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NATURAL LANGUAGE PROCESSING IN HEALTHCARE

A Special Focus on Low Resource Languages

Edited by
Satya Ranjan Dash
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NATURAL LANGUAGE PROCESSING IN HEALTHCARE

As Natural (NLP) gets more and more traction in healthcare applications, there is a growing demand for developing solutions that can understand, analyze, and generate languages that humans can understand. This book showcases the current advances and scenarios of NLP-based solutions for healthcare and low-resource languages.

Natural Language Processing in Healthcare: A Special Focus on Low Resource Languages covers the theoretical and practical aspects as well as ethical and social implications of NLP in healthcare. It showcases the latest research and developments contributing to the rising awareness and importance of maintaining linguistic diversity. The book goes on to present current advances and scenarios based on solutions in healthcare and low-resource languages and identifies the major challenges and opportunities that will impact NLP in clinical practice and health studies.

This book is self-contained, comprehensive, and will be useful to researchers, academicians, technologists, and students.

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Preface

As technology enters more and more areas of our lives, including healthcare situations, there is a growing demand for developing automatic solutions that can understand, analyze, and generate languages that humans speak. The case is more challenging for the low-resource languages. Without a special focus on these languages, the quality of the processing would not be sufficient and the health care solution would not reach the majority of the population who could obtain the benefit. The goal of this book is to collect current advances and scenarios of language processing solutions for healthcare and low-resource languages. Data extracted from the clinical text and clinically relevant texts in languages other than English add another dimension to data aggregation. After years of neglect, low-resource languages (be they minority, regional, endangered, or heritage languages) have made it to the scene of computational linguistics, as increased availability of digital devices, which makes the request for digital usability of low-resource languages stronger. Much clinical information is currently contained in the free text of scientific publications and clinical records. For this reason, Natural Language Processing (NLP) has been increasingly impacting biomedical research. NLP researchers face the need to establish clinical text processing in a language other than English, and clinical informatics researchers and practitioners are looking for resources and NLP tools and techniques for their languages to speed up clinical practice and/or investigation.

The primary element in communication is information exchange. People living in less connected areas are often unable to get the kind of information they need, due to various socioeconomical and technological barriers. As a result, they miss out on crucial knowledge required to improve their well-being. Technology pervades all aspects of society and continues to change the way people access and share information, learn and educate, as well as provide and access services in the healthcare sector and others. Language is the main medium through which such transformational technology can be integrated into the socioeconomic processes of a community. NLP and speech systems, therefore, break down barriers and enable users and whole communities with easy access to information and services.

NLP is an active field of research that aims to teach computers to understand human language. Low-resource natural language processing has recently attracted much attention among NLP researchers due to its need and potential. The low-resource languages are languages that have not enough digital data to train robust NLP technologies, and as a result, few or no automated language processing systems exist for them. The research on these languages and building NLP applications for such languages can reinforce the ties between the world and ensure its diversity. The ability to analyze the clinical text in languages other than English opens access to important medical data concerning the cohorts of patients who are treated in countries where English is not the official language. This edition aims to capture NLP developments in healthcare and their applications across scientific disciplines for low-resource languages. It helps students, researchers, and professionals of the NLP community as well as interdisciplinary researchers involved in the field.

Chapter 1 describes a clinical practice by machine translation on low-resource languages. The chapter starts with the history of translation technologies that have played a vital role in the various crisis and relief scenarios as the Haitian earthquake in 2010 and Translators without Borders (TWB), respectively. The recently dissolved Standby Task Force (SBTF) deployed NLP to tackle misinformation during Coronavirus Pandemic 2019. Chapter 2 presents feature analysis and classification of impaired language caused by brain injury. Language impairment occurs from different illnesses, having a variety of causes. This focuses on the analysis of impaired language caused by a traumatic brain injury (TBI), which can vary from aphasia, apraxia, dysarthria, or other sorts of alterations. Chapter 3 represents a review of NLP for mental disorders. In this chapter, the authors provide an overview of NLP applications and datasets dedicated to address problems related to mental health. The chapter focuses on the different applications proposed, the types of data sources these applications use, and the languages they cover.

Chapter 4 presents an interesting example, healthcare NLP infrastructure for the Greek language. The infrastructure was developed initially for the processing of general language, and extended later on to incorporate biomedical texts as well. The infrastructure comprises: (a) components developed de novo to meet the needs of the domain-specific requirements, such as a biomedical corpus, a generic and application-independent medical ontology, and a multi-word term extraction mechanism, (b) general language processing tools that were enhanced for the processing of the corpus, such as tokenization and sentence splitting tools, and a lexicon-based morphosyntactic tagger. Chapter 5 deals with the recognition of medical domain multiword units (MWU) in texts written in Croatian language. The focus is on the automatic recognition of complex MWUs in low resource settings. Chapter 6 developed HealFavor, a chat-based application for healthcare which is extended with machine translation. This application is inherently designed to personalize the interaction between the user and the system. It allows the user to interact with the system as they would interact with a real-life person, and hence its design must provide real-time feedback and deliver precise decisions. Chapter 7 focuses on the development of a machine translation system for promoting the use of a low-resource language in the clinical domain. In this chapter, the authors describe the approach of developing an MT system for translating clinical text from Basque into Spanish.

Chapter 8 represents the study of various approaches proposed by researchers for detecting and extracting Adverse Drug Reactions (ADRs) from clinical reports, electronic health records, patient narratives, patient's social media queries, and posts. Chapter 9 proposes that methods for detecting fake news so far have assumed that all content in a document is deceptive; however, those texts can include truthful claims. This study shows that the performance of fake news detection can increase if the text is first automatically summarized. The summarization process removes secondary ideas from documents and deceptive claims then stand out clearer for the subsequent classification as truthful or deceptive. The classification results on datasets in Arabic and English languages show an F-measure over 92%. The last chapter presents a setting employing NLP tools to improve patient-provider secure email communication via machine translation.

