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A Systematic Review of Natural Language Processing in Healthcare

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Abstract

Systematic reviews and meta-analyses to identify existing clinical natural language processing (NLP) systems that create structured information from unstructured free text have chosen a systematic strategy for reporting items. The study gathers data on the natural language processing methodologies, strategies, procedures, frameworks, and reviews utilized in healthcare applications. We used standard indices like Google Scholar, Scopus, and Web of Sciences to look for articles about NLP in healthcare. We looked for conference proceedings and journal papers published between 2005 and 2020. From the accessible sources, articles concentrating on NLP in the healthcare system were chosen. Forty research articles were evaluated based on their focus on successful activities in the research field. Nineteen publications dealt with methodology, three with frameworks, five with techniques, five with processes, and eight with review research papers. The NLP systems discussed in this paper cover a wide range of clinical and research objectives. This study looks for NLP systems that have tried to solve problems like "processing clinical free text and creating structured output." The data gathered from the highlighted studies was analyzed in order to priorities novel methods and difficulties in clinical NLP.

Keywords: Healthcare; Medical Terminology; Clinical Notes; Patient Inquiries; Natural Language Processing

I. Introduction

Natural language processing (NLP) is soaring because of its undoubted potential in interpreting complex, unstructured datasets, and in generating actionable intelligence. This data can be in any form, such as text, speech, visuals, etc. Connecting this power can unlock doors to unprecedented opportunities and maximize the organization's joint investment in terms of capital, human efforts, and time. NLP helps to process very large amounts of data presented in general linguistic form, and run superior machine learning algorithms on it to obtain important business insights.

NLP is even more valuable in the medical healthcare system, where massive amounts of facts are churned out constantly every day. A few aspects of healthcare that technology is transforming are free-text, clinical documentation improvement, data mining research, automated reporting, clinical trials, and decisions, etc. [1]. According to Dahmet et al., inappropriate usage of medical terminologies in the health care domain has raised various issues related to effective communication between patients and healthcare professionals [2]. As per Keifenheim, there is an effective relationship between the content (patient's query) and their way of communication [3]. The communication challenges confronted by healthcare professionals while interacting with patients are highly context-specific, especially when patients interact with their native language other than English (for example, Marathi). The health-related complaints of the Patients are recorded during their arrival in the emergency department (ED). The recorded information is available in an unstructured free-text format in the hospital database. This data is retrieved by healthcare professionals for categorizing and analyzing the symptoms described by patients to provide appropriate treatment [4] [5]. However, any discrepancy in this recorded data results in significant medical ignominy. According to Silverman, [6], these situations are more common when the patient's language is unfamiliar to clinicians. The symptoms of a disease can be recorded in several ways; for example, when a patient is complaining of chest pain, the symptoms can vary, such as chest tightness, chest discomfort, heartburn, pleurisy pain, and angina. These symptoms play an important role and act as the primary source of information for developing an appropriate diagnosis. Grouping the patient's symptoms and identifying the disease based on these symptoms can invite many challenges when it requires human intervention to handle these tasks. Meuter [7] proposes a process that can be highly subjective as it involves a lot of medical jargon to describe a patient's symptoms. Also, a lack of standard clinical terminologies used for describing the patient's complaints can increase the complexity of the diagnosis process. These complexities could worsen if the patient's language is not understandable by healthcare professionals. Manual translations of the symptoms from the patient's native language to English are not effective since there are high chances of miscommunication and they can be highly inaccurate.

Most of the recorded clinical information is in the form of unstructured free text, which makes it difficult for interpretation. The conversion of unstructured free text into a structured format is highly tedious and time consuming. Besides, it is not guaranteed that the conversion process incorporates all the valuable information. There are high chances of inaccurate interpretation and loss of significant data. Appropriate translation of unstructured information to structured information possesses certain advantages, such as:

1. The reduction of time required for manual expert review [9].
2. The secondary use of this data is for large-scale automated processing [8].

Patient's complaint data. Young [10] defines recent advancements in NLP approaches that have incorporated various advanced techniques such as machine learning and deep learning approaches for converting unstructured data. From the existing literary works, it can be observed that deep learning approaches have overpowered machine learning methods in terms of computational capability and accuracy. As per Esteva [11], most of the deep learning methods are trained using supervised learning approaches. The respective models are trained for efficient mapping of the diseases and for converting the raw data into appropriate symptoms using specific medical terminology [11]. Deep CNN Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN) are the most prominent techniques used for NLP applications pertaining to the healthcare domain. RNN models such as Long-Short Term Memory (LSTM) and Reinforcement Learning (RL) are prominent deep learning models that have significant scope in the healthcare domain.

The review of this related literature on the application of natural language processing in health care seeks to study the present methods, algorithms, tools, and techniques. Besides finding the NLP-in healthcare approach, the researchers have revealed research problems that focus on applications of NLP in healthcare. Clinical notes and patient complaints are processed in a flexible language to extract relevant medical diagnostic terminology. Similarly, the underline survey of respective research is analyzed and presented in terms of suggestions in terms of the outcome gained in respect of the NLP approach used.

II. Materials and methods

The researcher conducted a literature evaluation in order to respond to the following research questions:

1. What methodologies, algorithms, tools, and strategies are currently being used to establish NLP in health care?
2. Which NLP approach was used to solve the health-care problem?
3. How does the research proposal stand out?
4. What recommendations do you have for the NLP method in terms of results?

The Kitchenham [12] guidelines are being used to conduct this review in this study. The three key processes involved in doing a systematic review in this state are as follows:

1) creates a review strategy 2) Conducting the Examination 3) Complete and submits the review. Kitchenham's review approach is depicted in Fig. 1. Identifying the review, specifying the research questions, and putting up the review technique are all things that must be done at the planning stage. These section's research questions were established in advance. In performing this review, we used Kitchenham's approach [12]. It is made up of a high-quality and widely acknowledged set of engineering guidelines for researchers. This research approach served as the basis for the method used in this review. It explains how the literature search, study selection, and source selection were done. The format suggested in Kitchenham's approach [12] is also used for the review report technique.

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Fig .1.Methodology for the review

III. Data Sources and search strategy

Standard indices such as Web of Sciences, Google Scholar, and Scopus were searched for conference proceedings and journal papers for the duration of *2005–2020*. The term "Natural language processes in Health Care", was the first term used as the string term for literature search. Keywords, abstracts, and the article's title were also used during the literature search.

The sources of the literature search using the search string mentioned above are shown in *Table 1* for journal articles and the number of papers from a specified journal and in *Table 2* for conference proceedings. A manual review of eligible publications was carried out in order to select the real papers to be included. *Table 3* lists a summary of the approaches and contributions of the respective researchers.

