff, "Information management to enable personalized medicine: Stakeholder roles in building clinical decision support," *BMC Med. Inform. Decis. Mak.*, vol. 9, no. 1, pp. 1–11, 2009, doi: 10.1186/1472-6947-9-44.

[9] A. Bucur *et al.*, "Workflow-driven clinical decision support for personalized oncology," *BMC Med. Inform. Decis. Mak.*, vol. 16, no. Suppl 2, 2016, doi: 10.1186/s12911-016-0314-3.

[10] J. Zhong and X. Yi, "Categorizing Patient Disease into ICD-10 with Deep Learning for Semantic Text Classification," *Recent Trends Comput. Intell.*, no. March, 2020, doi: 10.5772/intechopen.91292.

[11] R. Pivovarov and N. Elhadad, "Automated methods for the summarization of electronic health records," *J. Am. Med. Informatics Assoc.*, vol. 22, no. 5, pp. 938–947, 2015, doi: 10.1093/jamia/ocv032.

[12] H. J. Murff *et al.*, "Automated identification of postoperative complications within an electronic medical record using natural language processing," *JAMA - J. Am. Med. Assoc.*, vol. 306, no. 8, pp. 848–855, 2011, doi: 10.1001/jama.2011.1204.

[13] J. Pavlopoulos, V. Kougia, and I. Androutsopoulos, "A Survey on Biomedical Image Captioning," pp. 26–36, 2019, doi: 10.18653/v1/w19-1803.

[14] T. H. Payne, W. D. Alonso, J. A. Markiel, K. Lybarger, and A. A. White, "Using voice to create hospital progress notes: Description of a mobile application and supporting system integrated with a

commercial electronic health record," *J. Biomed. Inform.*, vol. 77, no. December 2017, pp. 91–96, 2018, doi: 10.1016/j.jbi.2017.12.004.

[15] J. Mahatpure, M. Motwani, and P. K. Shukla, "An electronic prescription system powered by speech recognition, natural language processing and blockchain technology," *Int. J. Sci. Technol. Res.*, vol. 8, no. 8, pp. 1454–1462, 2019.

[16] Z. Zeng, Y. Deng, X. Li, T. Naumann, and Y. Luo, "Natural Language Processing for EHR-Based Computational Phenotyping," *IEEE/ACM Trans. Comput. Biol. Bioinforma.*, vol. 16, no. 1, pp. 139–153, 2019, doi: 10.1109/TCBB.2018.2849968.

[17] H. Baumeister and C. Montag, *Digital Phenotyping and Mobile Sensing: New Developments in Psychoinformatics*. 2019.

[18] Y. Pan, B. Mirheidari, M. Reuber, A. Venneri, D. Blackburn, and H. Christensen, "Improving detection of Alzheimer's Disease using automatic speech recognition to identify high-quality segments for more robust feature extraction," *Proc. Annu. Conf. Int. Speech Commun. Assoc. INTERSPEECH*, vol. 2020-Octob, pp. 4961–4965, 2020, doi: 10.21437/Interspeech.2020-2698.

[19] R. Valencia-Garcia, R. Martinez-Béjar, and A. Gasparetto, "An intelligent framework for simulating robot-assisted surgical operations," *Expert Syst. Appl.*, vol. 28, no. 3, pp. 425–433, 2005, doi: 10.1016/j.eswa.2004.12.003.

[20] A. Europe, A. Search, and J. Europe, "[AESOP 3000--computer-assisted surgery , personal experience].," pp. 1–2, 2021.

[21] Y. Liu, C. Yang, and M. Wang, "Human-Robot interaction Based on Biosignals," *2020 Int. Symp. Auton. Syst. ISAS 2020*, pp. 58–63, 2020, doi: 10.1109/ISAS49493.2020.9378844.

[22] E. Amer, A. Hazem, O. Farouk, A. Louca, Y. Mohamed, and M. Ashraf, "A Proposed Chatbot Framework for COVID-19," pp. 263–268, 2021, doi: 10.1109/miucc52538.2021.9447652.

[23] A. A. Abd-alrazaq, M. Alajlani, A. A. Alalwan, B. M. Bewick, P. Gardner, and M. Househ, "An overview of the features of chatbots in mental health: A scoping review," *Int. J. Med. Inform.*, vol. 132, p. 103978, 2019, doi: 10.1016/j.ijmedinf.2019.103978.

[24] A. Ahmed, A. Hassan, A. A. Abd-alrazaq, N. Ali, and S. Aziz, "Anxiety and Depression Chatbot Features : A Scoping Review (Preprint) Anxiety and Depression Chatbot Features : A Scoping Review," no. January 2021, 2020, doi: 10.2196/preprints.26341.

[25] K. R. Singh, S. Dash, B. Deka, and S. Biswas, "Mobile Technology Solutions for COVID-19," *Stud. Syst. Decis. Control*, vol. 324, pp. 271–294, 2021, doi: 10.1007/978-3-030-60039-6_14.

[26] N. Ouerhani, A. Maalel, and H. Ben Ghézela, "SPeCECA: a smart pervasive chatbot for emergency case assistance based on cloud computing," *Cluster Comput.*, vol. 23, no. 4, pp. 2471–2482, 2020, doi: 10.1007/s10586-019-03020-1.

[27] D. S. Carrell *et al.*, "Challenges in adapting existing clinical natural language processing systems to multiple, diverse health care settings," *J. Am. Med. Informatics Assoc.*, vol. 24, no. 5, pp. 986–991, 2017, doi: 10.1093/jamia/ocx039.

[28] D. Khurana, A. Koli, K. Khatter, and S. Singh, "Natural Language Processing: State of The Art, Current Trends and Challenges," no. Figure 1, 2017, [Online]. Available: http://arxiv.org/abs/1708.05148.