Editor Biographies

Dr. Satya Ranjan Dash is a computer professional, with his research interest in machine learning, deep learning with NLP, Computational Biology, and Biomedical domain. He is currently working as an associate professor at KIIT University, India. His current research includes Natural Language Processing, particularly text summarization, topic detection, language detection, machine translation for low resource languages.

Dr. Shantipriya Parida is working as a Senior AI Scientist at Silo AI, Finland since Feb 2022. Before Silo, he was working as a post-doctoral researcher at Idiap Research Institute, Switzerland. His current research includes natural language processing, particularly text summarization, topic detection, language detection, machine translation for Indian languages, multi-modal machine translation, and corpus development for low resource Indian languages. Before Idiap, he was working as a Post-doctoral researcher with Prof. Ondřej Bojar at Charles University, Prague working on machine translation, and deep learning. He has expertise in machinelLearning, AI, computational neuroscience, product development, system/ solution architecture. He is an organizing committee member for Workshop on Asian Translation WAT2019, WAT2020, WAT2021, and WAT2022. Along with Prof. Ondřej Bojar, he organized the WAT Multimodal-Translation Task for many Indian languages (Hindi, Malayalam, and Bengali). He is part of the program committee/ organizer for many top-tier NLP conferences and workshops.

Dr. Esaú Villatoro Tello holds a tenure position at the Universidad Autónoma Metropolitana campus Cuajimalpa (UAM-C) in Mexico City. Currently, he is an academic visitor at Idiap Research Institute in Martigny Switzerland. His main research interests are related to Natural Language Processing, particularly authorship analysis, and non-thematic text categorization. He is an active member of several research groups and NLP organizations: the Language and Reasoning research Group at UAM-C, the Laboratory of Language Technologies at the National Institute of Astrophysics, Optics and Electronics, the Mexican Association for Natural Language Processing (AMPLN), the Hispano-American Network for Automatic Human Language Processing (RedHisTAL) and the Mexican Academy of Computer Science (AMEXCOMP).

Biswaranjan Acharya is an academic currently associated with Kalinga Institute of Industrial Technology Deemed to be University along with pursuing a Ph.D. in computer application from Veer Surendra Sai University of Technology (VSSUT), Burla, Odisha, India. He has received MCA in 2009 from IGNOU, New Delhi, India and M.Tech in Computer Science and Engineering in the year of 2012 from Biju Pattanaik University of Technology (BPUT), Odisha, India. He is also associated with various educational and research societies like IEEE, IACSIT, CSI, IAENG, and ISC. He has two years of industry experience as a software engineer, a total of ten years of experience in both academia of some reputed universities like Ravenshaw University and the software development field. He is currently working on research area multiprocessor scheduling along with different fields like Data Analytics, Computer Vision, Machine Learning, and IoT. He has more than 50 patents on his credit both national and international. He published some research articles in internationally reputable journals as well as serving as a reviewer.

Dr. Ondřej Bojar is a lead scientist in the field of machine translation in the Czech Republic. He works as an associate professor at the Institute of Formal and Applied Linguistics at Charles University. Machine translation has been in the center of his research interests since 2005, early in his Ph.D. studies. He has been regularly participating and since 2013 co-organizing WMT shared tasks with a specific focus on translation into Czech. His system has dominated English-Czech translation in the years 2013–2015, before deep learning and neural networks fundamentally changed the field. Ondřej's main focus now is a little broader and entails machine learning in general with explicit aims towards meaning representation and natural language understanding, including speech processing.

1 A Clinical Practice by Machine Translation on Low Resource Languages

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CONTENTS

1.1 INTRODUCTION: MEDICAL TRANSLATION

Machine Translation (MT) is a sub-field of computational linguistics that automatically translates words or phrases of one human language into another. MT is widely applied to the medical field due to the current growth in interest and success of new language technologies. Medical translation involves the communication of knowledge dealing with various specialties, such as psychology, sociology, pharmacology, psychiatry, and surgery. It is a specialized field of translation in providing healthcare assistance to minorities or foreigners. Hospitals across the country constantly require translation services to ensure fair treatment and correct diagnoses of patients' particular problems. It is crucial to clarify the aspects of an ailment with a doctor and a doctor to fully understand their treatment details. Medical translators are responsible for translating *patient records or medical-legal documents,* hospitals' informational brochures, instructions of use for the medical equipment into a second language. In addition, translators prepare medical files for patients who seek medical advice outside their country of residence. Medical translators require much attention to accurately translate various documents ranging from labels to

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TABLE 1.1
Rise of clinical text towards application

Timeline	Digitalization of Clinical Text
800 BCE to ~ 200 CE	Divine and mystical → observation and reasoning
1452–1516	Printed in Greek medical texts
1000–1800 AD	Greek and Arabic terminology by transliteration
End of 1800 AD	Local languages retaining the Græco-Latin
1964–1966	ELISA as a psychotherapist

brochures, medical and patient journals, training materials, and patents. Clinical document translation must be both medically precise and culturally sensitive. Medical professionals rely on medical translations to diagnose patients and monitor the treatment progress of their foreign-speaking patients. Translators have hand-picked clinicians and doctors who understand the content based on the first interaction with patients locally. Medical translators have related education and work experience in clinical laboratories, hospitals, community health centers, nursing homes, doctors' offices, blood donation centers, and other healthcare facilities. The misuse of medical terminology, inaccurate translation, or carelessness when translating medical reports and medical records can have serious consequences. The keys to producing a successful translation are a "lover of language, attentiveness, a hospitality to pursue mysterious terminology, and caring enough to get it exactly right".