Table 1.Literature sources from selected journals

Sr. No.	Journal Name	No. of articles from the source
1	JAMIA : Journal of the American Medical informatics association	01
2	SAGE Journal : Health Informatics Journal	01
3	AMIA: Annual Symposium Proceedings Archive	01
4	National Library of Medicine Pub Med	20
5	Research India Publications: Advances in computational sciences & Technology	01
6	ITHEA @ Business and engineering applications of intelligent and information systems	01
7	Journal of Bio-Medical informatics	05
8	IEEE Computational Intelligence Magazine	01
9	International Journal of computer science and information security	01
10	Research India Publications: Journal of Theoretical and applied information technology	01
11	Nature of medicine	01
12	International Journal of applied engineering research	01
13	International Journal of Computer Science Trends and Technology (IJCST)	01
14	International Journal of Medical Informatics	01
15	JMIR Medical Informatics	01
16	BMC Medical Informatics and Decision Making	02
17	Journal of software engineering & applications	01
18	Journal of Hospital Librarianship	01
19	International Journal of nursing studies	01
20	International Journal of E-Health & Medical Communications	01
21	Journal of Theoretical and Applied Information Technology	01

Table 2.Literature sources from conference proceedings

Sr. No.	Conference Proceeding Name	No. of articles from the source
1	Annual International Conference IEEE engineering medical biological science	01
2	Conference: Medical Informatics Europe (MIE)	01
3	International Conference on Analysis of images, social networks & Texts	01
4	Conferences in Research and practice in information technology	01
5	ACSW Frontiers 2007. The Australasian Workshop on Health Knowledge Management and Discovery	01
6	International Congress on Image & Signal processing Biomedical Engineering & Informatics(2019)	01
7	8th ACM International Conference on Bioinformatics Computational Biology & Health Informatics (2017)	01

1 Criteria for inclusion

The authors chose articles that focused on the use of natural language processing in health care and diagnosis systems. The papers were analyzed and assessed over the course of 16 years based on how well they fit within the research questions stated in this study's materials and procedures.

2 Exclusion criteria

The following criteria were used for limiting, filtering, and setting the boundaries of the research papers during the literature search. The year of publication was set from 2005 to 2020. Presently, only English-based journal articles and conference papers are considered. The publication document type was set to only include journal articles and conference papers.

3. Study Selection

To see how Natural Language Processing (NLP) is being used in healthcare by researchers, we searched in PubMed for any full-text English-language case reports, clinical trials, and original research articles that used the phrase "Natural language processing in healthcare." After downloading *125* citations relevant to a string, we eliminated duplicate articles and discovered *90* articles to use. Finally, we applied inclusion criteria and found *40* research publications. The research articles had to be verified to ensure that their findings fit into delivering the necessary solutions to the research concerns addressed over the course of the 16-year study. In Fig 2. Flow chart outlining article extraction, screening, and inclusion for schematic reviews and meta-analysis style flowchart.

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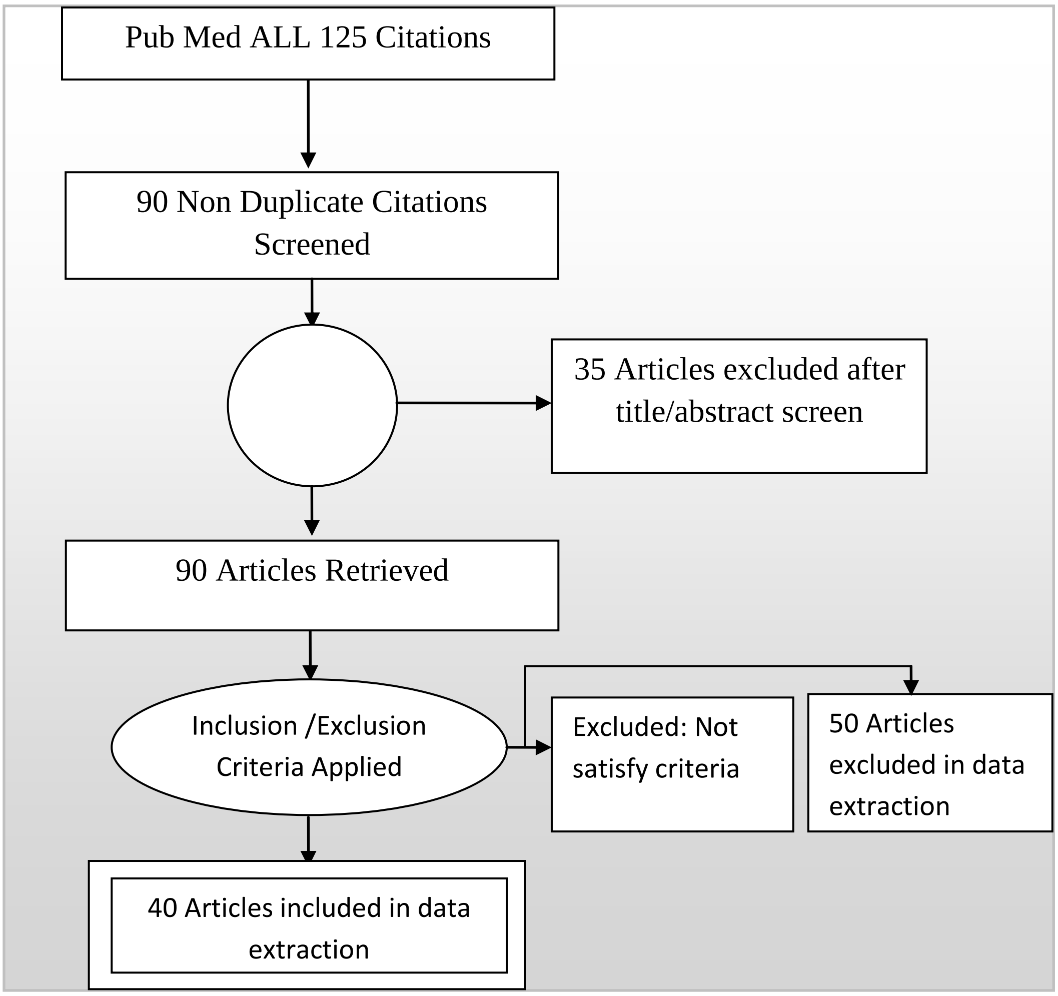

4 Data Extraction and Synthesis

The extracted information from the studies includes the problem, methods, source of data, and major contributions that were used in establishing NLP in health care. The forms of information that were defined to carry out this review comprise identification of studies, motivation, methods, and the results obtained. The approach used in the ontology design forms the basis for consideration in the extraction of methodology; so also the research focus, the employed techniques as well as their suggestions. The result consideration is based on NLP approach in work and application focal point research. The primary parameters that we shall cover are as follows: system name and problem attended, source of data, approach, and performance evaluation for review papers on NLP in healthcare. In *Table* 3. Mention summary of system parameters that above mentioned and contributions considered.