Medical jargon is full of sequences of words and idioms, which may sound unusual in everyday speech. Scientific language is a long-standing partner for clinical research organizations. A survey of medical translators (O'Neill 1998) reported that translators are not physicians but specialize in medical translation. Furthermore, the study revealed that medical translators acquire background knowledge by joining different medical courses, studying medication, working in a situation directly or indirectly related to healthcare, or participating in medical translation courses. Translation requires more than translating phrases in one language for another, adhering to grammar rules, and choosing the appropriate register. A translator has an excellent command of both the source and target languages and needs to be very sensitive to written and implied words. In the literature, several levels are passed to reach the current medical–digital applications. They are increasingly being developed in health prevention, diagnostics, and therapy to promise great benefits and potential. Table 1.1 depicts a timeline with the corresponding rise in digitalization of clinical text.

1.2 IMPORTANCE OF MT SYSTEM AND LOW RESOURCE LANGUAGES

MT plays an essential role in a society where different languages are spoken. It removes the language barrier and digital division in society by providing access to all the local languages that a person can understand.

During the Haitian earthquake in 2010, translation technologies played a crucial role in various crisis and relief scenarios that act as disaster prevention and management. Air, land, and sea transport facilities, communication systems, hospitals, and electrical networks were damaged by the earthquake, which hampered early rescue and aid efforts. The earthquake caused an urgent need for outside rescuers to communicate with Haitians whose only language is Haitian Creole. As a result, a mobile translation program to translate between English and Haitian Creole was quickly written (Lewis 2010). Microsoft research developed a web-based English/Creole translator on the Internet, adding disaster-specific words and phrases to the database. Building a more robust system, Microsoft regularly updates more parallel sentences and phrases in the system by taking medical terminology and other emergency-type notifications and translating them into Haitian-Creole. In addition, Microsoft Translator's extensive API provides support to other software and Web sites. Developers trained an MT engine (Lewis 2010) by searching parallel data compiled by linguists (Rogl 2017), pre-translated medical terms for the rescue teams as Creole to English emergency text messages.

The Covid-19 pandemic showed that the NLP and telehealth technology are not just passing trends in the medical industry. On the contrary, Covid-19 has hit businesses like never before, and the health sector has found it very hard to cope with this sudden change in reality. However, it saw challenges and opportunities which it did not see in the last few decades. As a result, the healthcare industry has transformed rapidly in the last decade. Patient data management is now electronically managed using Electronic Health Records (EHR) or Electronic Medical Records (EMR). With the Covid-19 pandemic and its consequences of lockdowns, the medical industry took responsive measures as lucky enough to benefit from the outbreak, such as supermarkets and the home health with fitness niche. Medical translation has shaped the staggering progress and collective international effort to deal with the coronavirus outbreak made throughout 2020. Coronavirus outbreak has multiplied the logistical barriers for medical interpretation. Medical interpreters must work remotely, multiplying the challenges for front-line doctors and non-English-speaking patients. These issues are not unique to Covid-19. Recently, Ebola outbreaks in Africa and natural disasters in Haiti have seen localized problems. Those worst affected by such issues do not necessarily speak the same language as aid workers and national organizations. Thus, it makes a case for increased attention to language translation in crisis communication.

One of the most pressing challenges has been delivering health advice and guidelines to the people in their native language. However, the issue persists for people residing in different countries when they are not native speakers of the national language. The medical translation practices and translation technology allow us to close these language gaps.

1.2.1 Low Resource Language

Low-resource languages are those that have relatively fewer data available for training conversational AI systems. For example, among 7011 world languages, there are still several languages that are native to a sizable number of people but which may not have considerable amounts of data sets for training an AI model. The importance of providing accurate and human-developed low-resource translations ensures that they do not leave behind individuals with limited English proficiency in response to natural disasters for public safety. MT is currently being developed in the clinical field to improve patient-provider and patient-staff communication in multilingual clinical settings and increase access to health education resources in low-resource languages.

India is a multilingual country as most people speak and understand more than one language or dialect that uses a different script. A famous aphorism depicts India's linguistic diversity: "कोस कोस पर बदले पानी और चार कोस पर वाणी" (Every 3 km (approximately 1 "kos"), the taste of water changes, every 12 km, the language). Articles 344 (O'Neill 1998) and 351 of the Constitution of India, titled the Eighth Schedule, recognizes 22 languages as official languages of the states of India. India is home to more than 19,560 languages or dialects and nearly 97% population in the country call one language included in the 22 scheduled languages as their mother tongue. The remaining 3% speak other languages, according to the Census 2011[1]. With a 121 crore population, 121 languages are spoken by 10,000 or more people in the country.

Language is a critical element of culture and language diversity increases the cultural richness and beauty of linguistic diversity of literature from these different languages. The state of Assam is a gateway of India's North Eastern Region close to its international borders with Bangladesh and Bhutan. Assamese, recognized as an official language of Assam, a branch of Indo-Aryan language, is the easternmost Indo-European language, spoken by over 14 million speakers and serves as the lingua franca of the region. Assamese is an anglicized form of the actual name Asamiya (অসমীয়া). The sister language of Assamese are (Bengali, Maithili, and Oriya) developed from Magadhi Prakrit. The Assamese script has a total of 52 characters with 41 consonants and 11 vowels similar to the Devnagari.

1.2.2 Structure of Medical Word-Formation

Most anatomical and clinical terms used in medicine today are Latin or Latinized Greek words, the origin of which can be traced back to the fifth century BC. The physician in ancient Rome or Greece communicated in native languages. Latin was the pre-dominant language used in medicine until the 18th century. Following are a few examples of Greek and Latin prefixes and suffixes with their meaning in Table 1.2 (Fischbach 1998; DžUGANOVá 2013; Karwacka 2015; (42)). When it splits the whole term into its components, then it readily grasps the meaning. As an example, hypoglycemia broken down into hypo (below normal), glyc (sugar), and emia (blood) indicates an insufficient blood sugar level.

Medical terms are similar to learning a new language, like jigsaw puzzles. Terminologies are constructed of small pieces that make each word unique, but the pieces can be used in different combinations in other words as well (Chabner 2020). Studying medical terms analyzes the words by breaking them into parts;

TABLE 1.2

Prefixes and suffixes with their meanings

Prefix	Meaning	Suffix	Meaning
a-	absence of	-algia	pain
brady-	slow	-ectasia	dilatation
dys-	difficult	-ectomy	excision
hyper-	above normal	-emia	blood

terminology is related to the human body's structure and function, and identical pronunciation with a different meaning. The formation of medical word analysis is shown below:

- Morphological through derivation, compounding, abbreviation.
- Medical terms have pretty regular morphology, derived from Greek and Latin languages. The root words are combined with prefixes (start of a word) and suffixes (end of a word). The vowel "o" acts as a connection to the prefix to root words. Medical terms can contain multiple root words in various combinations:
    - Myocardium(মায়'কাৰ্ডিয়াম) = myo- (prefix) + card(ium) (root)
    - Endocarditis(এণ্ড'কাৰ্ডাইটছি) = endo- (prefix) + card (root) + -itis (suffix)
    - Cytology(চাইট'লজী) = cyt(o) (root) + -logy (suffix))
    - Gastroenterology(গষ্ট্ৰ'এণ্টৰে'লজি) = gastr(o) (root) + enter(o) (root) + -logy (suffix)
    - Adenoma(এডনে'মা)= aden(o) (root) + oma (suffix)
    - Hydroxynitrodihydrothymine(হাইড্ৰ'ক্সনিাইট্ৰ'ডাইহাইড্ৰ'থায়মাইন) = Hydro (root) + xy (suffix) + nitro (root) + di (suffix) + hydro (root) + thy (suffix) + mine (suffix)
    - Hydroxywybutine (হাইড্ৰ'ক্সবিডিটাইন) = Hydro (root) + xy (suffix) + wy (suffix) + butine (suffix)
- Most medical terms are compound words made up of prefixes, suffixes and may include multiple roots. Examples are blood donor, blood pressure, and blood group, etc.
- An abbreviation is a contracted form of a word or phrase such as (AIDS (এইড্ছ), HIV (এইচ.আই.ভি.), and Covid (ক'ভিড)).
- Collocation: co-occurrence or combination of words on the syntagmatic level.
    - collocations: haematostasia
    - synonymic variations: myeloproliferative syndrome→myeloproliferative disease and myeloproliferative disorder
    - forming of multi-word phrases: Coronavirus disease 2019
- Borrowing words from other languages: loan words are lexical borrowings adopted from foreign languages by root-for-root, word-for-word, or literal

translation. Some examples are chorion, diabetes, myopia, ophthalmia, pneumonia, trauma (Greek origin), femur, humerus, occiput, mandible, puncture, pulp (Latin origin), and diarrhea, diphtheria, disease, dislocation, malaise (French origin)
- Clipped words occur after discarding either the final (exam**ination**:পৰীক্ষা), beginning (**uni**versity:বিশ্ববিদ্যালয়), central (**in**flu**enza**: ফ্লু) or end part (polio**myelitis**: পলিঅ’).

1.2.3 Difficulties of Medical Translation

Most people without a medical education do not understand the meaning of some typical sentences (text has its definition) written as Triage notes. The sentences do not have a subject due to those not being grammatically correct. Doctors annotate concisely by using a lot of jargon. These are the typical sense of the word but not considering a different language. NLP practitioners have the responsibility for cleaning these texts by using off-the-shelf NLP libraries and algorithms.

Consider the example of de-identified triage notes for deciphering taken from emergency room visits.

- States started last night, upper abd, took alka seltzer approx 0500, no relief. nausea no vomiting
- Since yesterday 10/10 constant Tylenol 1 hour ago. +nausea. diaphoretic. Mid abd radiates to back
- Generalized abd radiating to lower × 3 days accompanied by dark stools. Now with bloody stool this am. Denies dizzy, sob, fatigue.

Sentences have different semantics: “Sob” might be shortness of breath, different grammar: “since yesterday 10/10” (10/10 refers to the intensity of pain), and diverse vocabulary (abdominal can be abd).

1.3 APPROACHES TO BUILDING MT SYSTEM

MT solutions for the healthcare industry can broadly be categorized into rule-based, statistical, and neural types similar to usual MT categories. The evolution of MT is depicted in Table 1.3. Early Rule-based MT (RBMT) language experts manually

TABLE 1.3
Evolution of machine translation

Timeline	Evolution of MT
1950–1980	RBMT
1980–1990	EBMT
1990–2015	SMT
2015–Till Date	NMT

crafted many rules to translate one language into another language. It relies on sophisticated built-in linguistic rules, millions of bilingual dictionaries for each language pair, and extensive lexicons with morphological, syntactic, and semantic information. These rules were applied to the input text and generated the translation of the target texts. Users can improve translation quality by adding terminology into the translation process by creating user-defined dictionaries, which override the system's default settings. A quality RBMT system is computationally expensive due to training time and ongoing improvement of the system.