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Table 3. Summary of approaches and contribution considered

System & Ref.No.	Author with Year	System Name	Problem Attended	Source of Data	Approach	Level of Language Status	Performance Evaluation
System1 [35]	Wendy W Chapman , L ee M Christensen, Michael M Wagner, Peter J Haug, Oleg Ivanov, John N Dowling et. al.[2005]	Classifying free-text triage chief complaints into syndromic categories with natural language processing.	An application for classifying chief complaints into syndromic categories is presented.	800 chief complaints	Used a natural language processing text classifier	International	Accuracy = 90% precision of 0.97 and 0.96
System2 [38]	John Patrick,YefengWang,Peter Budd. [2006]	SNOMED Clinical System.	Automatic conversion of free text into a medical ontology.	Real time Data. Clinical Notes	A medical concept from the SNOMED Clinical Terminology that can be identified automatically.	International	Performance was within acceptable time and accuracy constraints.
System3 [24]	Jon Patrick , Yefeng , wang , Pater Budd . [2007]	SNOMED Clinical information Management.	To translate free text clinical notes into medical terminology and perform simple term composition.	Electronic medical record of patients	Use the core algorithm Token Matcher for mapping text to SNOMED CT terminology.	International	The system performed within acceptable time and accuracy constraints.
System4 [23]	Jagan Dara , John N owling, Debb ieTravers, Gr egory F Cooper, Wendy W Chapman. [2008]	Evaluation of preprocessing techniques for chief complaint classification.	To determine whether preprocessing chief complaints automatically classifying	28,990 chief complaints	Use of two preprocessors: 1. Chief complaint processor 2. Emergency medical	International	Accuracy =85%

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			them into syndromic categories improves classification performance.		text processor		
System5 [17]	Emilia Apostolova, David Channin, Dina Demner-Fushman, Steven L. Lytinen, Daniela Stan Raicu. [2009]	Automatic Segmentation of Clinical Texts.	This study attempts to automatically segment medical reports into semantic sections.	The dataset 215,000 free-text radiology reports	Use of the baseline algorithm and support vector classifier.	International	Accuracy=90 %
System6 [20]	HuaXu,Shane PStenner, Son Doan, Kevin BJohnson, Lemuel R Waitman, Joshua C Denny .[2010]	A medication information extraction system for clinical narratives.	The present system extracts medication information from clinical notes.	50 Discharge summaries and clinic visit notes	A medication representation model	International	F-measure = 93.2%
System7 [30]	O.Kaurova, M. Alexandrov, X. Blanco .[2011]	Classification of free text clinical narratives.	The current study aims to present SLR of academic articles on clinical text classification published from January 2013 to January 2018.	Use of 72 primary studies from 8 bibliographic databases	Use of sampling methodologies, feature engineering, machine learning algorithms, and performance measures.	International	Review paper is good in the breadth and accuracy of the discussion
System8 [25]	Kory Kreimeyer , Matthew Foster , Abhishek Pandey , Nina Arya , Gwendolyn	Natural language processing systems for capturing and standardizing unstructured	A systematic approach based on the Preferred Reporting Items for	Review of 71 different clinical NLP systems.	Query text NLP and structural data for inclusion and exclusion	International	Review paper is good in the accuracy of the discussion

	Halford , Sandra F Jones , Richard Forshee , Mark Walderhaug , TaxiarchisBotsis .[2017]	clinical information: A systematic review.	Systematic Reviews and Meta-Analyses.		criteria.		
System9 [13]	AlirezaRahimi, Siaw-TengLiaw, Jane Taggart, Pradeep Ray, Hairong Yu. [2012].	Developing Ontology for Data Quality in Chronic Disease.	Improving the data quality (DQ) of routinely gathered data for clinical care and research can help to enhance decision-making, evidence-based care, and patient outcomes.	Chronic disease data	Its ontology goes through five stages: specification, conceptualization, formalization, implementation, and maintenance.	International	In the electronic Practice Based Research Network (ePBRN), build an ontological method for developing the 3C of DQ for diabetes treatment.
System10 [27]	Mike Conway John ,N.Dowling Wendy .W.Chapman [2013]	A review of chief complaint based classifiers in North America.	Information Technology systems can use the automatic extraction of data from free text patient records to perform syndromic surveillance.	Fifteen Papers reviewed	Statistical approaches and keyword-based strategies are both employed.	International	This research examines fifteen North American systems.
System11 [19]	Hani Mowafi [1], Daniel Dworkis, Mark Bisanzo, Bhakti Hansoti, Phil Seidenberg, Ziad	A Priority for Global Emergency Care Research in Low-income Countries	The absence of research on emergency chief complaints globally—especially in low-income	Patient chief complaints	To map free-text strings to standard medical terminology, machine-based techniques	International	Propose a study agenda for chief complaints in low-resource settings.

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	Obermeyer, Mark Hauswald, Teri A Reynolds [2013]		countries.		have been designed.		
System12 [29]	Naveen Ashish [1], Lisa Dahm [2], Charles Boicey [2] [2014]	The pathology extraction pipeline for information extraction from pathology reports.	To create a system for extracting information from pathology reports with the purpose of storing the information in a research data warehouse.	Pathology reports	The method is based on machine learning algorithm (i.e. Sequence Mapping)	International	Extraction of several fields from pathology reports with excellent accuracy.
System13 [37]	Yizhao Ni [1], Stephanie Kennebeck [2], Judith W Dexheimer [3], Constance M McAneney [2], Huaxiu Tang [1], Todd Lingren [1], Qi Li [1], Haijun Zhai [1], Imre Solti [4] [2014]	Increasing the efficiency of patient identification for clinical trials in the emergency department	To develop an automated eligibility screening (ES) approach for clinical trials in an urban tertiary care pediatric emergency department (ED);	Between January 1, 2010 and August 31, 2012, we gathered eligibility criteria for 13 diseases.	Use the effectiveness of natural language processing (NLP), information extraction (IE), and machine learning (ML) techniques on real-world clinical data and trials.	International	Researchers demonstrated that NLP-, IE-, and ML-based automated ES could successfully select patients for clinical trials by utilizing the text of trial criteria and the content of EHRs
System14 [32]	Robert Bill, Serguei Pakhomov, PhD, Elizabeth S. Chen, PhD, Tamara J. Winden, MBA, Elizabeth W. Carter,	Automated Extraction of Family History Information from Clinical Notes.	This paper describes the development and evaluation of a natural language processing (NLP)	Sample of clinical notes	Use of UIMA (Unstructured Information Management Architecture) is a	International	The family history NLP system achieved F-scores of 66.9, 92.4, 82.9, 57.3, 97.7, and 61.9.