A significant development in MT happened in the 1990s when companies like IBM started to leverage statistical models that significantly improved translation quality. The corpus-based Statistical Machine Translation (SMT) approach to learning by automatically searching sentences and translating them into the target language. SMT searches for patterns in a large number of parallel texts able to assign the probability of a sentence from the target language being the translation of another sentence from the source language. Building an SMT system requires a massive number of parallel corpora between source and target languages at the sentence level. The quality of SMT extensively depends on the language pair of the specific domain being translated. The corpora building can often be challenging in the healthcare industry. There is a massive variation in named entities such as diseases, chemical compounds, active ingredients, gender, symptoms, dosage levels, dosage forms, route of administration, date, location, location-species, and adverse reaction. SMT technology is CPU intensive and requires an extensive hardware configuration to run translation models at a satisfactory performance quality. So, companies began to experiment with hybrid MT engines, which commonly combined SMT with RBMT. These advancements popularized MT technology and helped adoption on a global scale. The current state of the art in MT technology is Neural Machine Translation (NMT) harnesses the power of Artificial Intelligence (AI) and uses neural networks to generate translations. Language translation technology is continuously changing, bringing new functionalities and more significant benefits to the medical industry. The end-to-end training paradigm of NMT is the powerful modeling capacity of neural networks that can produce comparable or even better results than traditional MT systems. NMT uses a single large neural network to model the entire translation process, freeing the need for excessive feature engineering and employing continuous representations instead of discrete symbolic representations in SMT.

An encoder-decoder network is quite successful in different Recurrent Neural Network (RNN) variations in NMT consisting of two components: an encoder that consumes the input text and a decoder that generates the translated output text (Wolk and Marasek 2020). The encoder extracts a fixed-sized dense representation of the different length input texts. The task of the decoder is to generate the corresponding text in the destination language based on this dense representation from the encoder (Bahdanau et al. 2014; Cho et al. 2014). In 2017, MT made another technological breakthrough in NMT with the advent of transformer model (Vaswani et al. 2017) which is a state-of-the-art model for neural MT (Wu et al. 2016; Lakew et al. 2018; Wang et al. 2019). The model uses self-attention to speed up the training with significantly more parallelization. It follows the architecture of the

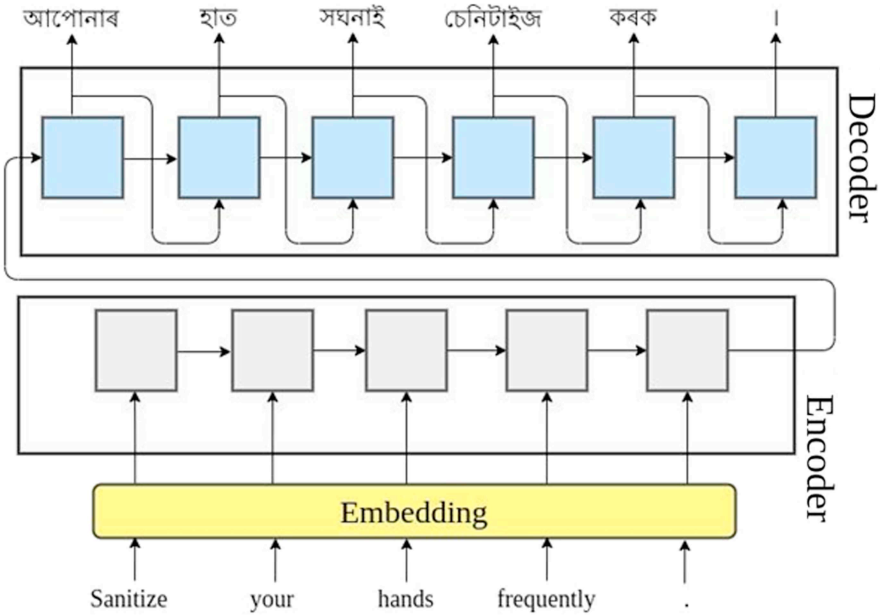

FIGURE 1.1 Schematic diagram of medical-text translation.

encoder-decoder model by using stacked attention and point-wise fully connected layers for both the encoder and the decoder. The encoder can work on the input sequence in parallel and the decoder is auto-regressive. Previous output symbols influence each output and output symbols are generated one at a time (Figure 1.1). Several works in MT, especially in the health domain on low resource languages, are summarized in Table 1.4 below.

Since the application scenarios and markets for MT are extensive, many companies and organizations in different parts of the world are making attempts to build their own MT systems. Very few of them have focused on the medical and pharmaceutical industry, perhaps because of its tremendous difficulty in translation and high information security requirements. The professional translators convey the original tone and intent, considering cultural and regional differences between source and target languages. Professional medical translation services with the localization industry can help healthcare professionals make more informed decisions regarding treatments or medical procedures. As the English language has not been widely used for official communication in Assam, professional Assamese translation services can help them capture the healthcare industry. The trustworthy translation services (Integrated Language Solutions[2], Translation agency[3], PEC Attestation, Apostille & Translation Services India Pvt. Ltd.[4], Shakti Enterprise[5], Somya Translation Pvt. Limited[6], Linguainfo Language Translation Company[7], TRIDINDIA[8], and Honey Translation Services[9]) specifically related to medical and healthcare professionals supported by Assamese and other Indian languages save the lives of human beings.

TABLE 1.4
Major MT works on medical domain in low resource languages

Article	MT Approach	Evaluation/Key Findings
Zeng-Treitler et al. (2010)	RBMT	Babel Fish not adequate for medical records
Ruiz Costa-Jussà et al. (2011)	RBMT/SMT	SMT better than RBMT
Wu et al. (2011)	SMT	Best results of German, French, and Spanish
Dwivedi and Sukhadeve (2013)	RBMT	English-Hindi MT system for Homoeopathy.
Patil and Davies (2014)	SMT	GT not reliable for medical communication
Liu and Cai (2015)	Hybrid/SMT	GT performed better than hybrid system
Limsopatham and Collier (2015)	SMT	Map media messages to medical concepts
Wołk and Marasek (2015)	NMT	Comparison of SMT-NMT on Polish-English
Arcan and Buitelaar (2017)	NMT	Translating highly domain-specific expressions.
Khan et al. (2018)	NMT	Transfer learning by initializing parameters of NMT.
Skianis et al. (2020)	NMT	Generic, language-independent medical terminology translation

1.4 LEARNING TRANSPARENCY FOR PATIENT

It is essential to provide proper care to the patient. We can enhance the patient experience as it is always an epicenter of what technology evolved in the medical field by keeping patients' empathy in the heart, which is the best experience. Nowadays, people are more worried about their quality of care by moving to various doctor's chambers. The value-based care providers can create a care gap or performance report compared with a peer provider or government agency that enhances the value-based model. NLP can impact the patient experience and also value-based care. A patient can schedule the doctor's appointments online and prepare a form for the next day while staying away or sitting at home. In free-text clinical notes, much pertinent information for making correct predictions and recommendations is only available in healthcare. The free-text documents in the unstructured form are trapped enormously. NLP is a significant part of accumulating data from professional documents and clinical notes. The NLP is the primary use to transform the free (unstructured) text in documents and databases into normalized (structured) text. The structured data were suitable for analysis needed to make healthcare decisions that drive machine or deep learning algorithms. Horng et al. (2017) illustrate the benefit of extracting vital sign data and free text data to identify patients speculating of a life-threatening infection. These investigations used NLP to extricate data from the clinical text. Electronic health records (EHR) have become more prevalent across hospitals by implementing inpatient or ambulatory EHR systems.

Several MT systems for mobile or web applications facilitating doctor-patient communication have been built for low and under-resourced languages. Ahmad et al., (Musleh et al. 2016) developed a real-world Hindi-English SMT system for doctor-patient communication.

As healthcare advances to evolve to a more patient-oriented approach, patient expectations and demands will significantly push electronic communication. Many patients interested in using e-mail or other social media to communicate with their doctors are interested in receiving online health information from their doctor's office. For increasing numbers of providers and patients, Web messaging linked to a patient EHR is likely to become the preferred communication channel for routine clinical communications. A potential drawback of Web messaging is that it provides a less robust means of communication. Audio-video recordings allow patients to share information with caretakers and family members accurately. Experts agreed that one of the most significant benefits of recording visits is improving patients' recall and understanding of their medical conditions. Web messaging can be optimally integrated into healthcare delivery to improve safety, quality, and efficiency.

1.5 EVALUATION PROCEDURE AND METRIC ON MEDICAL DOMAIN

The evaluation of MT systems is important since its results show the degree of output reliability and are exploited for system improvements. Some freely available commercial software has implications of incorrect medical translation due to limitations in quality and considering ethnic diversity (Zeng-Treitler et al. 2010; Taylor et al. 2015; Anastasopoulos et al. 2021). There are many types of automated translation technology in the marketplace that can help automate the medical translation process. At times it becomes difficult for the translator to find exact words while translating because they have never heard of the new terms or esoteric expressions. An automated service was not a great fit for specific disaster vocabulary. The automatic translations hampered the Covid-19 response in some areas shown negatively impact communities of individuals with limited English proficiency during natural disasters. For example, in 2017, an automatic translation of a wildfire notice in California's Ventura county mistranslated the word "brush fire" using the Spanish word for "hairbrush" in place of "brush".

An inadequate translation in the medical field or misplacing of a word by a nonprofessional can lead to tragedy and cost a massive amount in medical malpractice compensation. In 2007, 47 patients had gone through a second knee replacement operation due to inaccurate translation. The translator translated the phrase "non-modular cemented" as "without cement" or "non-cemented", resulting in painful methods that needed months of recovery. In 1980 at Florida hospital, Willie Ramirez ended up quadriplegic because a certified medical interpreter in Oregon translated the Spanish word "intoxicado" as "intoxicated" which means "ingested something" (Spanish). A slight mistranslation can lead the healthcare practitioner down the wrong path, although they realize that a mistake was made, which may be difficult to backtrack in later stages.

Unlike general translations, medical translations should be done by highly-qualified translators who possess tremendous knowledge in the specific field. The quality of the text depends on sound medical knowledge and personal interest in the text.

Many anatomical and clinical terminologies that persist in medicine today are Latin or Latinized Greek words. These words can be traced back to the golden age of Greek civilization during the fifth century BC. Microsoft announced that Microsoft Translator would help users translate conversations, street signs, websites, and documents to Assamese language and vice-versa.

Evaluating the quality of MT requires an automatic method as human evaluation would be highly time-consuming and cost-inefficient to be evaluated. The criteria of translation quality are its adequacy and fluency. The most common evaluation metric is BiLingual Evaluation Understudy (BLEU) (Papineni et al. 2002). Given a human-generated reference sentence with a corresponding translated sentence, it calculates a score by comparing *n-gram* overlap. Two separate translators can not produce identical translations for the same sentence in the same language pair. A set of several rounds of iterations are required for fulfilling the client's requirement. Automated translations find difficulties in interpreting contextual and cultural elements of a text and quality is dependent on the type of system and how it has been trained.