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	MS, and Genevieve B. Melton, MD, MA [2014].		module based on the Unstructured Information Management Application (UIMA) for automated extraction of family history information with functionality for identifying statements, observations, and prediction ("indicator phrases").		framework for managing unstructured data.		
System15 [21]	J. McMurray, L.ZhuI.McKillopH.Chen. [2015]	Ontological modeling of electronic health information exchange.	Ontology was designed to measure and visualize regional interoperability.	Data from a regional health system	Using Protégé 4, a knowledge-based framework and open-source Web ontology language editor	International	Ontology was designed to measure and visualize regional interoperability.
System16 [15]	Chuchu Ye , Zhongjie Li , Yifei Fu , YajiaLan , Weiping Zhu , Dinglun Zhou , Honglong Zhang , Shengjie Lai , David L Buckeridge , Qiao Sun , Weizho	A practical tool to implement hospital based syndromic surveillance.	The system discusses and examines the use of a symptom-clicking-module (SCM) as part of a hospital-based syndromic monitoring programme.	A total of 1,730,797 patient encounters were recorded by SCM.	The clinicians used SCM to keep track of all of the patients who came in, and the data was automatically compiled and transmitted	International	Accuracy=92.1%

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	ng Yang . [2016]				in daily batches. Using pre-defined criteria, the symptoms were grouped into seven targeted syndromes, and statistical techniques were used to detect temporal anomalies in the data series.		
System17 [39]	PragyaTripathi, Prof. ManjushaDeshmukh.[2017]	Building A database Driven Reverse Medical Dictionary.	The goal of the project was to create a fully complete reverse medical lexicon in order to improve the efficiency of health treatment consultations. Through an intelligent health care system, consumers can get rapid guidance on their health difficulties using a reverse medical vocabulary.	User input which is the number of symptoms. Total inputs:50	Use of three Modules divided into three parts Preprocessing, filtering and Rank.	Maharashtra	Accuracy=92 %

System18 [36]	YacineJernite, Yoni Halpern, Steven Horng, David Sontag. [2018]	Predicting Chief Complaints at Triage Time in the Emergency Department.	This study describes a method that aids in the achievement of this objective by creating an extended ontology of chief complaints and automatically predicting a patient's top complaint based on their vitals and the nurses' description of their state upon arrival.	A dataset of 97000 triage notes	Use of linear support vector machine.	International	Proposed a system for predicting a patient's main complaints based on a description of their current condition is Good enough
System19 [28]	MisaUsui , EijiAramaki, TomohideIwao , Shoko Wakamiya, Tohru Sakamoto , Mayumi Mochizuki . [2018]	Extraction and Standardization of Patient Complaints from Electronic Medication Histories for Pharmacy co vigilance.	The goal of this study was to develop a system for collecting and standardizing patient complaints from computerized medication histories gathered at a Japanese community pharmacy in order to identify potential adverse drug event (ADE)	A data set of 5000 patient complaints	Use of search rules on morphological analysis and speech.	International	System performance was .66 regarding precision, .63 in recall, and .65 for the F-measure.

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			signals.				
System20 [34]	.Steven Horng , Nathaniel R Greenbaum , Larry A Nathanson , James C McClay , Foster R Goss, Jeffrey A Nielson . [2019]	Modern Ontology of Emergency Department Presenting Problem.	Numerous attempts have been made to create a standardized "presenting problem" or "chief complaint" list to characterize the nature of an emergency department visit.	A total of 180,424 patient visits were included in the study	Use of Hierarchical Presenting Problem ontology.	International	Ontology successfully captured structured data for 95.9%.
System21 [14]	BarathiGaneshHb, U. Reshma, SomanKp, M. Anand Kumar. [2020]	Natural Language Understand for Medical Texts.	Natural Language Understanding is one of the essential tasks for building clinical text-based applications	Digital data in the form of clinical reports	Vector space models are used, as well as sequential modeling jobs.	National	performance of 93.8% as F1 score for i2b2 clinical corpus and achieves 97.29% as F1 score for GENIA corpus
System22 [26]	Li Qing ,WengLinhong and Ding Xuehai. [2019]	Neural Network-Based Method for Medical Text Classification.	The approach creates sentence representations by combining two or more sentences. Dividing the document into segments and then combining them into a document representation	Use of medical records	Use of Neural Networks.	International	In this research researcher suggest a novel hierarchical neural network method for medical text classification. Accuracy = Good
System23 [40]	Justin F. Rousseau,Iva	Automated Retrieval of	Compare documentati	Electronic Health	Observational study	International	Analysis Study

	n K. Ip,Ali S. Raja,Vladimir I. Valtchinov,LailaCochon,Jeremiah D. Schuur,RaminKhorasani.[2019]	Data from Emergency Department.	on of relevant clinical information in electronic health record (EHR) provider note to computed tomography (CT) order requisition, prior to ordering of head CT for emergency department (ED) patients presenting with headache.	records	performed between April 1, 2013 and September 30, 2014 at an adult quaternary academic hospital		Accuracy=90 %
System24 [22]	Jackson M Steinkamp,WasifBala , Abhinav Sharma , Jacob J Kantrowitz . [2020]	Task definition, annotated dataset, and supervised natural language processing models for symptom extraction from unstructured clinical notes.	Machine learning (ML) and natural language processing have great potential to improve information extraction (IE) within electronic medical records (EMRs) for a wide variety of clinical search and summarization tools.	Use of 1,108 discharge summaries.	For a clinically motivated symptom extraction task, we present a task definition and detailed annotation requirements.	International	The system is highly customizable to individual workflows and allows each user to choose which data should be structured and which should be unstructured.
System25 [16]	Edward S. Klyshinsky, V.aleriaV.ictorovnaGribova, Carina	Formalization of Medical Records Using Ontology:	Medical records contain a textual description	Use of 100 medical records	To classify clinical statements into their assigned	International	The algorithm corrects syntactical mistakes according to

	Shakhgeldyan, E. A. Shalfeeva, Dmitry Okun, Boris I. Geltser, Olesia D. Karpik [2020]	Patient Complaints.	of such important information as patients' complaints, diseases progress and therapy		categories, a rule-based technique was applied.		the hierarchical information from the ontology. The resulting algorithm was proved on 3000 clinical records
System26 [31]	Pilar López-Úbeda *ORCID,Manuel Carlos Díaz-GalianoORCID,Arturo Montejo-RáezORCID, María-Teresa Martín-ValdiviaORCID andL. Alfonso Ureña-LópezORCID. [2020]	An Integrated Approach to Biomedical Term Identification Systems.	The authors present a unique architecture for developing biomedical term identification systems.	Textual collections with clinical records	In order to construct the Biomedical NER, we used certain NLP technologies. We begin by normalizing the content, which entails: • removing punctuation, • removing HTML elements, • transforming the entire text to lowercase, and • coding it in UTF-8.	International	BSB (Buscador Semántico Biomédico—Biomedical Semantic Search Engine)is an accurate system
System27 [18]	EngyYehia, Hussein Boshnak,SayedAbdel,GaberAmany,AbdoDoaa,S.Elzanfaly – [2019]	Ontology-based clinical information extraction from physician's free-text notes.	An information extraction system that extracts structured data from handwritten clinical notes by physicians.	The system is evaluated on real clinical notes	OB-CIE system can help physicians to document visit notes without changing their workflow.	International	F-measure of 94.90% and 97.80%