The adequacy, fluency measures the effectiveness of a translation. Adequacy expresses meaning from the source language to the target language. Fluency measures the grammatically well-formed and ease of interpretation of the sentence (idiomatic word choices). Different word choices and changing the word order that conveys the same meaning is the challenge of evaluating translations for a sentence.

BLEU, a corpus-based metric, calculates the automatic quality score for MT systems that estimate the correspondence between a translated output and a human reference translation (Papineni et al. 2002). The primary notion of BLEU is closer to a professional translation with its machine-translated output. BLEU counts the number of matches by comparing the *n-gram* of the candidate translation with the *n-gram* of the reference translation. The more matches, the better the translation quality, where matches are independent of their positions.

A low BLEU score means a high mismatch. A sequence of words or tokens occurring within a given window (where n is window size) is known as n-gram. A perfect match and mismatch result in a score of **1.0** and **0.0**, respectively. A translation that possesses exact words as in the references (more than one reference translation) satisfies the adequacy. The longer n-gram matches between reference and candidate translation tend to capture fluency. A BLEU score runs on a scale from **0** to **1**. The score is expressed as percentages rather than decimals (turned into a **0** to **100** scale) for better readability.

Mathematically, the BLEU score formula consists of two parts: the brevity penalty (BP) and the n-gram overlap are shown in the following Equation (1.1).

$$BLEU = BP.\ exp \sum_{n=1}^{N} w_n log p_n \tag{1.1}$$

where $BP = \{1,\ if\ c > r e^{\left(1-\frac{r}{c}\right)},\ if\ c \leq r$ and $P_n = \frac{\sum\sum Count\,(n-gram)}{\sum\sum Count\,(n-gram)}$

The brevity penalty (BP) penalizes the BLEU score if the candidate sentence is shorter than the reference sentence. BP compensates for the possibility of high precision translation that is too short. Here **c** is the total number of unigrams

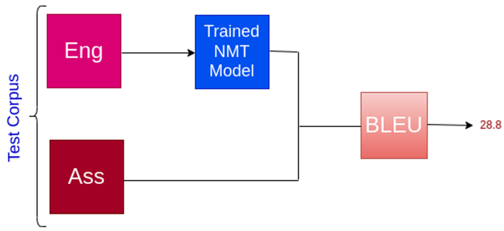

FIGURE 1.2 Schematic diagram of evaluation.

(length) in all the candidate sentences, and **r** is the sum of effective reference sentence length for each candidate sentence in the corpus. The two essential characteristics of translation are adequacy and fluency captured by the modified n-gram precision $\mathbf{p_n}$ score. $\mathbf{w_n}$ is n-gram precision weight. BLEU uses the value of **N** as 4. The number of word count for each candidate to its associated maximum reference count is a clip. Figure 1.2 depicts an evaluation process of the MT system using an automated evaluation matric BLUE. The test corpus of English(Eng)-Assamese(Ass) shows a dummy score of 28.8 for English to Assamese translation.

An example of reference sentence and its several translated (candidate) outputs from English (source) to Assamese (target) are illustrated here. The n-gram match (length) between candidate translation and the given target reference is shown at the end of each candidate translation.

Source Text: Wearing a face mask is compulsory in all public places.
Target Text: সকলো ৰাজহুৱা স্থানত মুখা পিন্ধাটো বাধ্যতামূলক।
Candidate1: মুখা পৰিধান কৰাটো এক বাধ্যতামূলক নিয়ম। (2-gram)
Candidate2: মুখৰ মুখা পিন্ধাটো বাধ্যতামূলক। (3-gram)
Candidate3: ৰাজহুৱা ঠাইত মুখা পিন্ধাটো বাধ্যতামূলক কৰা হৈছে। (4-gram)
Candidate4: সকলো ৰাজহুৱা স্থানত মুখৰ মুখা পিন্ধাটো বাধ্যতামূলক। (5-gram)

Nowadays, close derivatives of BLEU (METEOR, NIST, LEPOR, and F-Measure) are often used to compare the quality of different MT systems in enterprise use settings. Researchers worked on evaluating medical terminologies by SacreBLEU, BLEU, METEOR, and TER metrics as well. Skianis et al. (2020), attempted to develop a first baseline translation from English to French on numerous medical terminologies and datasets leveraging SMT and NMT present promising results for the (International Classification of Diseases) ICD11 classification (Skianis et al. 2020).

1.6 CURRENT TECHNOLOGIES

This section discusses the current state-of-the-art of MT technologies in clinical practices, healthcare, and medicine. Further, we investigate additional recent innovations in technology that can leverage the language industry within healthcare.

In 2010, deep neural network-style machine learning methods became widespread in natural language processing and achieved state-of-the-art results in many tasks. It is increasingly important in healthcare and medicine, where NLP is being used to analyze text and notes in electronic health records.

Different state-of-the-art deep learning techniques such as healthcare-specific named entity recognition models, word embeddings, and entity resolution models can extract clinical data from text. The improved methods of collecting high-quality data and advancements in the machine (deep) learning models fueled a new wave of healthcare practices. An EHR essentially stores patient records in unstructured and structured formats. To create a more intelligent healthcare system in which the best treatment decisions are computationally learned from electronic health record data by deep-learning methodologies. International technology giants like Google, Microsoft, IBM, and Amazon are all keen on developing MT. Since Google launched the NMT system in 2016, the improvement of the quality of MT has achieved more attention and interest from all other NLP tasks.

The transformer is a new type of neural network model that emerged in 2017 based on self-attention. The transformer model replaced previously dominated RNN (its variations are LSTM/GRU) and become a state-of-the model in MT and many other NLP tasks. Compared to RNN, transformers have much higher computational efficiency and can efficiently exploit the modern parallel hardware (GPU/TPU). It allows training on much larger models on a massive amount of data. The transformer framework overcomes the bottleneck in which the recurrent neural network model cannot be calculated in parallel. Many NMT engines produce sporadic errors while training the system. The popular approach in deep learning is pre-trained models which have been previously trained on large datasets. A pre-trained transformer model by fine-tuning can further improve performance, requiring fewer data and computational resources. It might help in the medical translation in low-resource languages.

The highly lexicalized nature of languages causes sensitivity of domain shift in the NMT system. One solution is lexicon induction to obtain an in-domain lexicon and construct a pseudo-parallel in-domain corpus. The in-domain monolingual target corpus use word-by-word back translation for constructing the synthetic parallel in-domain corpus (Edunov et al. 2018; Hu et al. 2019). Furthermore, applying a pseudo-in-domain corpus with fine-tuning, a pre-trained out-of-domain NMT model called the unsupervised adaptation method is another explanation. Domain adaptation in MT can be applied when a large amount of out-of-domain data co-occur with a small amount of in-domain data (Soares and Becker 2018). A domain adaptation experiment containing a medical domain with the lexicon inclusion performs an acceptable accuracy in low resource language NMT. NMT with automated customization using domain-specific corpora say the medical domain is known as domain adaptation in MT (Arcan and Buitelaar 2017).

Intento[10] evaluated six domain adaptive NMT systems for English-to-German translation using biomedical corpora[11] of several sizes (from 10K to 1M segments) and evaluated them compared to stock MT engines. It was a breakthrough moment in MT, probably the biggest one since the invention of NMT.

A word in a sentence is often related to multiple domains that indicate its domain preference. The word in a distributed representation possesses embedding by mixing domain proportions from different domains. In a transformer architecture for different domains, carefully designing dot-product multi-head attention modules can achieve effective domain knowledge sharing in multi-domain NMT (Zeng et al. 2018).

A technique most commonly used in NMT, especially in a low resource language, is transfer learning, which falls under domain adaptation. Transfer learning is the process where a child model in one language pair (in-domain data) is trained by transferring the knowledge learned from an existing parent model in another language pair (out-of-domain data). By initializing the parameters in NMT from the previous model, an increase in training accuracy on out-of-domain and multiple in-domain datasets has been achieved for biomedical corpora (Khan et al. 2018; Peng et al. 2019).

Advanced models are used to predict hospital and professional billing codes for administrative cost reduction and billing process improvements using deep learning techniques (Joo et al. 2021). The rare words can not be translated correctly by a conventional NMT system. These are called out-of-vocabulary (OOV). NMT replaces these OOV as <unk> tokens that do not have any information. <unk> (unknown words) are unique words that cannot be translated into the target token during generation. So the possibility of a loss of translated information. A lexicon of biomedical vocabulary, MedDRA (Bo et al. 2007), is used for semantic disambiguation model to solve <unk> problem (Liu et al. 2020).

The roadblocks to bringing medicine into the data-driven period are cultural and operational. It is time to safely bring huge medical data repositories and advanced learning algorithms together with physicians to make a deep-learning healthcare system. Deep learning, the newest iteration of machine learning methodologies, is now performing at state-of-the-art levels in previously difficult tasks such as language processing, information retrieval, and forecasting. India is home to many native languages that become linguistic diversity in a multilingual country with a growing population. Multilingual challenge with multilingual technology. A study from Google (Johnson et al. 2017) showed that using multilingual data when training NMT systems can improve translation performance, especially when using a many-to-one scheme.

The Covid-19 pandemic has shown the need for multilingual access to hygiene and safety guidelines and policies (Zeng-Treitler et al. 2010). A Multilingual Neural Machine Translation (MNMT) can be employed to translate biomedical text (O'Brien and Federici 2019). A large number of domain tags from generic and biomedical data use to train the MNMT system (Bérard et al. 2020).

1.7 CONCLUSION

Medical translation is a crucial factor in disseminating new knowledge and discoveries in the medical field. Still, it can also be a critical factor in the provision of global and foreign health services.

It cannot deny the need for machine-translated content in healthcare. Its credibility and increased use of social media during Covid-19 pandemic can only be expedited with more robust training data for learning the model (O'Neill 1998).

The traditional approaches for translating text are time-consuming and require a series of labor-intensive levels. Because of the inefficiency and expense of conventional translation, companies and agencies are looking for faster, cost-efficient, and better performance in terms of accuracy. The neural MT with transformer model has been using a state-of-the-art method and architecture for MT. Language technologies have been steadily advancing to deliver high-quality translated documents that can be used for official purposes.

Covid-19 is posed the history's biggest translation challenge because it not only involved translating one or a small number of primary languages in a single region but also on a scale of thousands of languages across the world. Several crowd-sourced translation projects spread the knowledge to fight Covid-19 to healthcare workers worldwide[12].

In medicine, there is no room for mistakes and errors, which is a challenge for translators. Different language technologies and advanced methods can overcome that. In the not-too-distant future, MT will be capable of translating a text in the biomedical domain at the required quality. It will improve patient monitoring, which will improve patient outcomes. Now, the machine is acting as the rescuer in medicine in day-to-day life.

NOTES

1 https://censusindia.gov.in/2011Census/C-16_25062018_NEW.pdf
2 https://www.integratedlanguages.com/
3 https://translation.agency/
4 https://pecattestation.com/
5 http://www.shaktienterprise.com/
6 http://www.somyatrans.com/
7 https://linguainfo.com/
8 https://www.tridindia.com/
9 http://www.honeytranslations.com/
10 https://inten.to
11 https://ufal.mff.cuni.cz/ufal_medical_corpus
12 https://covidtranslate.org

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