System28 [33]	S. M. Meystre, GuerganaSavova , K.C. Kipper-Schuler, J.F. Hurdle. [2020]	Extracting Information from Textual Documents in the Electronic Health record: A Review of Recent Research.	Examine recent published research on information extraction from textual documents in the electronic health record in this paper (EHR).	In this review, 174 papers were chosen and discussed.	Literature review of the research published after 1995	International	Performance of information extraction systems with clinical text has improved since the last systematic review in 1995
System29 [41]	Hsin-Min Lu [1], Hsinchun Chen, Daniel Zeng, Chwan-Chuen King, Fuh-Yuan Shih, Tsung-Shu Wu, Jin-Yi Hsiao . **[2009]**	Multilingual chief complaint classification for syndromic surveillance: An experiment with Chinese chief complaints.	To ease data collection and analysis for automated syndromic surveillance, CCs must be grouped into established syndromic categories.	Using statistical approaches, a set of 470 Chinese key words was retrieved from around one million Chinese CC data.	A novel Chinese CC classification system is proposed here, based on a Chinese-English translation module and an existing English CC classification method.	International	Accuracy = 90%
System30 [42]	Zheyu WangHaoce Huang[1]Li-jun CuiJuan ChenJiye An2H. Duan3H. Ge4N. Deng [2019]	Using Natural Language Processing Techniques to Provide Personalized Educational Materials for Chronic Disease Patients in China: Development and Assessment of a Knowledge-	The goal of this project was to create a health recommender system in China that would deliver relevant teaching materials for chronic disease patients and assess its effectivenes	50 patients will be tested, and 100 educational documents will be distributed.	Ontology and numerous natural language processing (NLP) approaches were used to create a knowledge-based recommender system.	International	A novel Chinese CC classification system leveraging a Chinese-English translation module is better than other

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		Based Health Recommender System.	s.				
System31 [43]	Hsin-MinLu[a]DanielZeng[ab]LeaTrujillo[c]KenKomatsu[c]HsinchunChen[a] . [2008]	Ontology-enhanced automatic chief complaint classification for syndromic surveillance.	A new ontology-enhanced automatic CC classification approach is presented in this paper. In a medical ontology, using semantic relations	Real World Data set.	The UMLS-based Weighted Semantic Similarity Score (WSSS) grouping mechanism is used.	International	Our ontology-enhanced strategy outperforms the benchmark methods in terms of sensitivity, F measure, and F2 measure, according to this study.
System32 [44]	System32[44]	A Neuro-ontology for the neurological examination.	Based on UMLS Met thesaurus concepts, we investigated the feasibility of recording the neurological examination as machine-readable codes.	A dataset of 2386 test-cases was constructed based on 419 published neurological illnesses.	Using 1100 concepts from the UMLS Met thesaurus,	International	The Neurology Examination Ontology (NEO), which was created by combining different terminologies in UMLS.
System33 [45]	Shachi Mall, Umesh Chandra Jaiswal. [2018].	Survey of Machine Translation for Indian Languages to English and Its Approaches.	The purpose of this paper is to discuss the various methodologies used in translation systems for Indian languages to English languages.	A total of 16 research papers on the conversion of Indian languages to English have been published.	List the numerous MT approaches for converting Indian languages into other languages, as well as their advantages and disadvantages.	National	Accuracy=80 % For Indian Language Hindi. Chunk performance is improved.
System34 [46]	Jagan Dara , John N	Evaluation of Preprocessin	To see if preparing	Using two preprocessor	We preprocess	International	CCP exhibited high

	Dowling, Debbie Travers, Gregory F Cooper, Wendy W Chapman [2008]	g techniques for Chief complaints.	chief complaints before automatically categorizing them into syndromic groups improves classification accuracy.	s, chief complaints were preprocessed (CCP and EMT-P)	ed chief complaints using two preprocessors (CCP and EMT-P) and evaluated whether classification performance increased for a probabilistic classifier (CoCo)		accuracy=85 % (Chief Complaints preprocessing)
System35 [47]	MikeConway aJohn N.Dowlingb Wendy W.Chapmana [2013]	Using chief complaints for syndromic surveillance: a review of chief complaint based classifiers in North America[47]	This article examines fifteen syndromic monitoring systems in North America, including those in cities, counties, states, and the federal government.	Reviewed fifteen research papers	The studies on classifiers can be classified into two categories: statistical methods and keyword-based methods.	International	All of the systems examined can be linked to respiratory and gastrointestinal disorders.
System36 [48]	YanshanWang,LiweiWang,MajidRastegar,Mojarad,SungrimMoon,FeichenShen,NaveedAfzal,SijiaLiu,YuqunZeng,SaeedMehrabi,SunghwanSohn,HongfangLiu [2018]	Clinical information extraction applications: A literature review.	A survey of the literature for clinical data extraction applications.	There are 263 publications that have been thoroughly reviewed.	A literature search was conducted using Ovid MEDLINE In-Process & Other Non-Indexed Citations, Ovid MEDLINE, Ovid EMBASE, Scopus,	International	For title and abstract screening, a total of 1917 publications were identified. 263 articles were chosen and discussed in this evaluation from among these publications.

					Web of Science, and ACM Digital Library for publications published between January 2009 and September 2016..		
System37 [49]	B Hansoti [1 2], E Hahn [# 3], A Rao [# 3], J Harris [4], A Jenson [4], N Markadakis [4], S Moonat [4], V Osula [4], A Pousson [4] [2021]	Calibrating a chief complaint list for low resource settings: a methodological case study.	This research was done as part of a wider prospective observational study on human immune Deficiency virus testing in South African emergency departments.	Paper case report forms were used to collect data on 3357 patients.	The frequency of concordance between the coded chief complaint word and the selected symptom(s) from the pilot symptom list was determined by two members of the study team.	International	A systematic process for calibrating a chief complaint list for the local context was described in this study.
System38 [50]	M. Musa, M. Othman, Waleed Mugaheed Al-Rahimi [2014]	Ontology knowledge map for enhancing Health care services: a case of emergency unit of specialist hospital.	Offer an ontology knowledge map-based strategy for locating superfluous transactions that need to be modified in order to improve healthcare administration.	Use of Electronic Health records	We chose the Ontology as the study's base because it is thought to be capable of providing a better understanding of an organization's	National	One of the ways we recommended is to automate the emergency departments by introducing EHR systems, which will make it easier for the actors in the unit to rapidly and accurately obtain all of the

					dynamics, allowing for a good alignment between enterprise design and operation, and allowing for a systematic reengineering plan.		information they need about a patient.
System39 [51]	Gangmin Li; Haowei Song; Hai-Ning Liang; Yuanying Qu; Lu Liu; Xuming Bai . [2019]	Medical Diagnosis by complaints of patients & machine learning.	The objective is to identify a link between the patient's complaints and probable diseases.	Data set of 10,000 authoritative Medical Website	The key to detecting correlations between patients' complaints and probable diseases is to use machine learning models, as described in this research.	International	Accuracy =75% Precision=81 % Recall=81%
System40 [52]	Adel Elmessiry1, Zhe Zhang2, William O. Cooper3, Thomas F. Catron4, Jan Karrass5, Munindar P. Singh6 [2017]	Leveraging Sentiment analysis for classifying patient complaints.	The goal of this study is to automate the classification of patient complaints in order to enhance triage and response times.	Use of Electronic Health records	Using increased linguistic inquiry and a word count lexicon, map each complaint to a vector.	International	Accuracy=84 %

IV. Results and Discussion

Out of the forty (40) possible research works, nineteen (19) of the initiatives considered in the research works were methodology-based; five (05) were technique-based; three (03) were framework-based; five (05) were process-based; and eight (08) were reviews of those already in existence. In terms of the use of the Protege-owl editor tool, Protégé 4, OWL 2, OWL, and SNOMED CT, the approaches considered are ontology-based, as shown in Table 3.The main contributions include but are not limited to; modeling of protégé-based knowledge representation for linking concepts and data for diabetes diseases; mobile-based health care ontology; classification of diseases based on phenotypes, progress in service delivery and availability of reliable health data. The results of the review are

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shown in Table 4. Below, along with a graphical representation in Fig 3. It gives a summary of the quantity of studies per initiative discovered. It showed the statistics of features that attempt to improve healthcare operational processes. These features are capable of being used as the basis for techniques, frameworks, processes, methodology, and reviews.

Table 4. Summary of quantity of studies per initiative

System No.	System Name	Types of Initiative	Type of Method/Tech./Process/ Frame/Review
System1[35]	Syndromic Bio surveillance system [35]	Method	Experimental
System2[38]	SNOMED Clinical System [38]	Method	Experimental
System3[24]	SNOMED Clinical information Management[24]	Method	Experimental
System4[23]	Evaluation of preprocessing techniques for chief complaint classification[23]	Process	Process Mapping: Use of two preprocessors (CCP and EMT-P)
System5[17]	Automatic Segmentation of Clinical Texts[17]	Method	Experiment Setup: Rule Based Algorithm
System6[20]	A medication information extraction system for clinical narratives [20]	Method	Mixed Method
System7[30]	Classification of free text clinical narratives[30]	Review	Systematic Review
System8[25]	Natural language processing systems for capturing and standardizing unstructured clinical information: A systematic review [25]	Review	Systematic Review
System9[13]	Developing Ontology for Data Quality in Chronic Disease [13]	Technique	Developed an ontological toolkit to support research and quality improvement studies
System10[27]	A review of chief complaint based classifiers in North America[27]	Review	Literature Review
System11[19]	A Priority for Global Emergency Care Research in Low-income Countries[19]	Review	Systematic Review
System12[29]	The pathology extraction pipeline for information extraction from pathology reports[29]	Process	Sequence Mapping
System13[37]	Increasing the efficiency of patient identification for clinical trials in the emergency department[37]	Technique	Use of leveraging natural language processing, information extraction & Machine learning technologies
System14[32]	Automated Extraction of Family History Information from Clinical Notes[32]	Framework	Unstructured Information Management Architecture
System15[21]	Ontological modeling of electronic health information exchange [21]	Framework	Conceptual Framework
System16[15]	A practical tool to implement hospital based syndromic surveillance[15]	Process	Sequential Mapping
System17[39]	Building A database Driven Reverse Medical Dictionary[39]	Method	Experimental
System18[36]	Predicting Chief Complaints at Triage Time in the Emergency Department[36]	Method	Experimental
System19[28]	Extraction and Standardization of Patient	Method	Experimental

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	Complaints from Electronic Medication Histories for Pharmacy co vigilance[28]		
System20[34]	Modern Ontology of Emergency Department Presenting Problems[34]	Method	Classification
System21[14]	Natural Language Understand for Medical Texts[14]	Framework	Linear
System22[26]	Neural Network-Based Method for Medical Text Classification[26]	Method	Experimental
System23[40]	Automated Retrieval of Data from Emergency Department [40]	Method	Observational
System24[22]	Task definition, annotated dataset, and supervised natural language processing models for symptom extraction from unstructured clinical notes[22]	Techniques	Develop model for symptom extraction from unstructured clinical notes.
System25[16]	Formalization of Medical Records Using Ontology: Patient Complaints[16]	Method	Experimental
System26[31]	An Integrated Approach to Biomedical Term Identification Systems[31]	Framework	Modular Based
System27[18]	Ontology-based clinical information extraction from physician’s free-text notes[18]	Process	Rule Based
System28[33]	Extracting Information from Textual Documents in the Electronic Health record: A Review of Recent Research[33]	Review	Systematic Review
System29[41]	Multilingual chief complaint classification for syndromic surveillance: An experiment with Chinese chief complaints[41]	Method	Experimental
System30[42]	Using Natural Language Processing Techniques to Provide Personalized Educational Materials for Chronic Disease Patients in China: Development and Assessment of a Knowledge-Based Health Recommender System[42]	Technique	Rule Based Approach
System31[43]	Ontology-enhanced automatic chief complaint classification for syndromic surveillance[43]	Method	This paper uses two popular CC classification methods using a real-world dataset.
System32[44]	A Neuro-ontology for the neurological examination[44]	Method	Use of Ontology
System33[45]	Survey of Machine Translation for Indian Languages to English and Its Approaches[45]	Review	Review on 16 research papers
System34[46]	Evaluation of Preprocessing techniques for Chief complaints[46]	Process	We preprocessed chief complaints using two preprocessors (CCP and EMT-P)
System35[47]	Using chief complaints for syndromic surveillance: a review of chief complaint based classifiers in North America[47]	Review	Review on 15 research papers
System36[48]	Clinical information extraction applications: A literature review[48]	Review	Review 263 articles selected for review
System37[49]	Calibrating a chief complaint list for low resource settings: a methodological case study[49]	Method	Paper presents methodological strategy that can be exported to other settings to refine a local

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			chief complaint list.
System38[50]	Ontology knowledge map for enhancing Health care services: a case of emergency unit of specialist hospital[50]	Method	Method based Ontology
System39[51]	Medical Diagnosis by complaints of patients & machine learning[51]	Technique	Machine learning
System40[52]	Leveraging Sentiment analysis for classifying patient complaints[52]	Method	Vector Based

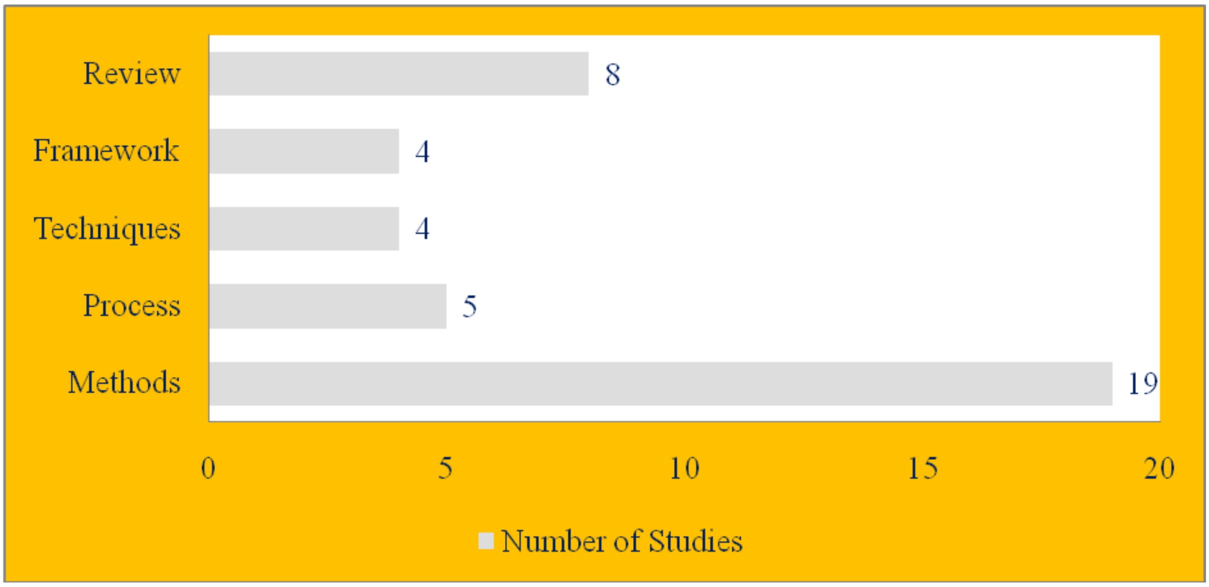

Fig. 3. Summary of quantity of studies per initiative discovered

V. Strengths

Our research offers three major advantages: First, this is the first systematic review that we are aware of that focuses on the evaluation of NLP algorithms in healthcare or clinical practice. Second, we conducted our search using a broad number of databases, yielding publications from a variety of sources, including bioinformatics, medical journals, and computer science conferences. Third, we synthesized and harmonized previous statements and guidelines to arrive at our conclusions.

VI. Conclusion

This review summarizes the known literature on the application of NLP in healthcare. It contributes by making thorough information about existing methodologies, contributions to improving the quality of health services, and limits available to researchers in the field. It also detailed the motives of individual researchers, as well as their contributions to improving health care through the application of NLP and the limitations of their studies. It was also demonstrated that different researchers in this sector used diverse techniques to improve health care using NLP. Certain methodologies, techniques, processes, and frameworks were used in certain approaches, while others were adaptations of those that already existed. The need for ontology-based models to better health service delivery for both patients and healthcare providers was revealed by this health care NLP review. This research could be used to help researchers in the field of NLP in healthcare identify gaps and areas that need to be investigated or improved. This will increase the research area's contribution even more.

References

1. Robby Gupta, Natural Language Processing in Healthcare. (2019).
2. Dahm, M. R., Tales of time, terms, and patient information-seeking behavior—an exploratory

qualitative study. Health communication, 27(7), (2012) 682-689.
3. Keifenheim, K. E., Teufel, M., Ip, J., Speiser, N., Leehr, E. J., Zipfel, S., & Herrmann-Werner, A., Teaching history taking to medical students: a systematic review. BMC medical education, 15(1), (2015) 159.
4. Wagholikar, A. S., Lawley, M. J., Hansen, D. P., & Chu, K. , Identifying symptom groups from emergency department presenting complaint free text using SNOMED CT. In AMIA Annual Symposium Proceedings (Vol. 2011, p. 1446). American Medical Informatics Association. (2011).
5. Cyrus, J. W. , A review of recent research on internet access, use, and online health information seeking. Journal of Hospital Librarianship, 14(2), (2014) 149-157.
6. Silverman, J., Kurtz, S., & Draper, J. , Skills for communicating with patients. crc press.(2016)
7. Meuter, R. F., Gallois, C., Segalowitz, N. S., Ryder, A. G., & Hocking, J., Overcoming language barriers in healthcare: A protocol for investigating safe and effective communication when patients or clinicians use a second language. BMC health services research, 15(1), (2015) 371.
8. Kreimeyer, K., Foster, M., Pandey, A., Arya, N., Halford, G., Jones, S. F., &Botsis, T. ,Natural language processing systems for capturing and standardizing unstructured clinical information: a systematic review. Journal of biomedical informatics, 73, (2017)14-29.
9. Van Rosse, F., de Bruijne, M., Suurmond, J., Essink-Bot, M. L., & Wagner, C. , Language barriers and patient safety risks in hospital care. A mixed methods study. International Journal of Nursing Studies, 54, (2016) 45-53.
10. Young, T., Hazarika, D., Poria, S., & Cambria, E., Recent trends in deep learning based natural language processing. IEEE Computational intelligence magazine, 13(3), (2018)55-75.
11. Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K. ... & Dean, J. , A guide to deep learning in healthcare. Nature medicine, 25(1), (2019)24-29.
12. Barbara Kitchenham , Procedures for Performing Systematic Reviews,1-27.(2004)
13. AlirezaRahimi, Siaw-TengLiaw, Jane Taggart, Pradeep Ray, Hairong Yu. Developing ontology for data quality in chronic disease management.(2012)
14. BarathiGaneshHb, U. Reshma, SomanKp, M. Anand Kumar- MedNLU: Natural Language Understand for Medical Texts. (2020) (PP.3-21).
15. Chuchu Ye , Zhongjie Li , Yifei Fu , YajiaLan , Weiping Zhu , Dinglun Zhou , Honglong Zhang , Shengjie Lai , David L Buckeridge , Qiao Sun , Weizhong Yang ,- SCM: a practical tool to implement hospitalbasedsyndromic surveillance.(2016).
16. Edward S. Klyshinsky, V.aleriaV.ictorovnaGribova, Carina Shakhgeldyan, E. A. Shalfeeva, Dmitry Okun, Boris I. Geltser, Olesia D. Karpik ,- Formalization of Medical Records Using Ontology: Patient Complaints Emergency Department Presenting Problems – the Hierarchical Presenting Problem ontology. (2020) (PP.143-153).
17. Emilia Apostolova, David Channin, Dina Demner-Fushman, Steven L. Lytinen, Daniela Stan Raicu. -Automatic Segmentation of Clinical Texts.(2009)
18. EngyYehia, Hussein Boshnak,SayedAbdel,GaberAmany,AbdoDoaa,S.Elzanfaly –,ontology-based clinical information extraction from physician's free-text notes.(2019)
19. Hani Mowafi , Daniel Dworkis, Mark Bisanzo, Bhakti Hansoti, Phil Seidenberg, ZiadObermeyer, Mark Hauswald, Teri A Reynolds - Making Recording and Analysis of Chief Complaint a Priority for Global Emergency Care Research in Low-income Countries.(2019)
20. HuaXu,Shane P Stenner, Son Doan, Kevin B Johnson, Lemuel R Waitman, Joshua C Denny , -MedEx: A medication information extraction system for clinical narratives.(2010) (PP 19-24).
21. J. McMurray, L.ZhuI.McKillopH.Chen.(2015) -Ontological modeling of electronic health information exchange.(PP 169-178).(2015)
22. Jackson M Steinkamp,WasifBala , Abhinav Sharma , Jacob J Kantrowitz ,Task definition, annotated dataset, and supervised natural language processing models for symptom extraction from unstructured clinical notes.(2020)
23. JaganDara , John N Dowling, Debbie Travers, Gregory F Cooper, Wendy W Chapman,Evaluation of preprocessing techniques for chief complaint classification.(2008)
24. Jon Patrick , Yefengwang , Pater Budd ,- An Automated System for Conversion of Clinical Notes into SNOMED Clinical Terminology Using Ontology's for Information Management on Electronic Clinical Records.(2007)
25. Kory Kreimeyer , Matthew Foster , AbhishekPandey , Nina Arya , Gwendolyn Halford , Sandra F Jones , Richard Forshee , Mark Walderhaug , TaxiarchisBotsis, Natural language processing systems for capturing and standardizing

unstructured clinical information: A systematic review.(2017)
26. Li Qing ,WengLinhong and Ding Xuehai ,- A Novel Neural Network-Based Method for Medical Text Classification.(2019)
27. MikeConway ,JohnN., Dowling Wendy ,W.Chapman.,- Using chief complaints for syndromic surveillance: A review of chief complaint based classifiers in North America.(734-743).(2013)
28. MisaUsui , EijiAramaki, TomohideIwao , Shoko Wakamiya, Tohru Sakamoto , Mayumi Mochizuki , Extraction and Standardization of Patient Complaints from Electronic Medication Histories for Pharma co vigilance: Natural Language Processing Analysis in Japanese.(2018)
29. Naveen Ashish, Lisa M Dahm , Charles MichealBoicey ,- Pathology Extraction Pipeline: The pathology extraction pipeline for information extraction from pathology reports.(2014)
30. O. Kaurova,M. Alexandrov,X. Blanco ,- Classification of free text clinical narratives.(2011)
31. PilarLópez-Úbeda ,Manuel Carlos Díaz-Galiano, Arturo Montejo-Ráez, Maria Teresa Martín-Valdivia. ,An Integrated Approach to Biomedical Term Identification Systems.(2020)
32. Robert Bill, SergueiPakhomov, PhD, Elizabeth S. Chen, PhD, Tamara J. Winden, MBA, Elizabeth W. Carter, MS, and Genevieve B. Melton, MD, MA , Automated Extraction of Family History Information from Clinical Notes.(2014) (PP 1709–1717).
33. S. M. Meystre, GuerganaSavova , K.C. Kipper-Schuler, J.F. Hurdle,- Extracting Information from Textual Documents in the Electronic Health record: A Review of Recent Research.(2020)
34. Steven Horng , Nathaniel R Greenbaum , Larry A Nathanson , James C McClay , Foster R Goss, Jeffrey A Nielson ,- Consensus Development of a Modern Ontology of Emergency Department Presenting Problems.(2019) (PP 409-420).
35. Wendy W Chapman , Lee M Christensen, Michael M Wagner, Peter J Haug, Oleg Ivanov, John N Dowling, Robert T Olszewski , Classifying free-text triage chief complaints into syndromic categories with natural language processing.(2005) (PP 31-40).
36. YacineJernite, Yoni Halpern, Steven Horng, David Sontag , Predicting Chief Complaints at Triage Time in the Emergency Department.(2018)
37. Yizhao Ni , Stephanie Kennebeck , Judith W Dexheimer , Constance M McAneney , Huaxiu Tang , Todd Lingren , Qi Li , HaijunZhai , Imre Solti , Automated clinical trial eligibility prescreening: increasing the efficiency of patient identification for clinical trials in the emergency department.(2014)
38. John Patrick,YefengWang,Peter Budd , An Automated System for Conversion of Clinical Notes into SNOMED Clinical Terminology. (2006) (PP 219-226).
39. PragyaTripathi, Prof. ManjushaDeshmukh, Building A Scalable Database Driven Reverse Medical Dictionary Using NLP Techniques. (2017) (pp. 1221-1231).
40. Justin F. Rousseau,Ivan K. Ip,Ali S. Raja,Vladimir I. Valtchinov,LailaCochon,Jeremiah D. Schuur,RaminKhorasani. ,Can Automated Retrieval of Data from Emergency Department Physician Notes Enhance the Imaging Order Entry Process? (2019) (PP. 189-198).
41. Hsin-Min Lu [1], Hsinchun Chen, Daniel Zeng, Chwan-Chuen King, Fuh-Yuan Shih, Tsung-Shu Wu, Jin-Yi Hsiao, -Multilingual chief complaint classification for syndromic surveillance: An experiment with Chinese chief complaints.(2009)
42. Zheyu WangHaoce Huang[1]Li-jun CuiJuan ChenJiye An2H. Duan3H. Ge4N. Deng ,Using Natural Language Processing Techniques to Provide Personalized Educational Materials for Chronic Disease Patients in China: Development and Assessment of a Knowledge-Based Health Recommender System.(2019)
43. Hsin-MinLu[a]DanielZeng[ab]LeaTrujillo[c]KenKomatsu[c]HsinchunChen[a],Ontology-enhanced automatic chief complaint classification for syndromic surveillance.(2008) (PP.340-356).
44. Daniel B. Hier &Steven U. Brint , A Neuro-ontology for the neurological examination.(2020)
45. Shachi Mall, Umesh Chandra Jaiswal,Survey: Machine Translation for Indian Language. (2018) (PP. 202-209).
46. Jagan Dara , John N Dowling, Debbie Travers, Gregory F Cooper, Wendy W Chapman ,Evaluation of preprocessing techniques for chief complaint classification.(2008)
47. MikeConwayaJohn N.DowlingbWendy W.Chapmana , Using chief complaints for syndromic surveillance: A review of chief complaint based classifiers in North America.(2013)
48. YanshanWang,LiweiWang,MajidRastegar,Mojarad,SungrimMoon,FeichenShen,NaveedAfzal,SijiaLiu,YuqunZeng,SaeedMehrabi,SunghwanSohn,HongfangLiu,Clinical information extraction applications: A literature review (2018) (PP-34-49).
49. B Hansoti [1 2], E Hahn [# 3], A Rao [# 3], J Harris [4], A Jenson [4], N Markadakis [4], S Moonat [4], V Osula [4], A Pousson [4] ,Calibrating a chief complaint list for low resource settings: a methodologic case study.(2021)

50. M. Musa, M. Othman, Waleed Mugaheed Al-Rahimi, Ontology knowledge map for enhancing health care services: a case of emergency unit of specialist hospital.(2014)
51. Gangmin Li; Haowei Song; Hai-Ning Liang; Yuanying Qu; Lu Liu; Xuming Bai ,Medical Diagnosis by \Complaints of Patients and Machine Learning.(2019)
52. Adel Elmessiry1, Zhe Zhang2, William O. Cooper3, Thomas F. Catron4, Jan Karrass5, Munindar P. Singh6, Leveraging Sentiment Analysis for Classifying Patient Complaints.(2017)

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